

# Latent Class Models for Multivariate Categorical Data

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## Motivation: High-Dimensional Categorical Data

- ▶ We observe categorical vectors:

$$X = \left( X^{(1)}, \dots, X^{(m)} \right), \quad X^{(r)} \in \{1, \dots, C_r\}.$$

- ▶ The joint distribution has  $\prod_{r=1}^m C_r - 1$  parameters (exponential in  $m$ ).
- ▶ How do we model high-dimensional categorical data efficiently, without estimating an enormous joint table?

## Latent Class Model

Introduce a discrete latent variable  $H \in \{1, \dots, K\}$  and assume

$$X^{(1)}, \dots, X^{(m)} \perp\!\!\!\perp | H.$$

Then

$$P(X = x) = \sum_{k=1}^K P(H = k) \prod_{r=1}^m P\left(X^{(r)} = x^{(r)} \mid H = k\right), \quad \forall x \in \mathcal{X}.$$

Parameters:  $\pi_k = P(H = k)$ ,  $\theta_{rkc} = P(X^{(r)} = c \mid H = k)$ .

Dimension reduction:  $(K - 1) + \sum_{r=1}^m K(C_r - 1) \ll \prod_{r=1}^m C_r - 1$ .

Fit the model using EM algorithm.

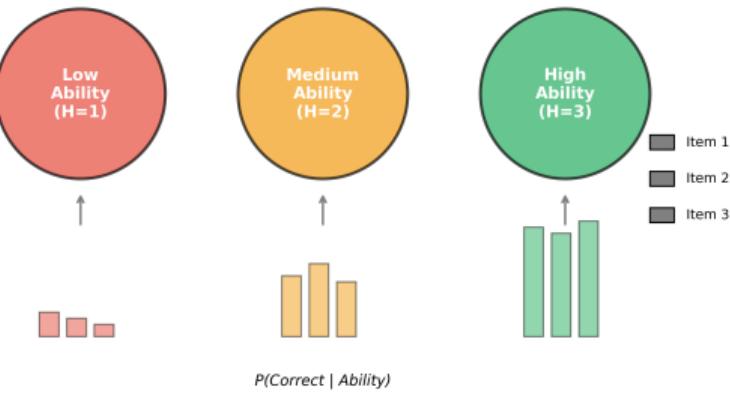
# Psychometrics / Educational Testing

## Observed Responses (3 binary items)

Student	$X^{(1)}$	$X^{(2)}$	$X^{(3)}$
1	1	1	0
2	1	0	1
3	0	0	0
4	1	1	1

$$X = (X^{(1)}, X^{(2)}, X^{(3)}), \quad X^{(r)} \in \{0, 1\}.$$

## Latent Ability Groups



Latent ability groups ( $H = 1, 2, 3$ ):  
Low / Medium / High ability

$$P(X = x) = \sum_{k=1}^K P(H = k) \prod_{r=1}^3 P(X^{(r)} = x^{(r)} \mid H = k).$$

# Statistical Computing Principles

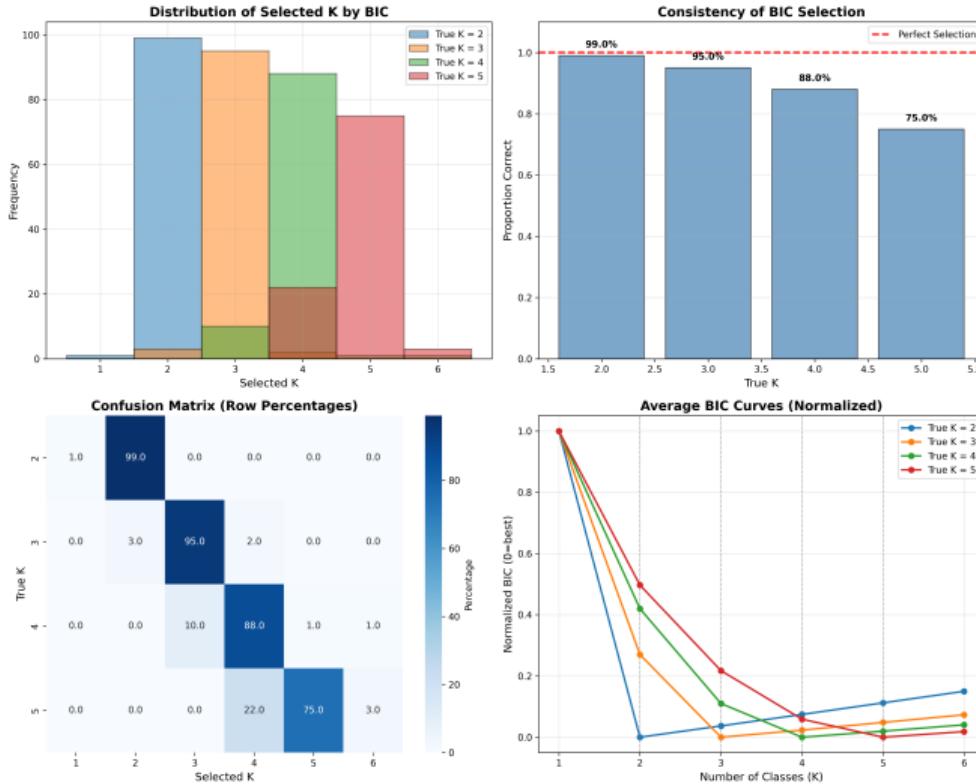
## **Techniques from the course applied in this project:**

- ▶ Vectorization of probability updates.
- ▶ Parallelization for Monte Carlo simulation studies.
- ▶ Log-sum-exp for numerical stability.
- ▶ Modular Python structure (initialization, fit, predict).
- ▶ Makefile.

# Structure of the Solution

1. **Define the latent class likelihood** (complete-data + observed-data versions).
2. **Implement EM algorithm** – Functions for E-step, M-step, log-likelihood, convergence check.
3. **Random initialization strategy** – Multiple starts to avoid poor local optima. – Label-switching mitigation via class ordering.
4. **Model selection loop over  $K$**  – Fit model for  $K = 1, \dots, K_{\max}$ . – Track log-likelihood paths and BIC values.

# Progress So Far



(BIC vs  $K$  from simulation. The jupyter notebook is here.)

# Remaining Work

The ultimate goal is to develop an end-to-end statistical software.

- ▶ **Simulation Studies**
  - ▶ Parameter estimation in different configurations.
- ▶ **Software Packaging**
  - ▶ Create a clean module + README.
  - ▶ Makefile.
  - ▶ Unit tests for key steps.