Mesoscopic description of deviations from gravity models in Austrian migration flows

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Modeling migration

Statistical modeling of migration (and mobility) data[1]:

- understand driving forces
- make predictions
- test hypothesis

Internal migrations in Austria[2]

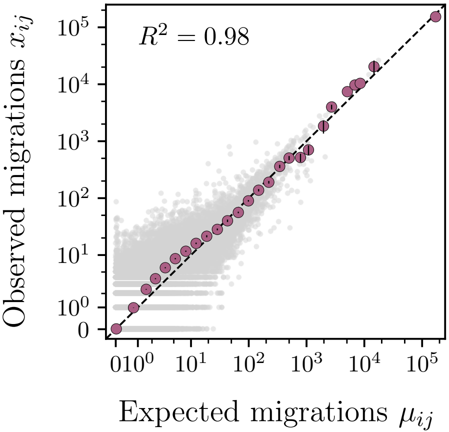
`MIGSTAT - Wanderungsstatistik` - all relocations of the Austrian residents from 2002 to 2021: Changes of main residence between and within Austrian municipalities ($\sim 6.5 - 8 \times 10^5$/y)

[1] H. Barbosa, *et al.*, Physics Reports 734, 1 (2018)
[2] `https://data.statistik.gv.at/`

“Gravity” models[3]

The rate of movement (x_{ij}) between two locations increases with the product of their populations (p_i, p_j), and decays with their distance (d_{ij}):

$$\mathbb{E}[x_{ij}] \equiv \mu_{ij} = K \frac{\left(p_i p_j\right)^{\alpha}}{d_{ij}^{\beta}}$$

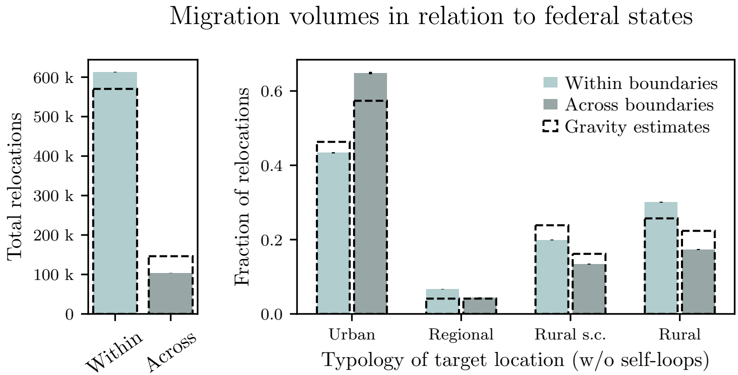


[3]G. K. Zipf, American Sociological Review, Vol. 11, No. 6 (1946)

"Gravity" models

What else is there? Is this enough to describe the data?

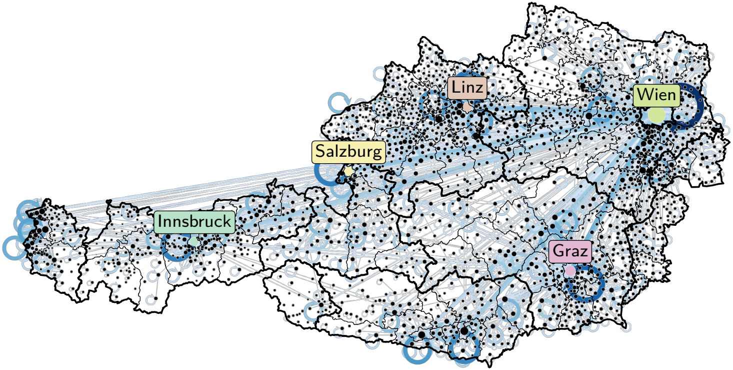
e.g. hidden discrepancies in relation to geographical and urban-rural information.



Network models

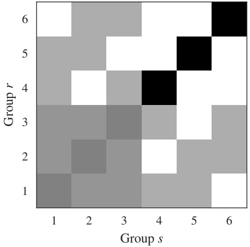
General approach: migration phenomena are **fundamentally relational**.

