Internal migrations in Austria: modeling and inference of temporal graphs

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Motivation: understanding migrations

1. Migrations play a **central role**[1] **in socioeconomic development:**
   - Urbanization
   - Segregation
   - Gentrification
   - ...
2. **The driving forces of migration phenomena are multiple**[2] (*e.g.* labor market imbalances, wealth inequalities, ...)
3. **Much attention in research devoted to international migration, less is known about internal migrations**
   - Most of migration events occur within national boundaries
   - Lack of analysis at the local level limits our ability to assess local policies

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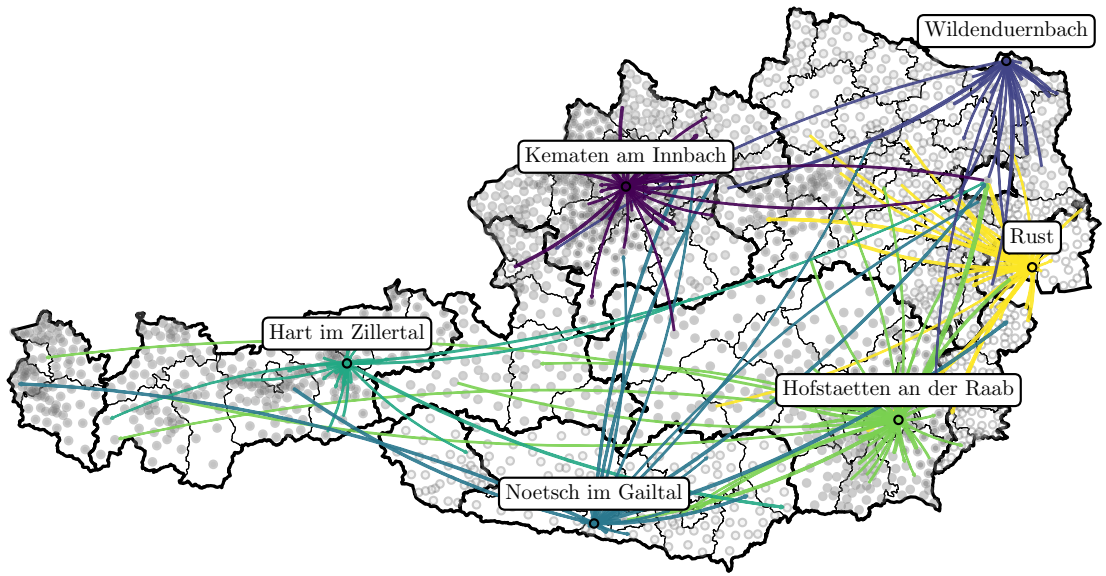
[1] Papademetriou, D. G. & Martin, P. L. *The unsettled relationship: Labor migration and economic development.* **33** (Greenwood Publishing Group, 1991).

[2] Moser, M. & Schnetzer, M. The income–inequality nexus in a developed country: Small-scale regional evidence from Austria. *Regional Studies* **51,** 454–466 (2017).

Migrations and network science

Migration patterns are **fundamentally relational**: movements of people between spatial regions

→ weighted, directed, and time-annotated network



Relocations in 2021 from and to six selected municipalities in Austria

A data-driven analysis of migration phenomena requires tools from network science.

Problems related to data quality

Typically, in large-scale scientific studies:

- **Low-resolution data** (*e.g.* country/city level, yearly resolution)
- Data originates from **different sources**:
  - Different definition of migration events
  - Different sampling procedures
  - ...
- Limitations when **matching to other socioeconomic factors** (*e.g.* sociodemographic, census, *etc.*)

Relocation data from Austria, the MOMA project

"Microdata For Research" by Statistik Austria
`MIGSTAT - Wanderungsstatistik` - all relocations of the Austrian residents from 2002 to 2021:

- From abroad to Austria ($\sim 1 - 2 \times 10^5$/y)
- Departures from Austria ($\sim 7 - 10 \times 10^4$/y)
- Changes of main residence between and within Austrian municipalities ($\sim 6.5 - 8 \times 10^5$/y)

> *The aim of this project is to [...] reveal the nation-wide, multi-scale, hierarchical internal flow of people [in Austria] over a period of more than two decades, together with its latent social and economic correlates.*


