

# Revisiting Rogers and Castros multi-exponential models for migration estimation

UoROS2020

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## Migration age schedule: Why is important?

- ▶ It describes the migration age pattern associated to selectivity as an interaction of push and pull factors in origin-destination areas.
- ▶ It allows visual comparisons about the intensity and the migrant population general structure.

## Rogers and Castro model 1981

- ▶ It estimates a migration schedule based on exponential curves that belong to a demographic behaviour.
- ▶ Give us some demo-economic parameters.
- ▶ Other alternatives are kernel smothing (in case of under-5 child over estimation suspicion) and non parametrical parameters based on the curves.
- ▶ Ohter definitions: post-retirement (Wilson, 2020)
- ▶ Other options: non-parametric measures based on the form (Bernard, 2013).

# Uses

- ▶ Some countries still need methods to smooth migration and grasp the mean behaviour of the migration calendar.
- ▶ There are opportunities to use it in estimation children under 5 years old. P. e. When empirical data shows it historically. (!!)
- ▶ Population projections.

# Migration parameters

Multi-exponential model:

$$M(x) = a_1 e^{-\alpha_1 x} + a_2 e^{-\alpha_2(x-\mu_2) - e^{-\lambda_2(x-\mu_2)}} + a_3 e^{-\alpha_3(x-\mu_3) - e^{-\lambda_3(x-\mu_3)}} + a_4 e^{\lambda_4 x} + c$$

- 7,9,11 y 13
- $M(x)$ : Standardized age rate  $x$ .
- $\mu_2, \mu_3$ : Location parameters.
- $a_1, a_2, a_3, a_4$ : Levels and equation coefficients.
- $\alpha_1, \lambda_2, \alpha_2, \lambda_3, \alpha_3, \lambda_4$ : Demo-economic descriptions.
- **Ratios:**
  - $a_1/a_2$ : Dominant labour curve
  - $a_2/a_1$ : Infant dependency indicator
  - $\lambda_2/\alpha_2$ : Labour curve asimetry

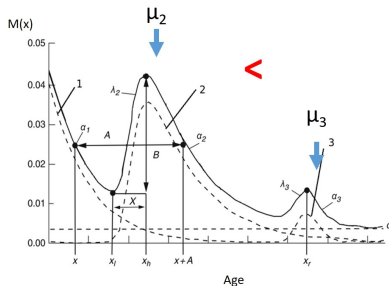
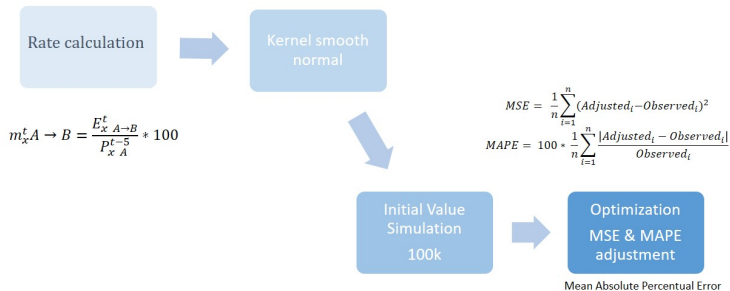


Figure 1: Based in Rogers and Castro, 1981

# Procedure



# migraR package

elflacosebas Update README.md		93a2e38 on 3 Sep	🕒 133 commits
📁 .Rproj.user/E68A6BE5	new commit for update and check spelling		3 months ago
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📄 .gitignore	attempt to define well the functions		3 years ago
📄 DESCRIPTION	new commit for update and check spelling		3 months ago
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📄 build.R	new commit for update and check spelling		3 months ago
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README.md



## migraR

R package for migration analysis focused now on the Rogers and Castro multi exponential model and the estimation of the parameters using a simulation based on uniform a priori distributions for each parameter between 0 and 1, and 0 to 100 in the case of the location parameters corresponding to ages in the migration pattern.

