GOV 2001/ 1002/ E-200 Section 11
Choice Modeling and Future Directions in Methods[1]

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[1] These section notes are heavily indebted to past Gov 2001 TFs for slides and R code.

LOGISTICS

Reading Assignment- UPM Chapter 8, Glasgow et. al., 2012

Final Paper Due April 27th at 5:00 pm. But with automatic extensions to May 5th at 5:00 pm.

Final Exam (for E-school students not doing the paper) Released on April 27th. You will "check out" the exam on Canvas any time during exam period. After check-out, you will have 1 week to finish. The final deadline is May 14th at 5:00 pm.

Fill out the RSVP for the party on May 7th! We only have 4 respondents so far!

OVERVIEW

- In this section you will...

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    - learn how to model choice data

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  - learn how latent space models work.
  - learn how to generalize from an unrepresentative sample.
  - learn how to think about learning methods beyond this course!

OUTLINE

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- Systematic component:

$$\pi_{ij} = \frac{\exp(\eta_{ij})}{\sum_{k=1}^{K} \exp(\eta_{ik})}$$
$$\eta_{ij} = X_i \beta_j$$

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- How many parameters are we estimating? $J - 1 \times$ length of β.
- Likelihood $L(\beta|X, Y)$:

$$\propto \prod_{i=1}^{N} \prod_{j=1}^{J} \pi_{ij}^{Y_{ij}}$$

$$\propto \prod_{i=1}^{N} \prod_{j=1}^{J} \left[\frac{\exp(\eta_{ij})}{\sum_{k=1}^{K} \exp(\eta_{ik})} \right]^{Y_{ij}}$$

$$\propto \prod_{i=1}^{N} \left[\prod_{j=1}^{J-1} \left[\frac{\exp(X_i \beta_j)}{1 + \sum_{k=1}^{K-1} \exp(X_i \beta_k)} \right]^{Y_{ij}} \times \left[\frac{1}{1 + \sum_{k=1}^{K-1} \exp(X_i \beta_k)} \right]^{Y_{iJ}} \right]$$

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- Ratio of choice probability of category 1 to 2 does not depend on any other category:

$$\frac{\pi_{ij}}{\pi_{ik}} = \frac{\frac{\exp(\eta_{i1})}{\sum \exp(\eta_{ik})}}{\frac{\exp(\eta_{i2})}{\sum \exp(\eta_{ik})}} = \frac{\exp(\eta_{i1})}{\exp(\eta_{i2})} = \frac{\exp(X_i\beta_1)}{\exp(X_i\beta_2)}$$

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  - New probs: $Pr(\text{Car}) = .5$, $Pr(\text{Red Bus}) = Pr(\text{Blue Bus}) = .25$. $\frac{Pr(\text{Car})}{Pr(\text{Red Bus})} = \frac{.5}{.25} = 2 \neq 1$

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Z_j are covariates for alternative j and γ are estimated coefficients.

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OUTLINE

Choice Models

Ideal Point Models

Modern Survey Sampling

Learning more methods

Latent Space Modeling

European Parliament. Photo by David Iliff. License: CC-BY-SA 3.0

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- Simple metrics like % agreement miss important variation in agenda.

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- **Goal:** Infer latent ability/preferences from observed outcomes (test questions/votes).
- Starting point for poli-sci: Clinton, Jackman, Rivers (2004) "The Statistical Analysis of Roll Call Data" APSR.

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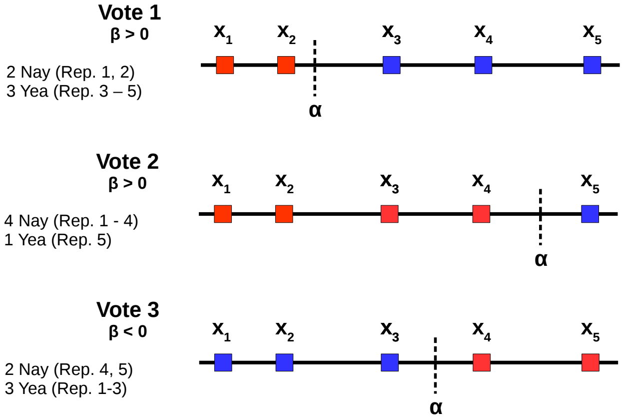
IRT Example

Figure: Example of latent space model with no voting error



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- More simply - it's just a hard likelihood to maximize!

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  - MCMC methods repeatedly take draws from these conditionals. Markov chain theory tells us that this converges to drawing from the true posterior!

What IRT models can show us.

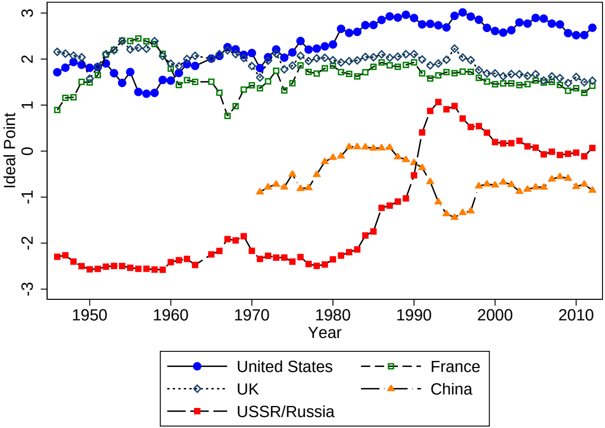

Figure: Dynamic ideal point estimates of P5 countries from UNGA voting - Voeten et. al. (2015)

OUTLINE

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  - Step 4: Calculate weights for your observations such that the (weighted) sample distributions of covariates match the population distributions.

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- **Intuition:** Upweight observations that are rare relative to population. Downweight observations that are common.

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  - Step 4: Repeat across all of the variables in sequence until convergence (no change in weights).

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  - E.g.: Don't just learn "text analysis," learn how to think about high-dimensional data where $p >> n$.

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    - More complex examples: instrumental variables, regression discontinuity

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  - I can write down a really complicated model... but it's useless if I can't estimate it!
  - I can get a really efficient estimate of some regression parameter... but if I want to claim causality, it's useless if I can't also argue that it identifies a causal parameter of interest.
- **Main Takeaway:** Think first in terms of what you need to better argue from your data, then go out and find what you don't know.

Questions

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