Tiago P. Peixoto


Márton Karsai


Mathias Czaika


Martina Contisciani

Two facets of modeling migrations

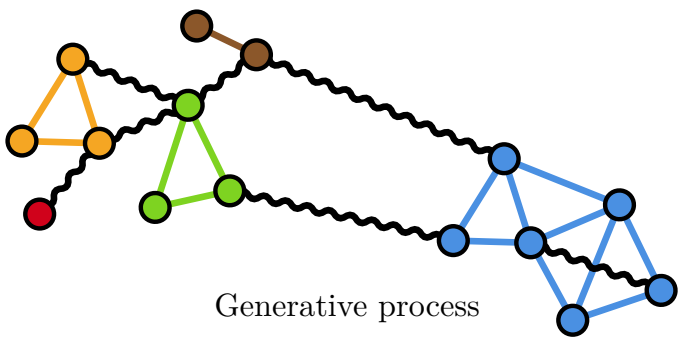
Effective modeling:

- Identify patterns and mesoscopic structures in the data (*e.g.* modules, temporal regimes...)
- Formulate new generative models for temporal graphs

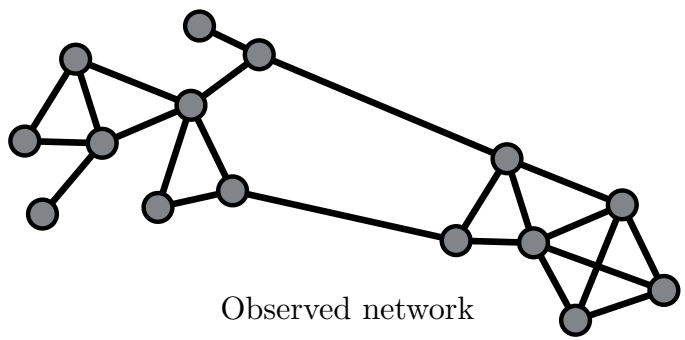
Mechanistic modeling:

- Identify and validate in a data-driven fashion the driving forces of migration phenomena

→ **Formulate mixed effective-mechanistic models.**[3]



Generative process



Observed network

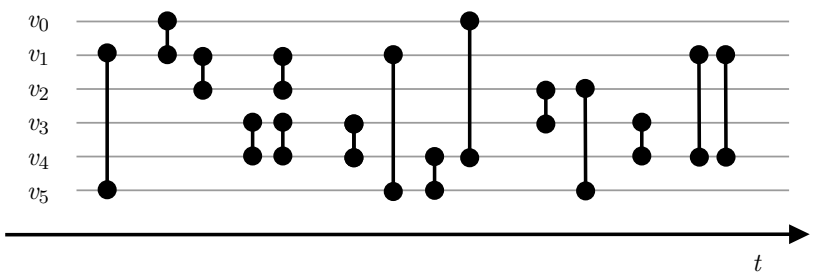
[3] Peixoto, T. P. Disentangling homophily, community structure, and triadic closure in networks. *Physical Review X* **12,** 011004 (2022).

Two approaches in modeling temporal graphs

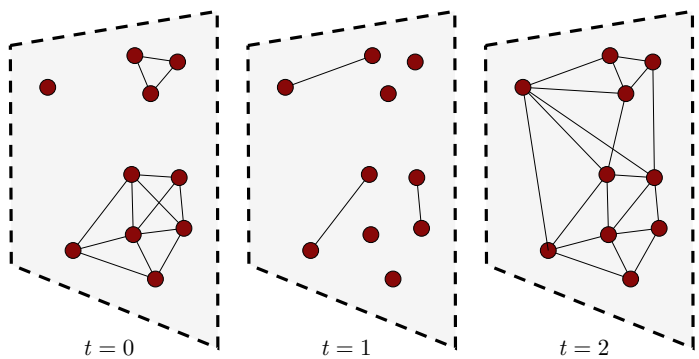
Generative models generate the **history** of the system $\{\mathbf{A}(t)\}$

Most approaches rely on a characteristic timescale[4]:

Short timescales
$\rightarrow$ static Markov chains with short term memory



Longer timescales
$\rightarrow$ temporal aggregation, discrete change points



[4] Peixoto, T. P. & Rosvall, M. in *Temporal network theory* 65–82 (Springer, 2023).

Bayesian formulations of the two approaches

Short timescales

- Dynamical extensions of models for static graphs[5]
- Markov chains with community structure[6]

Longer timescales

- Layered SBMs[7]
- Markov chains with change points[8]

The communities and the change points work **synergistically** with the Markov chains. The Bayesian formulation protects from overfitting.