More information: <https://github.com/elflacosebas/migraR>

# Example

```
# Calling packages and dataset.

library(migraR)
library(dplyr)
library(tidyverse)

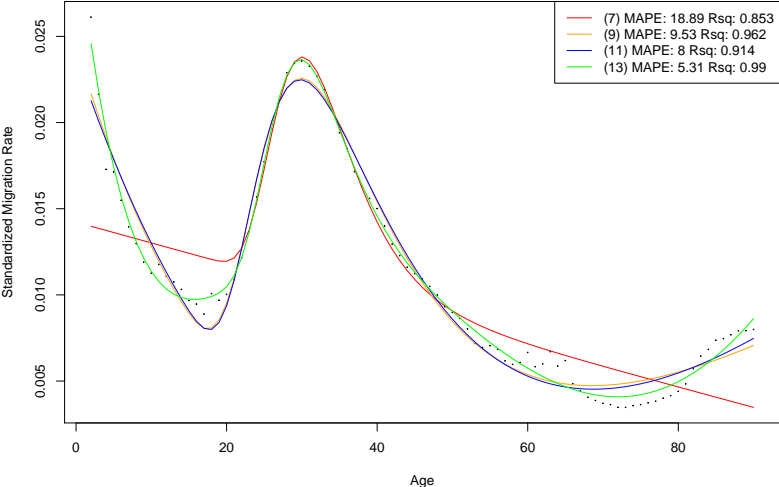
data("es_asmr")
data1 <- es_asmr[-c(1,2),c(1,6)]
colnames(data1) <- c("x","y")

# Fitting and Plotting data
fitted.val.7 <- best_migramod(dataIn = data1, maxite = 200, profile = "seven")
fitted.val.9 <- best_migramod(dataIn = data1, maxite = 200, profile = "nine")
fitted.val.11 <- best_migramod(dataIn = data1, maxite = 200, profile = "eleven")
fitted.val.13 <- best_migramod(dataIn = data1, maxite = 200, profile = "thirteen")

x11()
plot(data1, cex=0.1, xlab = 'Age',
      ylab = 'Standardized Migration Rate')
lines(data1[,1], fitted.val.7$modelClass$value(fitted.val.7$bestParam,data1), col="blue")
lines(data1[,1], fitted.val.9$modelClass$value(fitted.val.9$bestParam,data1), col="orange")
lines(data1[,1], fitted.val.11$modelClass$value(fitted.val.11$bestParam,data1), col="blue", lty=3)
lines(data1[,1], fitted.val.13$modelClass$value(fitted.val.13$bestParam,data1), col="green")
legend('topright',
      legend = c(paste("(7)", "MAPE:", round(as.numeric(fitted.val.7$bestMAPE),2),
                    "R2:", round(as.numeric(fitted.val.7$bestRcuad),3)),
                paste("(9)", "MAPE:", round(as.numeric(fitted.val.9$bestMAPE),2),
                    "R2:", round(as.numeric(fitted.val.9$bestRcuad),3)),
                paste("(11)", "MAPE:", round(as.numeric(fitted.val.11$bestMAPE),2),
                    "R2:", round(as.numeric(fitted.val.11$bestRcuad),3)),
                paste("(13)", "MAPE:", round(as.numeric(fitted.val.13$bestMAPE),2),
                    "R2:", round(as.numeric(fitted.val.13$bestRcuad),3))),
      col = c("red", "orange", "blue", "darkgreen"), lty = c(2,6,3,5))
```



# Example



# Application Results

- ▶ Data on Latin American migration: REDATAM project  
<https://bit.ly/3qf454D>
- ▶ Most of the models adjusted ended in 11 or 13 parameters (115 out of 139 pairs of origin-destination).
- ▶ Many curves do not fit with the pattern because there is a curve between 5 and 15 aprox that we have called: Child migration delay.
- ▶ Candidate to be a mechanism of migration (internal or international).
- ▶ Worst estimation of the post-retirement migration peak.

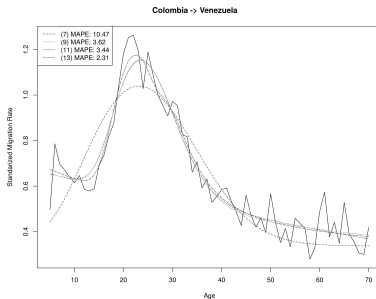
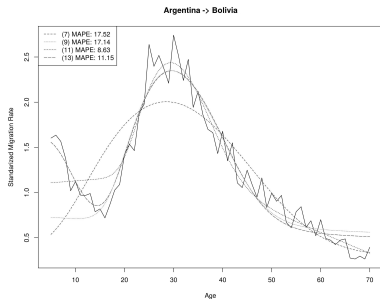
# Results: Two examples

Model 1: Colombia - Venezuela (Hombres)

Model 2: Colombia - Venezuela (Mujeres)

Model 3: Argentina - Bolivia (Hombres)

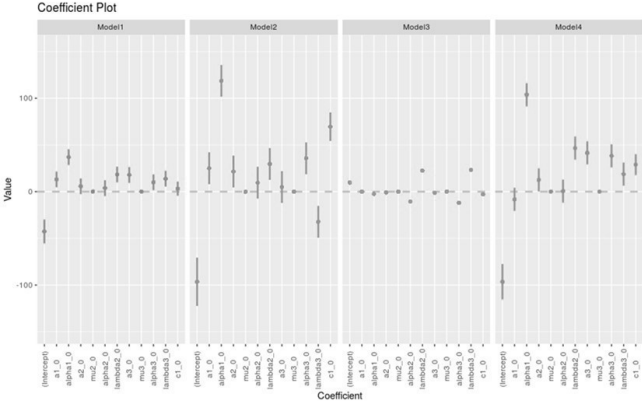
Model 4: Argentina - Bolivia (Mujeres)



