A model of urban evolution based on innovation diffusion

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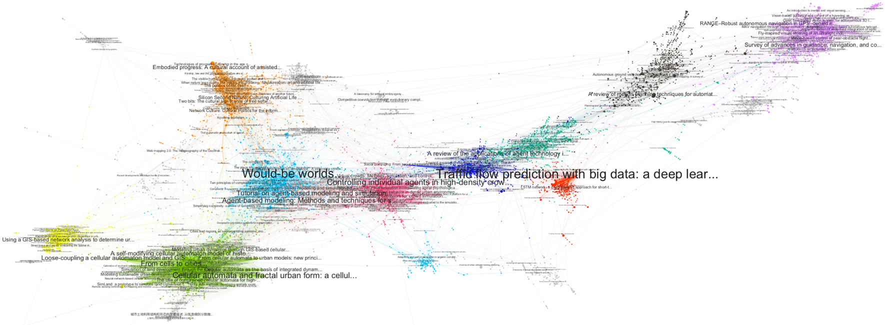
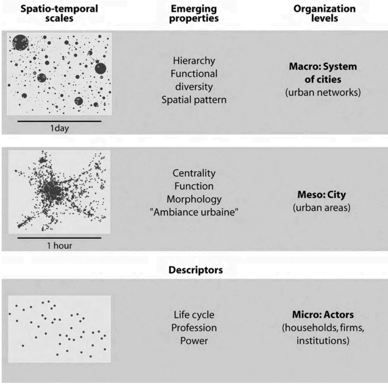
Urban systems and Artificial Life

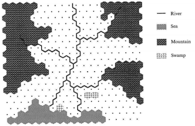


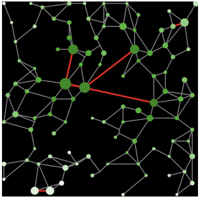
Citation network of ALife studies of urban systems [Raimbault, 2020a] arXiv:2002.12926

Transfer of concepts: Urban morphogenesis, bio-inspired design, urban ecology, autopoiesis [Batty and Marshall, 2009]

Urban evolution extending cultural evolution, cities as agents with their proper genome and evolutionary dynamics?







An evolutionary urban theory considering cities as systems within systems of cities [Pumain, 2018]; Simpop 1 model [Sanders et al., 1997]; SimpopNet model [Schmitt, 2014]

Innovation diffusion

$\rightarrow$ **Innovation diffusion** is a crucial process in artificial life evolutionary systems and open-ended evolution [Bedau et al., 2000]

$\rightarrow$ Artificial societies used to study the dynamics of innovation [Zenobia et al., 2009]

$\rightarrow$ Innovations diffuse hierarchically in systems of cities [Hagerstrand et al., 1968], potential explanation of urban scaling laws [Pumain et al., 2006]

Innovation diffusion as a privileged entry to understand urban evolution

Research objective

$\rightarrow$ Concepts of urban evolution do not necessarily capture essential processes (transmission and transformation) in the literature

$\rightarrow$ Need for simple models with explicit urban genome at the system of cities scale

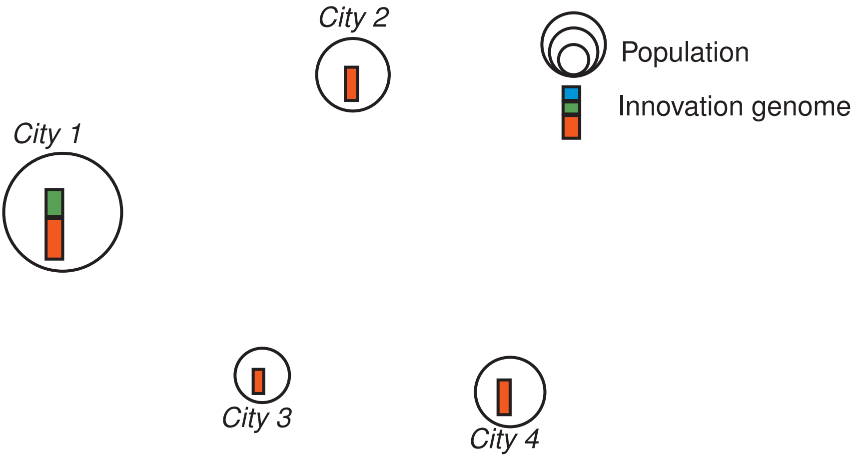
Research objective:

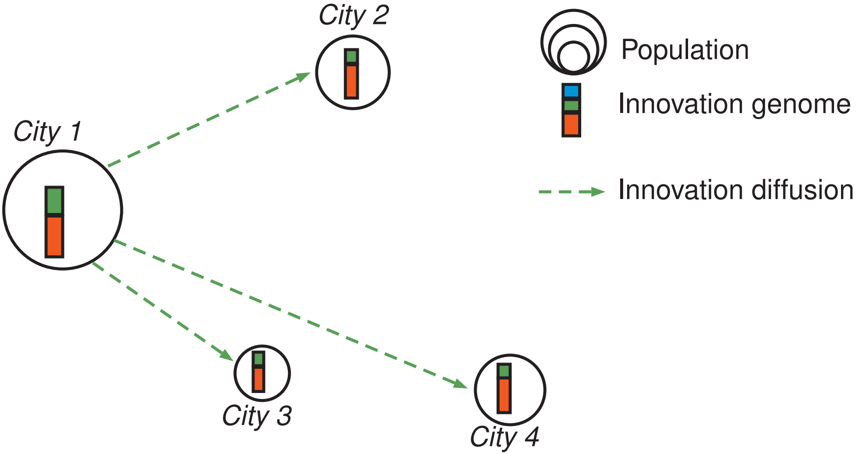
Describe and systematically explore an urban evolution model based on innovation diffusion, for urban dynamics at the macroscopic scale

Model rationale

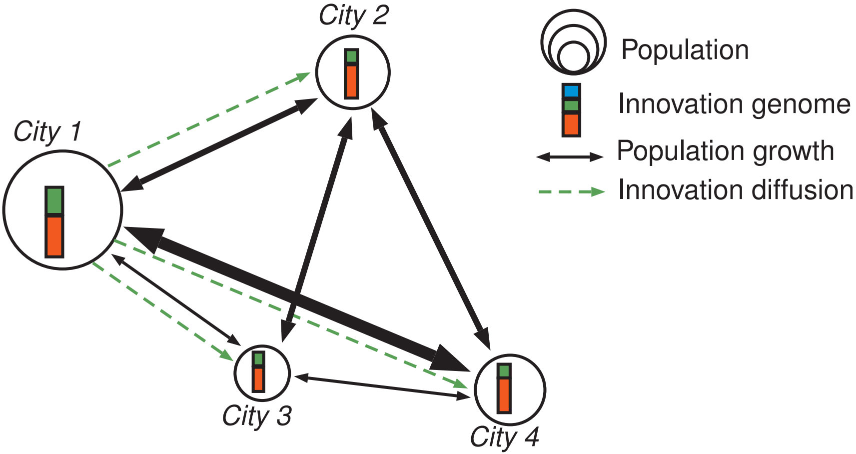
- Agents are cities, macroscopic scale (regional, country, continental) and long time scales (century)
- Cities characterized by their size in terms of population; genome as adoption proportions of innovations (social or technological) for each city (one single dimension to simplify)
- Following [Favaro and Pumain, 2011], attractivity of cities due to level of innovation drive their population growth through spatial interactions; innovation diffuse through an other spatial interaction model [Fotheringham and O'Kelly, 1989]
- Mutations occur in cities as new innovations appear