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[5] Zhang, X. *et al.* Random graph models for dynamic networks. *The European Physical Journal B* **90,** 1–14 (2017).

[6] Peixoto, T. P. & Rosvall, M. Modelling sequences and temporal networks with dynamic community structures. *Nature communications* **8,** 582 (2017).

[7] Peixoto, T. P. Inferring the mesoscale structure of layered, edge-valued, and time-varying networks. *Physical Review E* **92,** 042807 (2015).

[8] Peixoto, T. P. & Gauvin, L. Change points, memory and epidemic spreading in temporal networks. *Scientific reports* **8,** 15511 (2018).

Community structure and change points

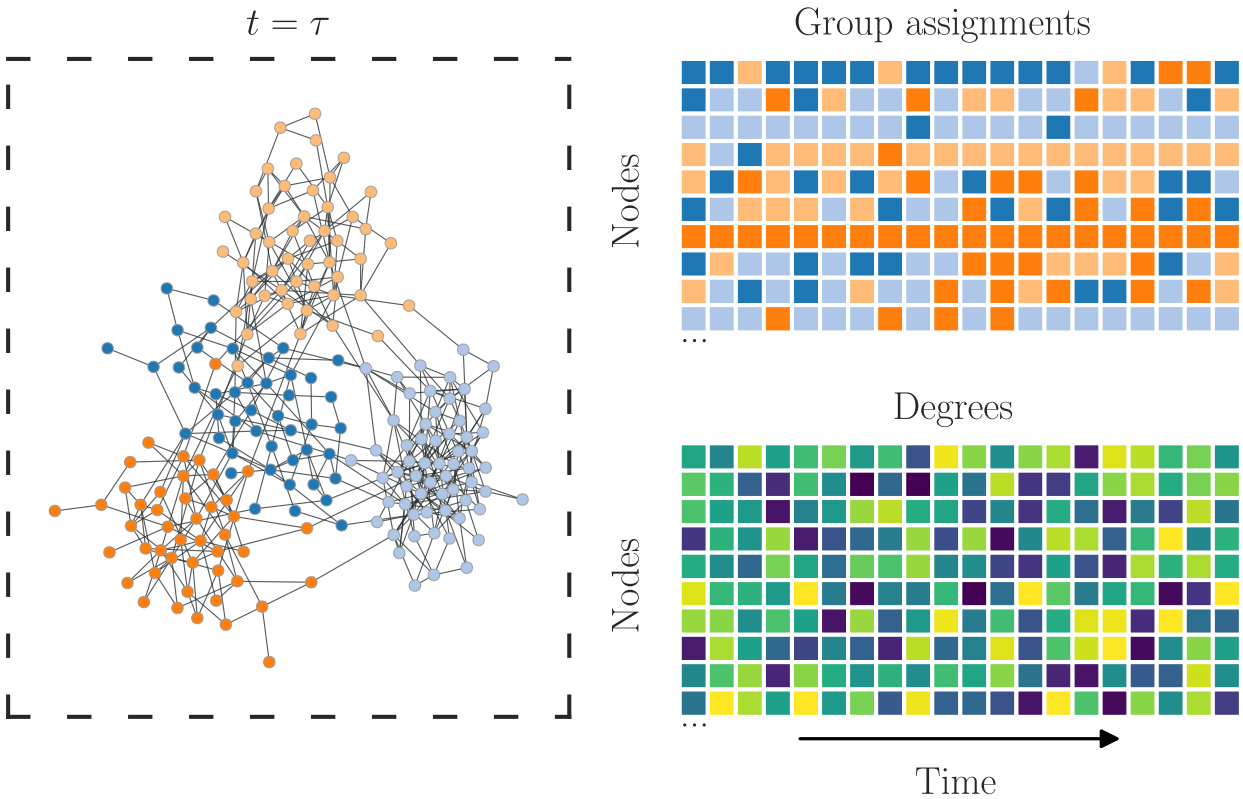
Migration phenomena (and many other systems) exhibit dynamics at multiple **structural** and **temporal** scales.

> Formulate new generative models for temporal graphs with **dynamic community structure** and **change points**.