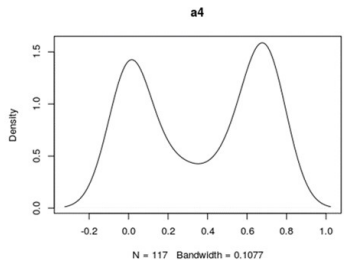
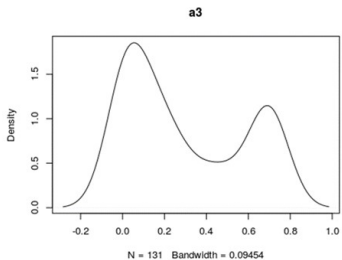
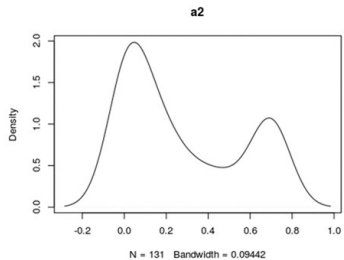
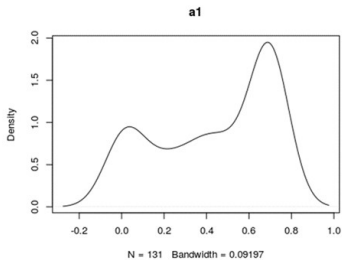
# Results Final parameters

Parametros	Mujeres: Colombia – Venezuela 2011			Mujeres: Argentina – Bolivia 2001		
	Valor	5%	95%	Valor	5%	95%
a1_0	0.512	0.225	0.877	0.863	0.224	0.877
$\alpha 1_0$	0.654	0.225	0.878	0.394	0.224	0.878
a2_0	0.058	0.224	0.878	0.398	0.226	0.877
$\mu 2_0$	<b>38.000</b>	<b>23.000</b>	<b>87.000</b>	<b>23.000</b>	<b>23.000</b>	<b>87.000</b>
$\alpha 2_0$	0.826	0.227	0.878	0.876	0.224	0.878
$\lambda 2_0$	0.253	0.226	0.877	0.031	0.226	0.878
a3_0	0.837	0.226	0.878	0.686	0.223	0.877
$\mu 3_0$	<b>27.000</b>	<b>23.000</b>	<b>87.000</b>	<b>21.000</b>	<b>23.000</b>	<b>87.000</b>
$\alpha 3_0$	0.806	0.227	0.877	0.751	0.224	0.877
$\lambda 3_0$	0.534	0.224	0.878	0.008	0.225	0.877
a4_0	0.531	0.224	0.877	0.624	0.227	0.877
$\lambda 4_0$	0.782	0.225	0.878	0.562	0.225	0.878
e1_0	0.085	0.248	0.975	0.573	0.251	0.976
a1_hat	0.690	0.700	0.700	0.700	0.700	0.700
$\alpha 1_hat$	0.028	0.013	0.127	0.017	0.001	0.179
a2_hat	0.700	0.000	0.700	0.700	0.000	0.700
$\mu 2_hat$	<b>32.481</b>	<b>19.879</b>	<b>88.000</b>	<b>17.854</b>	<b>23.229</b>	<b>88.000</b>
$\alpha 2_hat$	0.423	0.058	0.700	0.166	0.034	0.700
$\lambda 2_hat$	0.124	0.122	0.700	0.000	0.075	0.700
a3_hat	0.700	0.000	0.700	0.700	0.000	0.700
$\mu 3_hat$	<b>28.529</b>	<b>19.656</b>	<b>88.000</b>	<b>46.646</b>	<b>22.911</b>	<b>88.000</b>
$\alpha 3_hat$	0.150	0.064	0.700	0.360	0.041	0.700
$\lambda 3_hat$	0.527	0.136	0.700	0.083	0.081	0.700
a4_hat	0.670	0.619	0.700	0.685	0.700	0.700
$\lambda 4_hat$	0.000	0.000	0.516	0.000	0.000	0.167
e1_hat	0.690	0.645	0.700	0.685	0.700	0.700
ECM	0.023	0.062	4.618	0.297	3.365	34.645
MAPE	<b>2.316</b>	<b>3.616</b>	<b>24.904</b>	<b>6.420</b>	<b>12.817</b>	<b>54.731</b>