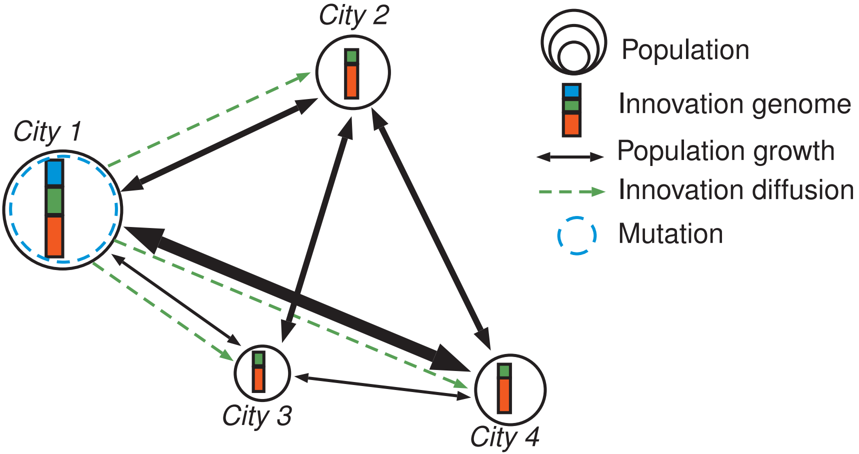
Model description




City 2
City 1
City 3
City 4
Population
Innovation genome
Innovation diffusion

Model description




City 2
City 1
City 3
City 4
Population
Innovation genome
Population growth
Innovation diffusion
Mutation

Model formalization

At each time step, with $P_i\left(t\right)$ population, $p_{c,j,t}$ genome, u_c utility of innovation

1. Crossover through the diffusion of innovations

$$\delta_{c,i,t} = \frac{\sum_j p_{c,j,t-1}^{\frac{1}{u_c}} \cdot \exp\left(-\frac{d_{ij}}{d_I}\right)}{\sum_c \sum_j p_{c,j,t-1}^{\frac{1}{u_c}} \cdot \exp\left(-\frac{d_{ij}}{d_I}\right)}$$

2. Population growth through spatial interactions $P_i\left(t\right) - P_i\left(t-1\right) = w_I \cdot \sum_j \frac{V_{ij}}{<V_{ij}>}$ with

$$V_{ij} = \frac{P_i\left(t-1\right) \cdot P_j\left(t-1\right)}{\left(\sum_k P_k\left(t-1\right)\right)^2} \cdot \exp\left(-\frac{d_{ij}}{d_G} \cdot \prod_c \delta_{c,i,t}^{\phi_{c,t}}\right)$$

   and $\phi_{c,t} = \sum_i \delta_{i,c,t} \cdot P_i\left(t-1\right) / \sum_{i,c} \delta_{i,c,t} \cdot P_i\left(t-1\right)$

3. Mutations with innovations introduced with probability $\beta \cdot \left(P_i\left(t\right) / \max_k P_k\left(t\right)\right)^{\alpha_I}$ and an initial penetration rate r_0; new utility u_c randomly distributed (normal or log-normal) with average current average utility and standard deviation a given parameter σ_U

Model indicators

- Average diversity

$$D = \frac{1}{t_f+1}\sum_{t=0}^{t_f}\left(1 - \sum_{i,c}\left(p_{c,i,t}\right)^2\right)$$

- Average utility

$$U = \frac{1}{t_f+1}\sum_{t=0}^{t_f}\sum_{i,c}\delta_{c,i,t}u_c$$

- Innovatitivity

$$I = \frac{\max c}{N\cdot\left(t_f+1\right)}$$

- Population trajectories, summarized by final hierarchy [Raimbault, 2020b]

Synthetic configurations

Model applied on synthetic systems of cities:

- random positions and rank-size hierarchy $P_i\left(0\right) = \frac{P_{max}}{i^{\alpha_0}}$ with $\alpha_0 = 1.0$ and $P_{max} = 100,000$
- countrywide urban system scale: $N = 30$ cities
- simulated for $t_f = 50$ macroscopic time steps (order of magnitude of a century)

