Innovation and informal knowledge exchanges between firms

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Sustainable development goals

Improvement of real lives? (DOLCE vita)

→ challenges of sustainable developments goals [Nations, 2016]: necessary transitions of multiple interconnected socio-technical systems

SDGs and innovation

→ **Innovation** central to evolution and artificial life

→ Central element at the intersection of several SDGs: 9 (innovation and infrastructure), 8 (economy), 11 (cities), 13 (climate)

→ Emergence of trade-offs between SDGs in systems of cities: example of innovation and emissions [Raimbault and Pumain, 2022]

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Research Article

Trade-offs between sustainable development goals in systems of cities

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Firm clusters and innovation

Literature on **firm clusters** in economic geography and regional science:

- Positive impact on innovation capabilities [Bittencourt et al., 2019]
- Intensity of social interaction and exchange of tacit knowledge [Gnyawali and Srivastava, 2013] [Arikan, 2009]
- Transfer of competences through employees [Almeida and Kogut, 1999]

Link between geographical niche and market niche?

- Niches in technological evolution [Schot and Geels, 2007]
- Evolutionary dynamics with specific processes (cf talk by R. Tucker yesterday) [Schamp, 2010]
- Multiple geographical scales from firms to cities [Raimbault, 2020]

→ focus on firms and employees as carriers of knowledge [Song, 2016]

Agent-based modeling innovation

Innovation emerging from the bottom-up, making agent-based models relevant:

- spatial diffusion of innovations [Kiesling et al., 2012]
- collective decision making and creativity [Sayama and Dionne, 2015]
- innovation niches [Lopolito et al., 2013], patenting [Dosi et al., 2021], evolution of technologies [Chen and Chie, 2006]
- role of space: multiple scales [Vermeulen and Pyka, 2018]
- Properties and effects of firm clusters [Fioretti et al., 2005]

Research objective

→ At the crossroads of these two literature streams, role of informal knowledge flows at the microscopic level within firm clusters?

→ Practical implications for urban and regional planning, and the (non-)implementations of clusters

Contributions:

1. Simple ABM simulating innovation within firms and informal knowledge flows between firms, similar to biogeography evolutionary algorithms
2. Instanciation on a specific synthetic fitness landscape
3. Systematic exploration and sensitivity analysis

Model agents

- Firms of size S_k as set of employees e_{ki} with $1 \leq i \leq S_k$, represented by their ideas (genotype) $e_{ki} = (x_j^{(ki)})(t) \in \mathbb{R}^G$.
- Geographical crossover between firms captures informal knowledge flows.
- Intra-firm evolution with selection of ideas driven by a fitness landscape.
- Companies have a "current product" $p_k(t) = (p_{kj})(t) \in \mathbb{R}^G$ with the corresponding fitness value $y_k(t)$ (social utility or company turnover).

Model description

At each time step:

1. Evolution of ideas within firms: probability of crossover for each employee p_C (copy of a share s_C of genome of one other random employee); mutations with probability p_M at the gene level (uniform variation $m \in [-x_M/2; x_M/2]$).
2. Implementation of new ideas: evaluation of the fitness function $y_{ki} = y(e_{ki})$, selection of the best product $p_k(t) = \mathrm{argmax}_i y_{ki}$; fixed share of employees s_P are selected to work on it in the next cycle and thus update their genome $e_{ik} = p_k$.
3. Informal knowledge between firms: probability of interacting for two employees of different firms given by a spatial interaction model

$$p_{ij} = p_E \cdot \exp\left(-d(k_i, k_j)/d_E\right)$$

Model indicators

1. Average fitness between firms $\bar{f}(t)$
2. Inequality between firms: entropy $\mathscr{E}_f$ of fitnesses
3. Diversity of products

$$d(t) = \frac{1}{2 \cdot N_f \cdot (N_f - 1)} \sum_{k \neq l} \left(1 - \frac{p_k(t) \cdot p_l(t)}{||p_k(t)|| \cdot ||p_l(t)||} \right)$$

Model setup

- Firm size follows a rank-size law $S_k = S_0 \cdot k^{-\alpha_S}$, with $S_0 = 100$ and $N_f = 10$ (medium-size cluster).
- Random location of firms $[0; 100]^2$ (one cluster simulated).
- Initial random genomes $[-10; 10]$, random initial product.
- Fitness landscape: random fitness landscape [Ma and Nakamori, 2005] combined with a Rastrigin function

$$y(\vec{x}) = -\sum_{i,j} m_{ij} \left[x_i^2 - 10 \cos(2\pi x_i) \right]$$

- Genome size $G = 10$; final time $t_f = 100$ ($\sim$10y).