# Results: Influence of initial values on the MSE

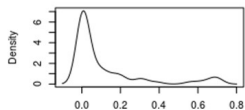


# Results: Final parameters



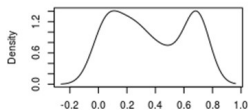
# Results: Final parameters

**alpha1**



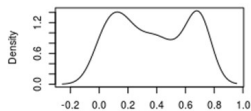
N = 131 Bandwidth = 0.03362

**alpha2**



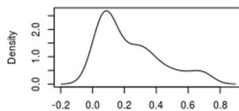
N = 131 Bandwidth = 0.08707

**alpha3**



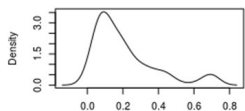
N = 131 Bandwidth = 0.08553

**lambda2**



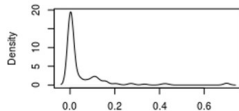
N = 131 Bandwidth = 0.06562

**lambda3**



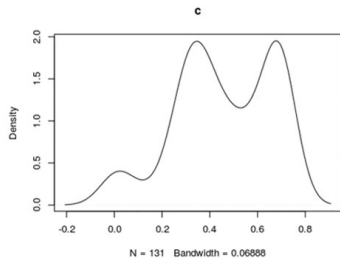
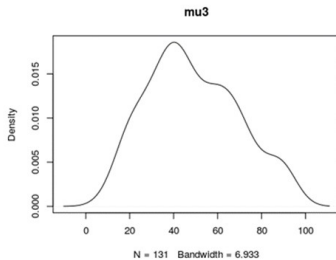
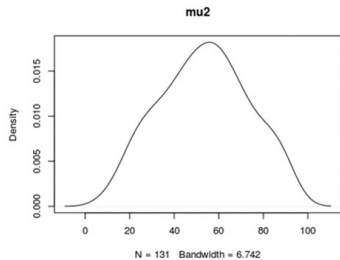
N = 131 Bandwidth = 0.04677

**lambda4**



N = 131 Bandwidth = 0.01326

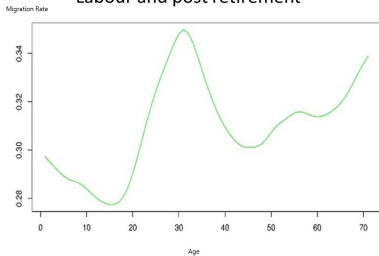
# Results: Final parameters



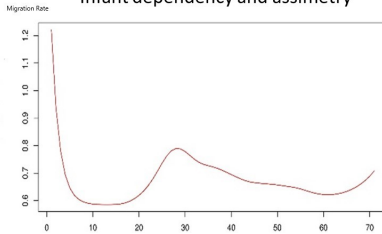


# Results: Typology

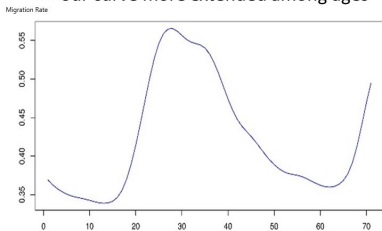
## Labour and post retirement



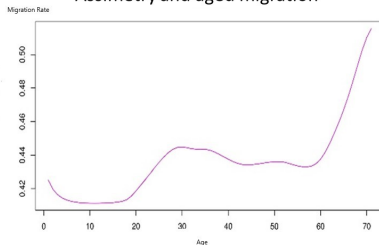
## Infant dependency and assimetry



## Labour curve more extended among ages

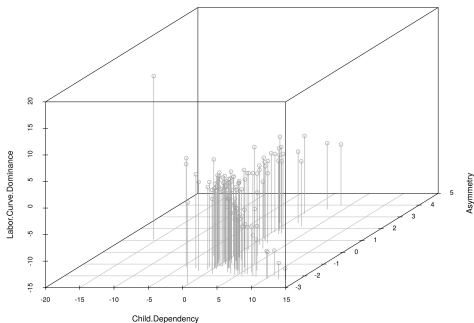


## Assimetry and aged migration



# Results

- ▶ Using the logarithm of the estimated ratios we can say that the latinamerican migration system has a medium-high child dependency, a predominance of labour force curve and a very asymmetric labour force curve, are congruent with the reality of Latin American migrations.



- ▶ The more child dependency the less is the symmetry.

## Why is important for the ILO?

- ▶ It is necessary to establish robust historical measures that allow their projection and allow to carry out public policy scenarios.
- ▶ Could be part of a country classification according to migration characteristics that lead to better standardization.
- ▶ Knowing various estimation methodologies provides feedback for the collection and harmonization data methods.
- ▶ Having other approaches to labour force estimation due to migration with other sources rather than LFS.

## Ongoing work

- ▶ Detection and analysis of international emigration using administrative register of migration Colombia (Statistics Colombia).
- ▶ Using Spanish administrative data to see a better child curve and defining what we could say about. 15 parameter model (A. Mendoza, Treasury - Colombia and J. Recano CED - Barcelona).
- ▶ Bayesian hierarchical model: Incorporate beta priors and some inputs as GDP and others.
- ▶ Combining this results with the ones obtained with the ILO bulk information (Advice M. Villareal, ILO)