Model parameters

Parameter	Not.	Process	Range	Def.
Number of cities	N	Spatial scale	$10; 100$	30
Initial hierarchy	α_0	System of cities	$0.5; 2.0$	1
Initial population	P_{max}	System of cities	$10^4; 10^7$	10^5
Simulation steps	t_f	Temporal scale	$10; 100$	50
Growth rate	w_I	Pop. growth	$0.001; 0.01$	0.005
Gravity range	d_G	Crossover	$0; 2$	1
Innovation range	d_I	Crossover	$0; 2$	1
Innovation rate	β	Mutation	$0; 1$	0.5
Innovation hierarchy	α_I	Mutation	$0; 2$	1
Innov. utility std.	σ_U	Mutation	$\left[0.7; 2\right]$	1
Penetration rate	r_0	Mutation	$\left[0.1; 0.9\right]$	0.5
Utility type	-	Mutation	{n;ln}	ln

Implementation

Model implemented in `scala`; relatively large parameter space

→ integration into the OpenMOLE model exploration open source software [Reuillon et al., 2013]

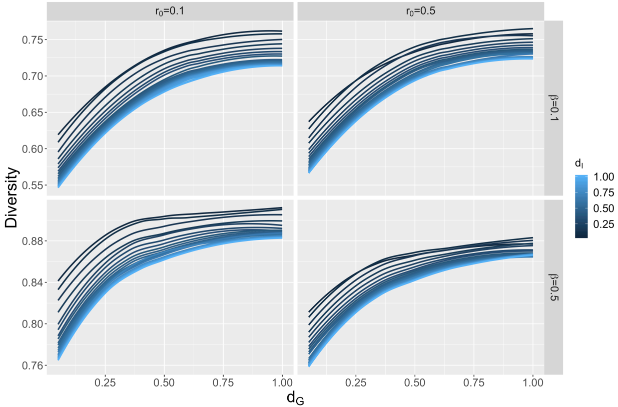
Enables seamlessly (i) model embedding; (ii) access to HPC resources; (iii) exploration and optimization algorithms

`https://openmole.org/`

- Latin Hypercube Sampling of 100 parameter points, 1000 replications for each
- Sharpe ratios have high values for all indicators and all parameters (minimum 1.7 for utility)
- Average and median relative distances defined as $\Delta_{ij} = 2\frac{\left|\mu_i - \mu_j\right|}{\sigma_i + \sigma_j}$ larger than one for all indicators: 50 repetitions in further experiments

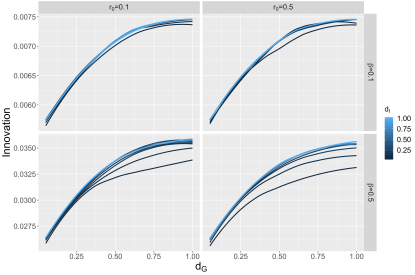
Model exploration: diversity

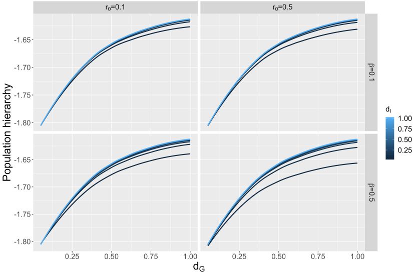
Grid sampling of the parameter space (23,168 points, 50 replications) with a finer grid on d_G and d_I; plots shown at $\alpha_I = 1$ and $\sigma_U = 1$



Diversity increases with interaction span with a plateau behavior, decreases with innovation diffusion span

