Switching Regressions and Strategic Reasoning: Estimating Mixture Probabilities

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Why Mixture Models?

The major puzzle

Congress must delegate to agencies in order to achieve policy goals. The empirical record of this relationship is mixed; studies suggest that agencies are minimally controlled and unresponsive.

- When is political control of agencies manifest?
- Given that agencies hold private information, how do we describe the unobservable dimension of agencies?

Conditional manifest control of Congress

• From Shipan (2004), a model of delegation

Figure 1: Unicameral Model of Delegation

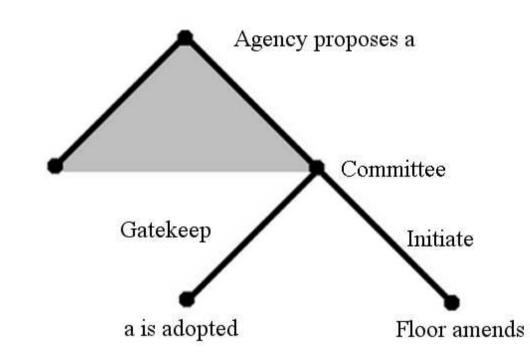


Figure 2: Sub game Perfect Equilibrium by Agency Ideology

Committee-Floor	Gatekeeping	Floor
C(F)	А	F
C	(F) C I	

Unobserved Heterogeneity

Table 1: Marginal effect of shifts in ideology on outcomes, known Agency position

	ΔC	ΔA	ΔF
$\overline{A > C(F) > F}$	+	0	-
C(F) > A > F	0	+	0
C(F) > F > A	0	0	+

Why mixtures models?

- Allows for a flexible interactive structure
- Ideology measures (e.g. Nominate) have no counterpart for agencies

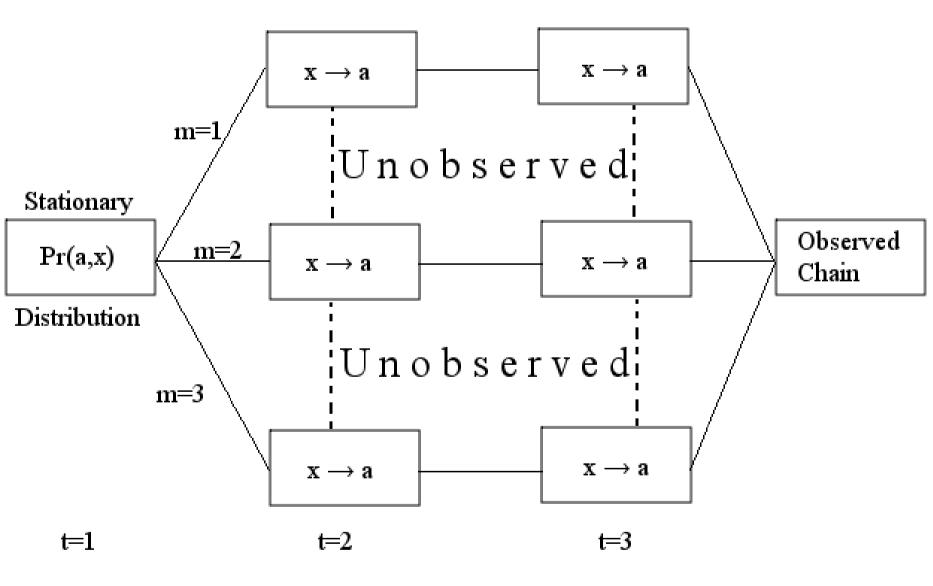
Regimes and Mixtures

- A basic model was first described by Goldfield and Quandt (1979), for two regimes (analogous to mixtures).
- Hamilton (1989) adapted Expectation Maximization algorithms to time-series problems, assuming a Markov process.
- This project implements a non-parametric mixture model with discrete actions from Kasahara and Shimotsu (Econometrica, 2009, hereafter KS).