Preliminary ideas:

- SBM with dynamic group assignments
- SBM with change points

SBM with dynamic group assignments



Fixed:

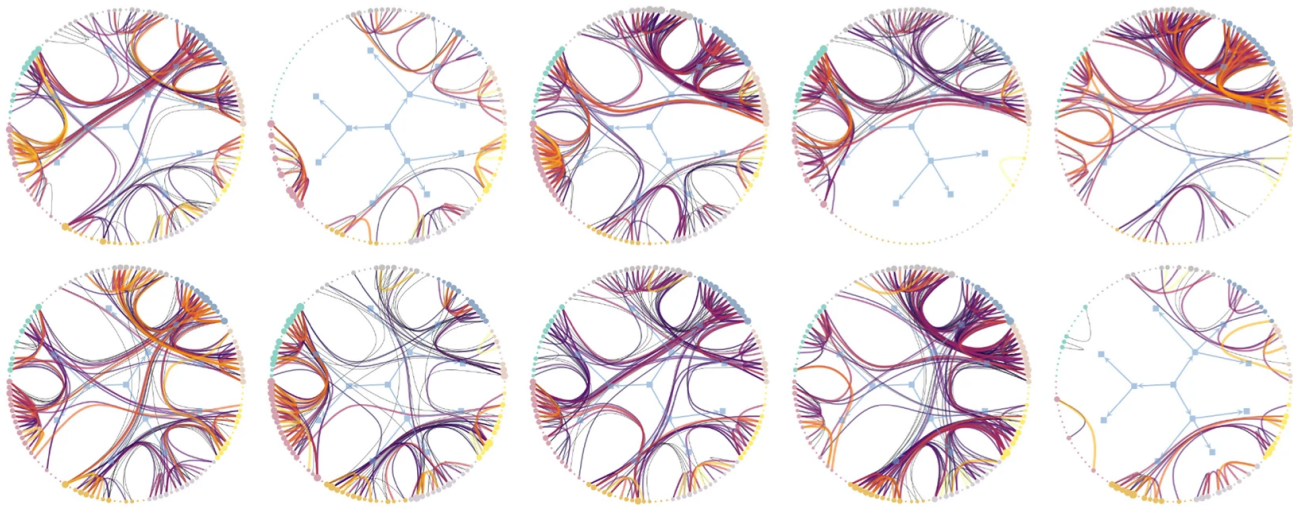
- $\mathbf{e} = \{e_{rs}\}$ group preferences

Time-dependent:

- $\{\mathbf{b}^t\} = \{\{b_i^t\}\}$ group assigments
- $\{\mathbf{k}^t\} = \{\{k_i^t\}\}$ degree sequences

SBM with change points

Existing work:
Static Markov chain of order n for the placement of edges, with the transition probabilities that change at given **change points**[9]



Network representation of the first 10 time segments found for the `sp_high_school_new` dataset

Incorporating the community structure in this model can allow for better compression of the observed networks.

[9] Peixoto, T. P. & Gauvin, L. Change points, memory and epidemic spreading in temporal networks. *Scientific reports* **8**, 15511 (2018).

Mechanistic models of mobility phenomena

Identify the smallest set of processes and parameters required to reproduce the patterns seen in the data in a stylized manner.

Existing mechanistic models for human mobility:

- Gravity models[10]
- Radiation models of mobility[11]
- Schelling's model of segregation[12]

Formulate these processes as generative models.

Example:

$$m_{ij} = K\frac{(p_i p_j)^\alpha}{d_{ij}^\beta} \Rightarrow P(I_{ij}|\lambda_{ij}) = \frac{e^{\lambda_{ij}}\lambda_{ij}^{I_{ij}}}{I_{ij}!} \text{ with } \lambda_{ij} = K\frac{(p_i p_j)^\alpha}{(d_{ij}+c)^\beta} \quad (1)$$

[10] Lewer, J. J. & Van den Berg, H. A gravity model of immigration. *Economics letters* **99,** 164–167 (2008).