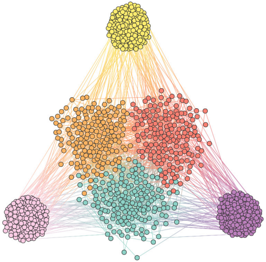
- Node i: municipality ($N = 2093$)
- *Directed and weighted* edge x_{ij}: relocations ($E \sim 70K$)
- Years 2002-2021, aggregated annually



Network models

Weighted Stochastic Block Model[4]: given a partition **b** of the municipalities into B groups, the migrations between two locations are sampled only according to their group memberships.

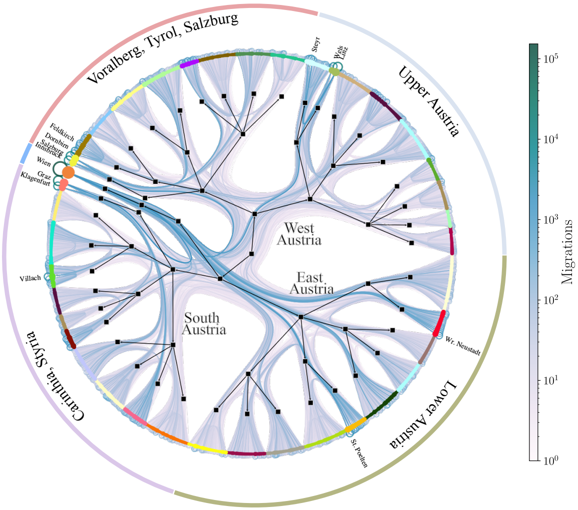




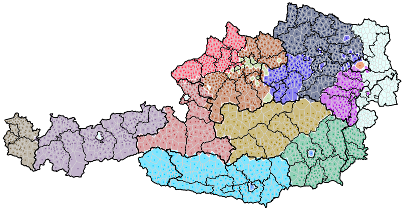
No assumption on locations, contiguity, or population.

[4] T. P. Peixoto, Physical Review E, 97, 012306 (2018)

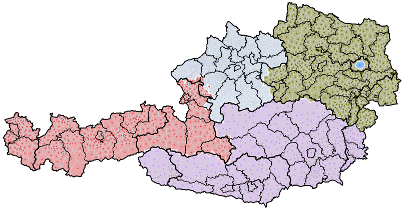
Inferred hierarchical partition



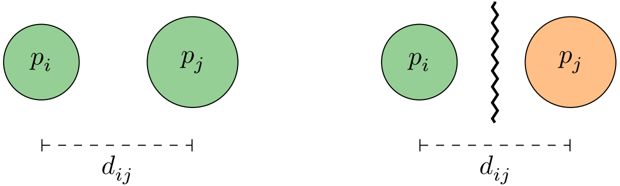
Inferred groups at level $l = 1$

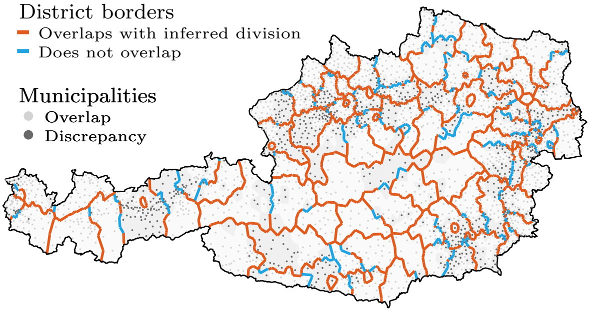


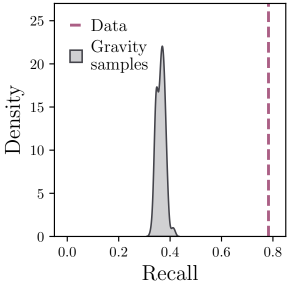
Inferred groups at level $l = 2$



Administrative barriers to migration







Main take-aways

- Migrations in Austria are driven by **more than gravity**
- Network methodology to go beyond traditional approaches
- Inferential clustering reveals effects of:
  - **administrative boundaries**
  - **urban-rural divide**
- Patterns are consistent over twenty years

Next steps

- Full mapping of the migration flows
- Understanding the **drivers of migration**
  (e.g. socio-economic/demographic predictors)

Thank you!