Assumptions

- Number of mixtures, $M \ge 2$
- Discrete actions, A
- Covariates which inform the actions, $x_t = \xi, \xi = \{1, ..., M 1\}$
- Markov process, $x_t = f(x_{t-1}, a_{t-1})$
- Observations are panels, with N panels, observed $T \ge 3$ times

Figure 3: Discrete Dynamic Markov Process



Identification

The probability of any observed panel

$$P(\{a_t, x_t\}_{t=1}^T) = \sum_{m=1}^M \pi^m p^{*m}(x_1, a_1) \prod_{t=2}^T f(x_t)$$

Observable information (actions and covariates) is used to create

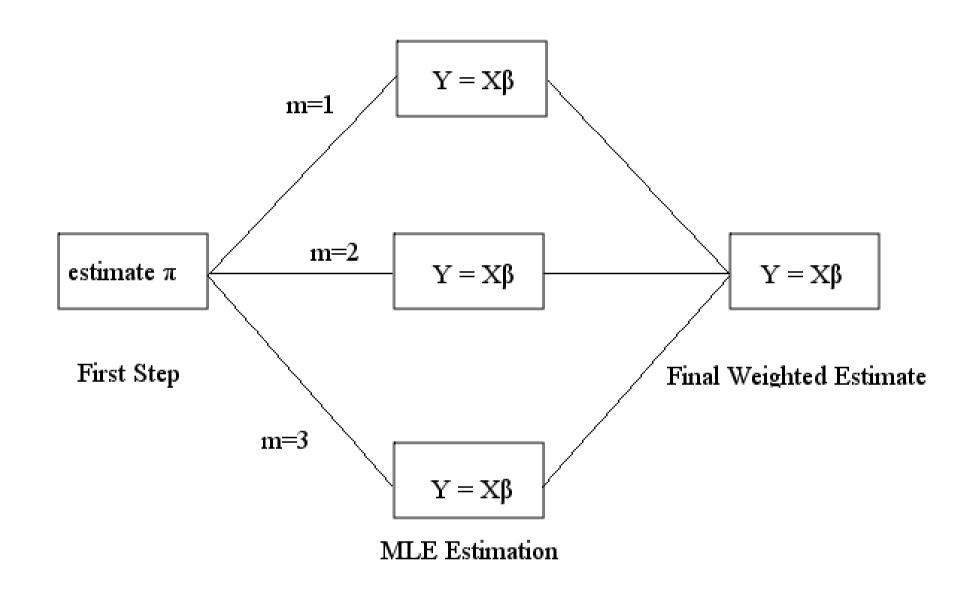
$$\tilde{P}(\{a_t, x_t\}_{t=1}^T) = \frac{P(\{a_t, x_t\}_{t=1}^T)}{\prod_{t=2}^T f(x_t | x_{t-1}, a_{t-1})},$$

and the differences in the actions due to the covariates are used to identify mixture probabilities.

How is it done?

Semi-parametric MLE

The KS non-parametric estimator for π^m can be used as weights for a mixture model which can be optimized with MLE.



Standard errors for π^m and β_m can be generated by means of non-parametric bootstrapping.

Take away points

- Intra-panel variation is a strong source of identification. – Adding additional agencies produces information efficiently.
- More variation is better. - Every combination of action and the covariates should be visited.
- Use this method to inform parametric or semi-parametric empirical models.
- Need new forms of data to accurately capture necessary variance.
- number of agencies must be studied quantitatively.



 $r_t | x_{t-1}, a_{t-1}) P^m(a_t | x_t)$

What does it mean?

 $MLE_{mixture} = \operatorname{argmax} ln(\pi_1 N(y - x\beta_1, \sigma_1^2) + \pi_2 N(y - x\beta_2, \sigma_2^2) + \pi_3 N(y - x\beta_3, \sigma_3^2))$

Figure 4: MLE Estimation Using π^m

– MLE is very easy after you have the π_m , and very hard with out it.

– Most studies of agencies currently focus on highly detailed records of a few agencies.

– Because the relationship between a few agencies and Congress varies relatively little, a larger

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