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Overview of models

Overview of models

The following tables provide an overview of the specified models and their main assumptions, with model extensions/changes highlighted in **bold**. For every model, the observed data are assumed to be complete (i.e., no missing data).

Model	Latent class memberships	Dependent variable	Constant & trend component ¹
1	constant, no explanatory variables	continuous, Normal, iid errors	pooled model, linear
2	constant, no explanatory variables	continuous, Normal, iid errors	pooled model, quadratic
3	constant, no explanatory variables	count , Poisson , iid errors	pooled model, linear
4	constant, no explanatory variables	count, Poisson, iid errors	pooled model, quadratic

Table 1: Overview of specified models

¹for each class

General notation

General notation

Latent class (aka, mixture component) c , for $c = 1, \dots, C$, where C is the number of classes

Individual n , for $n = 1, \dots, N$, where N is the number of individuals

Time period t , for $t = 1, \dots, T$, where T is the number of time periods

\mathbf{Y}^{obs} is a $N \times T$ matrix representing the observed dependent variable, where *obs* refers to simulated or actual data

\mathbf{X} is a matrix of size $N \times T$ representing the explanatory variable (e.g., time periods, starting at zero)

Model 1

Model 1 — latent class memberships

Constant over time periods (i.e., an individual does not switch between classes)

No explanatory variables incorporated to estimate the probability of an individual belonging to a certain class

Model 1 — dependent variable

Continuous

Normal (aka, Gaussian)

iid errors: independent (aka, uncorrelated) and identically distributed errors over individuals and time periods; however, the standard deviation of the errors is allowed to vary between classes

No missing data

Model 1 — constant and trend component

Constant without interindividual differences within-class (i.e., the constant is allowed to vary between classes but not within classes)

Linear (i.e., non-stationary, deterministic) trend component without interindividual differences within-class (i.e., the trend component is allowed to vary between classes but not within classes)

Based on Koop (2003), the assumption of no interindividual differences within-class regarding the constant and trend component correspond to a pooled model (i.e., a pooled model for each class)

Model 1 — likelihood

Based on Basturk (2010):

$$p(\mathbf{Y}^{obs} | \boldsymbol{\lambda}, \mathbf{M}, \boldsymbol{\sigma}) = \prod_{n=1}^N \sum_{c=1}^C \lambda_c \prod_{t=1}^T \text{Normal}(\mu_{c,n,t}, \sigma_c), \quad (1)$$

where $\boldsymbol{\lambda}$ is a row vector of size C representing the mixture proportions, averaged over individuals; thus,

$$0 \leq \lambda_c \leq 1 \quad \text{and} \quad \sum_{c=1}^C \lambda_c = 1. \quad (2)$$

Furthermore, \mathbf{M} is a C -tuple containing $N \times T$ matrices, and $\boldsymbol{\sigma}$ is a row vector of size C .

Model 1 — likelihood — continued

$$\mu_{c,n,t} = \beta_{0,c} + \beta_{1,c} x_{n,t}, \quad (3)$$

where β_0 is a row vector of size C representing the constant. Furthermore, β_1 is also a row vector of size C , and $\beta_{1,c} x_{n,t}$ represents the linear trend component. In order to solve the identification problem caused by label switching, either

$$\beta_{0,c} < \beta_{0,c+1} \quad (4)$$

or

$$\beta_{1,c} < \beta_{1,c+1} \quad (5)$$

defines a labelling restriction (Koop, 2003; Stan Development Team, n.d.).