Martina Contisciani

Márton Karsai

Tiago P. Peixoto

Check out the pre-print:

Multiscale patterns of migration flows in Austria: regionalization, administrative barriers, and urban-rural divides

`arXiv:2507.11503`

`thomas.robiglio@it-u.at`
`thomasrobiglio.github.io`
`skewed.de/lab`

Funded by:

Appendix

Gravity Model

The migration flows between two locations are modelled as Poisson-distributed random variables

$$I_{ij} \sim \text{Pois}(\mu_{ij})$$

with

$$I_{ij} = \begin{cases} x_{ij} + x_{ji} & \text{if } i \neq j \\ x_{ii} & \text{if } i = j \end{cases} \quad \text{and} \quad \mu_{ij} = \begin{cases} K\frac{(p_i p_j)^\alpha}{d_{ij}^\beta} & \text{if } i \neq j \\ C p_i^\delta & \text{if } i = j \end{cases}.$$

To generate directed synthetic networks, we sample the edge weights $\hat{x}_{ij}$ from the estimated Poisson gravity model rates as

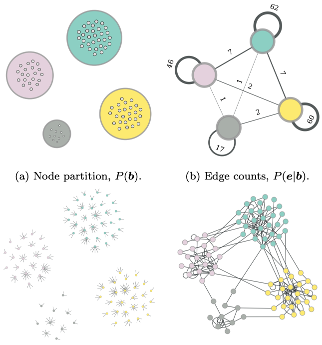
$$\hat{x}_{ij} \sim \begin{cases} \text{Pois}(\mu_{ij}/2) & \text{if } i \neq j \\ \text{Pois}(\mu_{ii}) & \text{if } i = j \end{cases}.$$

Stochastic Block Model

Given a partition $\mathbf{b}$ of the municipalities into B groups, the migration events from j to i depends only on their group memberships:

$$P(\mathbf{A} \mid \mathbf{e}, \mathbf{b}) = \prod_{ij} P(A_{ij} \mid e_{b_i, b_j})$$

- Microcanonical formulation
- Degree-corrected SBM



(a) Node partition, $P(\boldsymbol{b})$. (b) Edge counts, $P(\boldsymbol{e}|\boldsymbol{b})$.

(c) Degrees, $P(\boldsymbol{k}|\boldsymbol{e}, \boldsymbol{b})$. (d) Network, $P(\boldsymbol{A}|\boldsymbol{k}, \boldsymbol{e}, \boldsymbol{b})$.

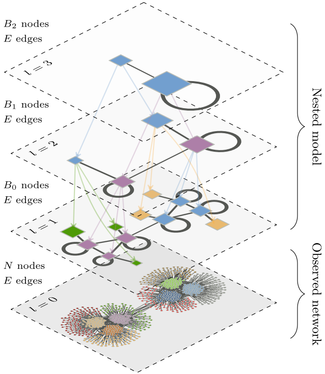
Nonparametric Bayesian framework[5] with the full joint distribution being:

$$P(\mathbf{A}, \mathbf{k}, \mathbf{e}, \mathbf{b}) = P(\mathbf{A} \mid \mathbf{k}, \mathbf{e}, \mathbf{b}) P(\mathbf{k} \mid \mathbf{e}, \mathbf{b}) P(\mathbf{e}) P(\mathbf{b})$$