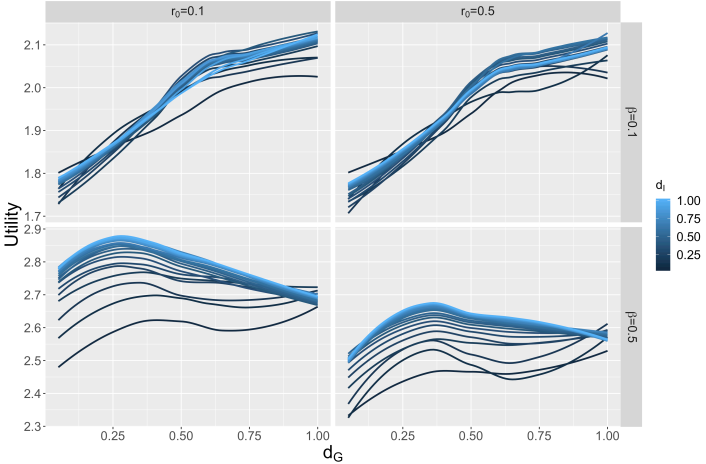
Model exploration: innovation and hierarchy





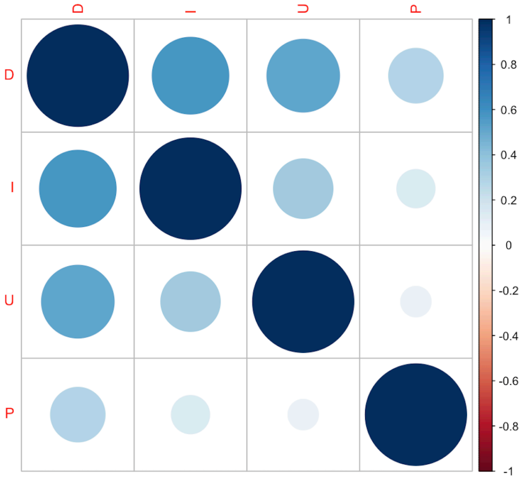
Systems with more interactions and diffusion are less unequal and innovate more

Model exploration: utility



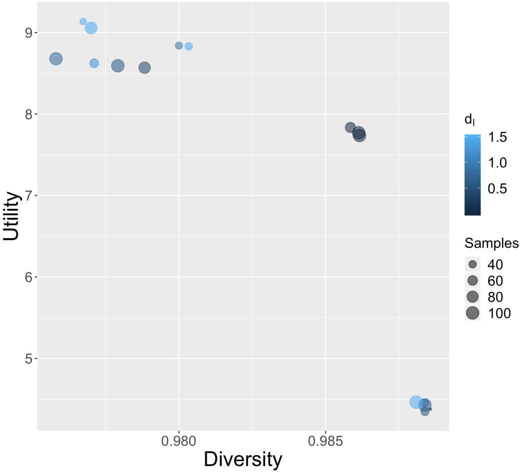
Piecewise behavior for low innovation rates; maximum as a function of d_G for high innovation: emergence of regional innovation clusters?

Correlations



Correlation matrix estimated over the whole exploration: innovation and population are not strongly correlated; 91% of variance on first two components

Model optimization



NSGA2 algorithm to simultaneously optimize utility and diversity: emergence of three compromize regimes; intermediate regime with low level of innovation diffusion

Discussion

Empirical and theoretical implications

→ Global integration of cities is not necessarily optimal in terms of overall utility

→ Urban evolution simulation model including explicit evolution processes and an urban genome

Future work and extensions

→ Multi-dimensional urban genome to capture multi-dimensionality of urban dynamics [Hidalgo et al., 2007]

→ Application to real systems of cities [Raimbault et al., 2020]: patent data as possible proxy for innovation dynamics [Bergeaud et al., 2017]

→ Processes at other scales, towards multi-scale models [Raimbault, 2019]

Conclusion

→ A simple model of urban evolution capturing complex dynamics at the macroscopic scale through the diffusion of innovations

→ An ALife approach to the simulation of urban systems: “Cities as they could be”

Open repositories for

- Model and results: `https://github.com/JusteRaimbault/UrbanEvolution`
- Simulation data: `https://doi.org/10.7910/DVN/Q5GKZ0`

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