Model 1 — deduction of likelihood

The latent discrete parameter z_n in $\{1, \dots, C\}$ indicates that individual n belongs to class c :

$$z_n \sim \text{Categorical}(\boldsymbol{\lambda}), \quad (6)$$

where \mathbf{z} is a column vector of size N . Therefore, the likelihood presented in equation 1 is deduced by marginalizing out z_n :

$$\begin{aligned} p(\mathbf{Y}^{obs} | \mathbf{z}, \boldsymbol{\lambda}, \mathbf{M}, \boldsymbol{\sigma}) &= \prod_{n=1}^N \prod_{c=1}^C \left(\lambda_c \prod_{t=1}^T p(y_{n,t}^{obs} | z_n, \mu_{c,n,t}, \sigma_c) \right)^{\mathbf{1}(z_n=c)} \\ &= \prod_{n=1}^N \sum_{c=1}^C \lambda_c \prod_{t=1}^T p(y_{n,t}^{obs} | \mu_{c,n,t}, \sigma_c) \\ &= \prod_{n=1}^N \sum_{c=1}^C \lambda_c \prod_{t=1}^T \text{Normal}(\mu_{c,n,t}, \sigma_c), \end{aligned} \quad (7)$$

where $\mathbf{1}(z_n = c)$ defines an indicator function.

Model 1 — log likelihood

Recall the likelihood presented in equation 1:

$$p(\mathbf{Y}^{obs} | \boldsymbol{\lambda}, \mathbf{M}, \boldsymbol{\sigma}) = \prod_{n=1}^N \sum_{c=1}^C \lambda_c \prod_{t=1}^T \text{Normal}(\mu_{c,n,t}, \sigma_c). \quad (1)$$

On the log scale, the likelihood is given by

$$\begin{aligned} & \log p(\mathbf{Y}^{obs} | \boldsymbol{\lambda}, \mathbf{M}, \boldsymbol{\sigma}) \\ &= \sum_{n=1}^N \log \sum_{c=1}^C \exp \left(\log \lambda_c + \sum_{t=1}^T \log \text{Normal}(\mu_{c,n,t}, \sigma_c) \right). \end{aligned} \quad (8)$$

Model 1 — prior

$$\boldsymbol{\lambda} \sim \textit{Dirichlet}(\boldsymbol{\alpha}), \quad (9)$$

where $\boldsymbol{\alpha}$ is a row vector of size C representing a hyperparameter. Furthermore, $\alpha_c = 1$ (i.e., $\boldsymbol{\lambda}$ is assigned a proper flat prior).

$$\beta_{0,c} \sim \textit{Normal}(\beta_{0,c,\mu}, \beta_{0,c,\sigma}), \quad (10)$$

where $\beta_{0,c,\mu}$ and $\beta_{0,c,\sigma}$ are hyperparameters.

$$\beta_{1,c} \sim \textit{Normal}(\beta_{1,c,\mu}, \beta_{1,c,\sigma}), \quad (11)$$

where $\beta_{1,c,\mu}$ and $\beta_{1,c,\sigma}$ are hyperparameters.

$$\sigma_c \sim \text{Normal}(0, \sigma_{c,\sigma}) \mathbf{1}(\sigma_c > 0), \quad (12)$$

where 0 and $\sigma_{c,\sigma}$ are hyperparameters. The Normal distribution is truncated to the left at zero, modeled via the indicator function $\mathbf{1}(\sigma_c > 0)$.

Model 1 — posterior for z_n

$$Pr(z_n = c | \mathbf{y}_n, \boldsymbol{\lambda}, \mathbf{M}_n, \boldsymbol{\sigma}) = \frac{\lambda_c \prod_{t=1}^T \text{Normal}(\mu_{c,n,t}, \sigma_c)}{\sum_{k=1}^C \lambda_k \prod_{t=1}^T \text{Normal}(\mu_{k,n,t}, \sigma_k)}. \quad (13)$$

On the log scale, the posterior for z_n is given by

$$\begin{aligned} & \log Pr(z_n = c | \mathbf{y}_n, \boldsymbol{\lambda}, \mathbf{M}_n, \boldsymbol{\sigma}) \\ &= \log \lambda_c + \sum_{t=1}^T \log \text{Normal}(\mu_{c,n,t}, \sigma_c) \\ & - \log \sum_{k=1}^C \exp \left(\log \lambda_k + \sum_{t=1}^T \log \text{Normal}(\mu_{k,n,t}, \sigma_k) \right). \end{aligned} \quad (14)$$

Equation 14 corresponds to the softmax function calculated on the log scale (Stan Development Team, n.d.).

References

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