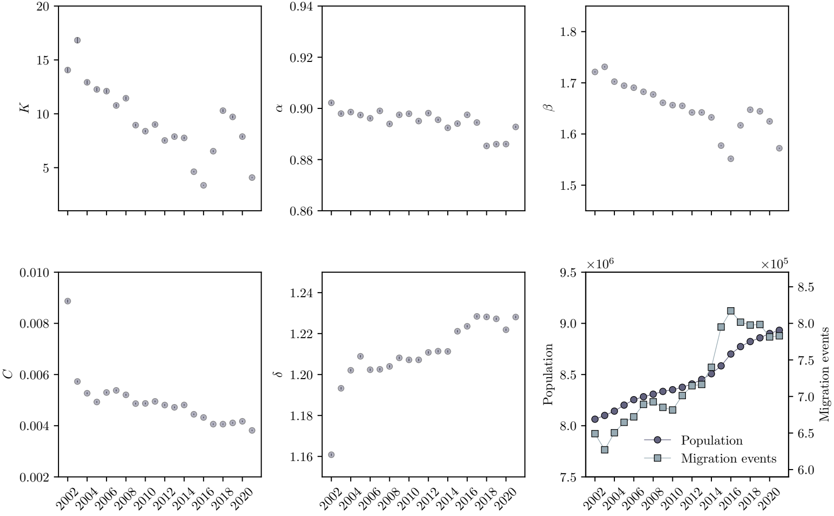
[5] T. P. Peixoto, Physical Review X 4, 011047 (2014)

Nested Stochastic Block Model

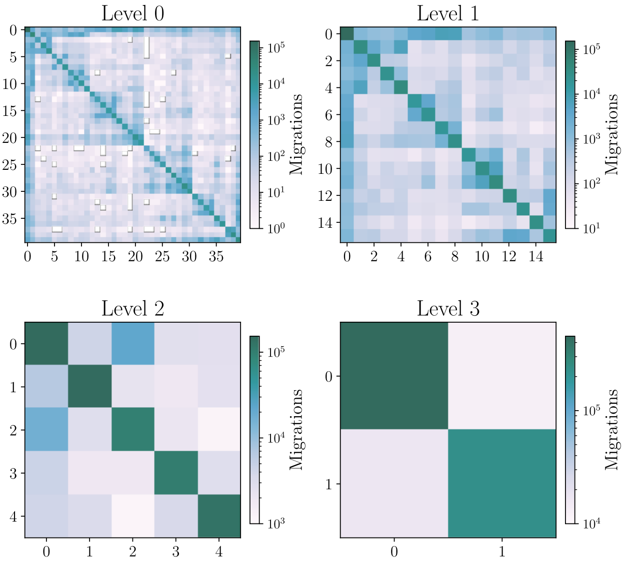
- $P(\mathbf{e})$ is chosen to enforce a hierarchical partition
- The inference of the hierarchical partition is performed through sampling from the posterior distribution $P(\{\mathbf{b_l}\} \mid \mathbf{A})$ using an agglomerative multilevel Markov chain Monte Carlo algorithm
- Robust against overfitting



