Item Response Theory Models

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MACS 40500: Computational Methods for American Politics

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Lecture Outline

Our Guiding Question

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How can we measure something we know exists and influences observed behavior, but we can't directly observe?

Challenges in Estimating Ideal Points via NOMINATE

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- Does not enable incorporation of auxiliary information

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- IRT was designed to solve this problem

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- How does ideology inform voting behavior in legislatures?
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- Recovering SCOTUS ideology from case decisions
  - *Attitudinalism*
  - If this theory is correct, then we should be able to look at SCOTUS decision records and recover some measure of ideology

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- Thus, the measures from IRT are *not atheoretic*, which limits *how* they can be used
  - We can't measure assuming some theory is true, and then use that measure to test the theory (e.g., $Y \rightarrow Y$)

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- The intuition: we look at a bunch of cases of different types of decisions, and then pick latent characteristics of people and their decisions that are most consistent with the observed patterns we see in their decisions
- Theoretically similar to MLE

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- By implication, the greater that distance, the more you benefit from saying yes or no (positive or negative, respectively)

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- If the result is positive, then you have a greater chance of making *yea* decision; if *negative*, then you have less chance of making yea decision

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- Thus, we are interested in calculating predictions of being over or below that line

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- **Another Solution**: in multiple parameters models (e.g., 2PL), we set a few representative actors as fixed values to anchor the latent scale, which allows for *relative* locations which solves the identification problem

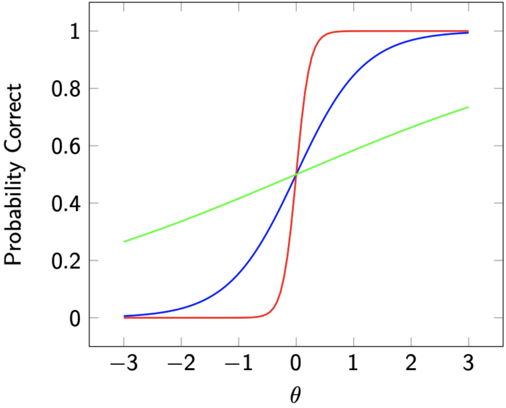
2PL

$$P(y_i = 1|\theta;\beta) = \frac{exp(D(\theta - \alpha))}{1 + exp(D(\theta - \beta))}$$

where

- θ is the ability (latent trait)
- α is the item discrimination parameter
- β is the item difficulty parameter
- D is a scaling factor, where set to ≈ 1.7 results in the logistic model behaving like standard normal case (thus you sometimes see the Rasch model as $P(y_i = 1|\theta;\beta) = \Phi(\theta - \beta)$)

2PL: Difficulty & Discrimination



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- IRT models involve the joint estimation of parameters: **difficulty** (1PL) and **discrimination** (2PL)

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- Thus, the ICC connects or links the subject's probability of success on an item to the trait measured by the set of test items

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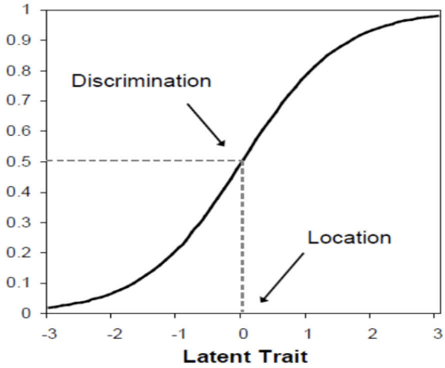

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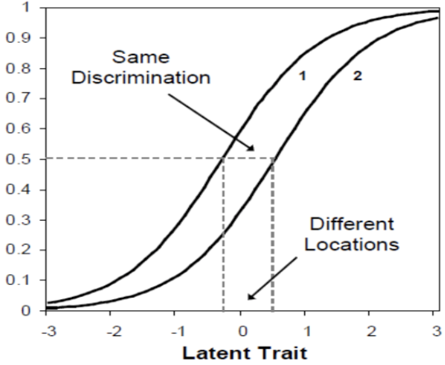

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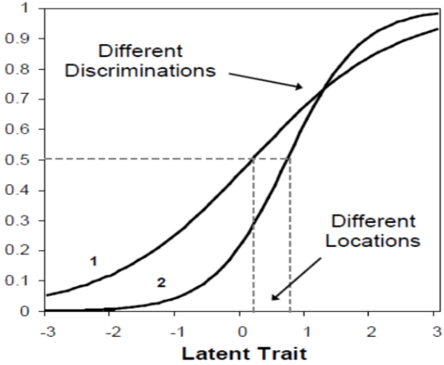

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- Data we see are the product of a single trial of repeatable experiment

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- Using Bayes' rule, we update beliefs about the parameter values, conditional on the data we get to see

An Example: The Linear Model

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- How can we estimate this model?
- OLS, ML, Bayesian
- if Gauss-Markov holds $[X'X]^{-1}X'y$ is BLUE

A Maximum Likelihood Approach

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- We maximize $\mathcal{L}(\cdot)$ with respect to the parameters to get ML estimate
- Which parameter values were most likely to have produced the observed data?
- We recognize that our parameter estimates are based on a single sample, so we use the sampling distribution to compute standard errors

A Bayesian Approach

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- We summarize that posterior distribution to calculate quantities of interest

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$$\mathcal{L}(\beta, \sigma^2 | y) \propto \mathcal{P}(y | \beta, \sigma^2) = \prod_{i=1}^{n} \phi\left(\frac{y_i - x\beta}{\sigma}\right) \times \mathcal{P}(\beta)\mathcal{P}(\sigma^{-2}) \tag{4}$$

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- $\mathcal{P}(\beta)$ is multivariate normal density and $\mathcal{P}(\sigma^{-2})$ is a Gamma density
- The idea is that we generate a posterior by combining the likelihood and multiplying it by the prior

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- Our prior is a uniform distribution $\mathcal{P}(\theta) = 1$ for $0 \leq \theta \leq 1$
- Our likelihood is $\mathcal{P}(\theta|y) \propto \left(\begin{array}{c} 10 \\ 7 \end{array} \right) \theta^7 (1-\theta)^3$

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- Classification is preferred in circumstances where there are low error rates and where the distribution of the errors is unknown
- If the error rate is too small, the parametric methods push ideal points to the edges of the space to maximize the log-likelihoods

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- There is a set of fixed legislators to identify the model
- This means we can estimate a 2PL model on the roll call matrix and interpret the results in terms of spatial voting as it relates to any proposal
- In sum, there are many ways to estimate these models: MCMC (`ideal()`): time consuming, but can derive the *complete* posterior; EM (`emIRT()`): fast, but requires bootstrapping to get standard errors because we are *approximating* the posterior; or even MLE

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- Estimates are only as good as the model, e.g.,
  - *Strategic voting*: all models assume elites are voting on their locations relative to cut point line
  - But *if* elites don't vote according to their own preferences, but based on all kinds of things like logrolling, etc., then we could get misleading estimates of ideal points
  - In other words, can't predict Y with Y

Lecture Outline

Coming Up

- Thursday: Application in `R` – SCOTUS Case Decisions