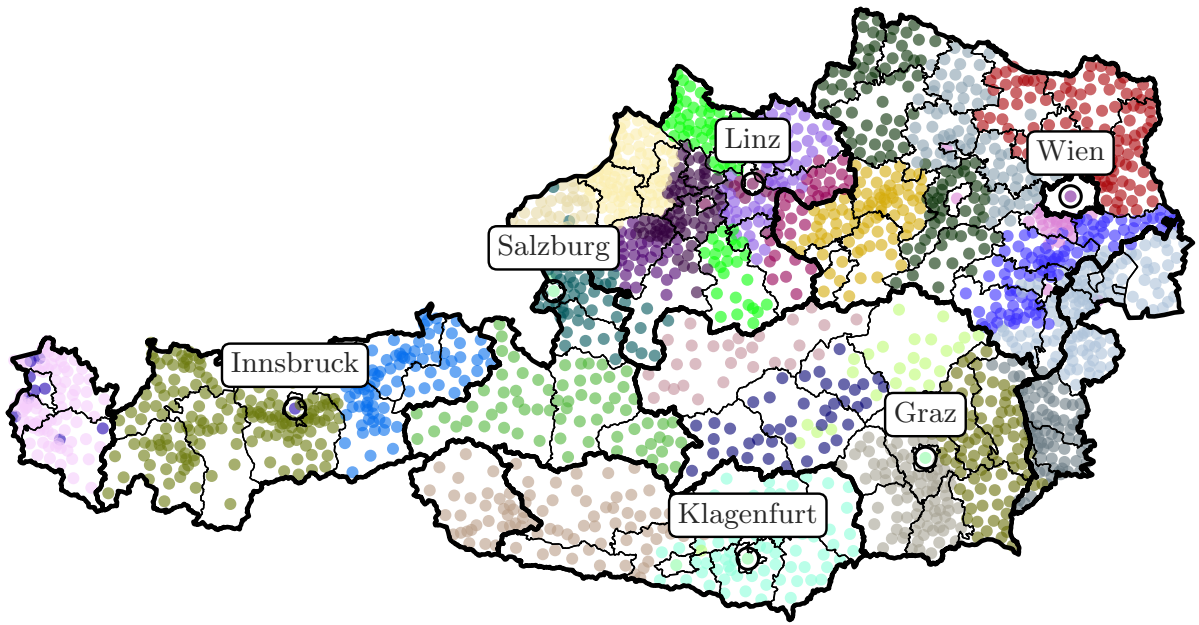
[11] Simini, F. *et al.* A universal model for mobility and migration patterns. *Nature* **484,** 96–100 (2012).

[12] Schelling, T. C. *et al.* Dynamic models of segregation. *Journal of mathematical sociology* **1,** 143–186 (1971).

Mixed effective-mechanistic models

Preliminary results:

1. Communities are geographically localized
2. Strong effect of administrative boundaries



Level 1 of the best partition found fitting a H-SBM to the gross migration flow of 2021

Not all patterns in the data are explained by the mechanistic models (*e.g.* gravity law)

Mixed effective-mechanistic models

Define a class of mixed **effective-mechanistic** models.

S. Kusch

Example: Gravity law + SBM

$$P(\mathbf{A}|\{\theta\};\{M_i\},\{d_{ij}\}) = \prod_{i,j} \frac{e^{\lambda_{ij}}\lambda_{ij}^{A_{ij}}}{A_{ij}!} \tag{2}$$

Where the **expected weight** of an edge is:

$$\lambda_{ij} = \lambda_{ij}^{\mathrm{g}} + \lambda_{ij}^{\mathrm{s}} \text{ with: } \begin{cases} \lambda_{ij}^{\mathrm{g}} = K\frac{(M_iM_j)^{\alpha}}{(d_{ij}+c)^{\beta}} & \text{(mechanistic)} \\ \lambda_{ij}^{\mathrm{s}} = \omega_{b_ib_j}k_ik_j & \text{(effective)} \end{cases} \tag{3}$$

Mixed effective-mechanistic models

The Poisson formulation allows us to write the observed graph as:

$$A_{ij} = G_{ij} + U_{ij} \tag{4}$$

with:

$$P(\mathbf{G}, \mathbf{U}) = \prod_{i,j} \frac{e^{\lambda^{\mathrm{g}}_{ij}} \lambda^{\mathrm{g}, G_{ij}}_{ij}}{G_{ij}!} \prod_{i,j} \frac{e^{\lambda^{\mathrm{s}}_{ij}} \lambda^{\mathrm{s}, U_{ij}}_{ij}}{U_{ij}!} \tag{5}$$

The inferential task will deal with the posterior distribution:

$$P(K, \alpha, \beta, c, \mathbf{b}, \mathbf{e}, \mathbf{G}, \mathbf{U} | \mathbf{A}; \{M_i\}, \{d_{ij}\}) \tag{6}$$

$\rightarrow$ The SBM component captures the **non-trivial structure of the residues** of the gravity law

Summary

Data-driven analysis of internal migrations in Austria, using high-resolution data from Statistik Austria.

Generative models for temporal graphs:

- Dynamic community structure
- Change points

Mechanistic models of mobility:

- Formulated as generative models to allow for a principled data-driven validation

Mixed mechanistic-effective models