Inferred Parameters Gravity Model

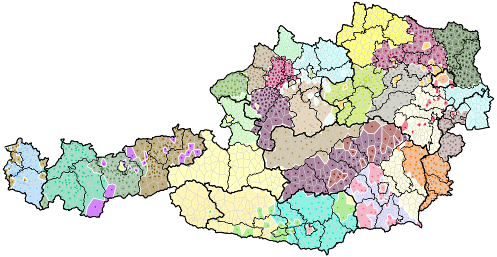


Inferred Affinity Matrices

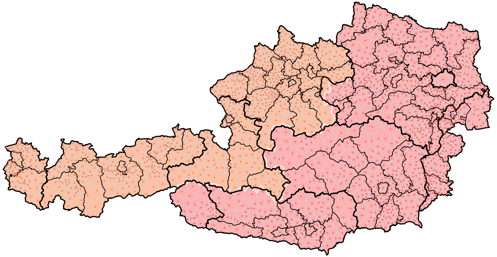


Inferred Partitions

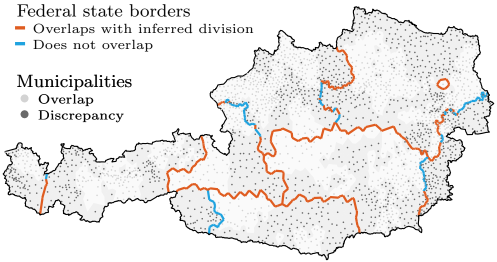
Inferred groups at level $l = 0$

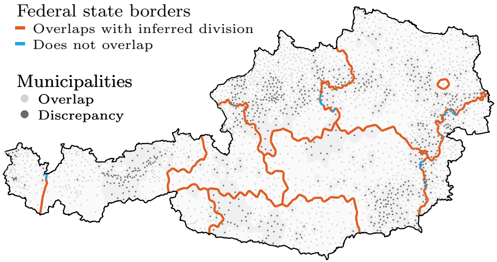


Inferred groups at level $l = 3$

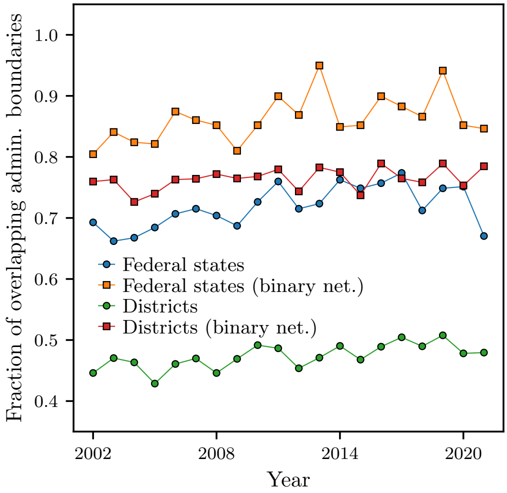


Federal State Boundaries

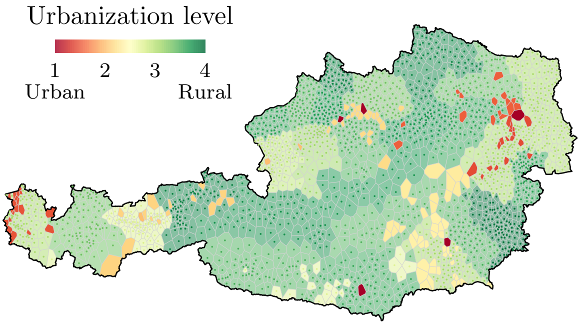


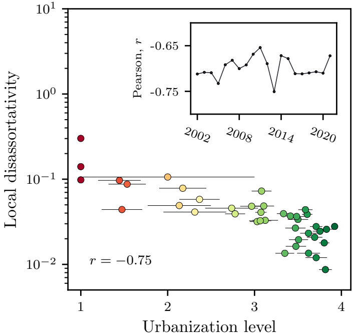


Administrative Boundaries Over Time



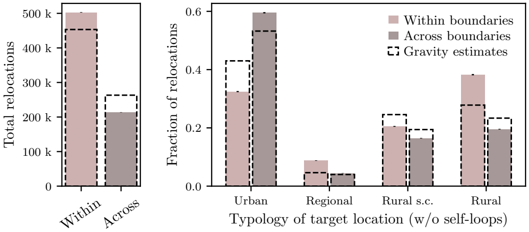
Urban-Rural Classification



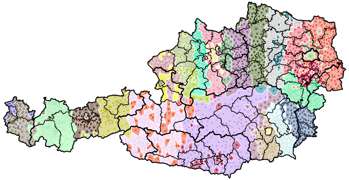


Additional Results

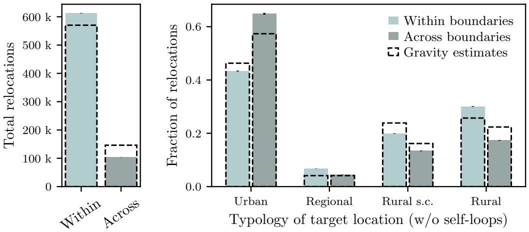
(a) Migration volumes in relation to districts



(b) Inferred groups from a gravity model sample



(c) Migration volumes in relation to federal states



(d) Comparison with gravity model samples