Model exploration and validation

→ Model implemented in scala.

→ Explored and validated using the OpenMOLE software [Reuillon et al., 2013]

Parameters explored:

- firm size hierarchy $\alpha_S \in [0.1; 2.0]$
- crossover probability $p_C \in [0; 1]$
- crossover share $s_C \in [0; 1]$
- mutation probability $p_M \in [0; 1]$
- mutation amplitude $x_M \in [0; 2]$
- product work share $s_P \in [0; 1]$
- interaction probability $p_E \in [0; 10^{-4}]$
- distance decay $d_E \in [1; 100]$

Statistical convergence

Internal model validation: 100 parameter points (Latin Hypercube Sampling) with 1000 stochastic replications each.

$\rightarrow$ relatively low stochastic variability: all indicators with Sharpe ratios above 4, except Δf with a median of 1.48.

$\rightarrow$ distance between average relative to standard deviations is high (median above 2.5).

Global sensitivity analysis

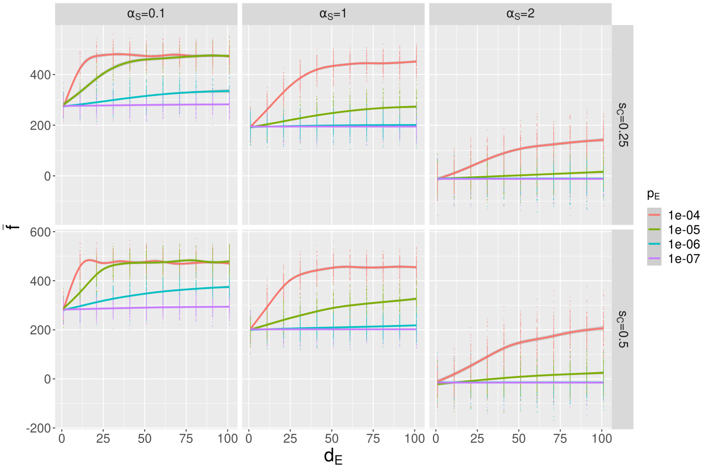
Global sensitivity analysis indices [Saltelli et al., 2008]

	α_S		p_C		s_C		p_M	
	F	T	F	T	F	T	F	T
b	0.001	0.002	0.001	0.003	$9\cdot10^{-4}$	0.002	0.41	0.75
$\bar{f}$	0.02	0.07	$6\cdot10^{-4}$	0.002	0.0	0.003	0.36	0.69
Δf	$7\cdot10^{-4}$	0.56	0.0	0.9	0.0	0.0	0.003	0.0
$\mathscr{E}_f$	0.14	0.64	0.0	0.44	0.27	0.36	0.48	0.84
d	0.007	0.13	0.001	0.04	0.01	0.1	0.45	0.7

	x_M		s_P		p_E		d_E		seed	
	F	T	F	T	F	T	F	T	F	T
b	0.17	0.52	0.03	0.13	$5\cdot10^{-4}$	0.002	$9\cdot10^{-4}$	0.002	0.003	0.007
$\bar{f}$	0.21	0.55	0.02	0.008	0.0	0.004	$4\cdot10^{-4}$	0.004	$8\cdot10^{-4}$	0.007
Δf	0.0	0.24	0.0	0.48	0.0	0.18	0.0	0.17	0.0	0.0
$\mathscr{E}_f$	0.014	0.35	0.23	0.41	0.16	0.39	0.0	0.40	0.05	0.46
d	0.21	0.42	0.0	0.1	0.003	0.09	0.006	0.09	0.006	0.05

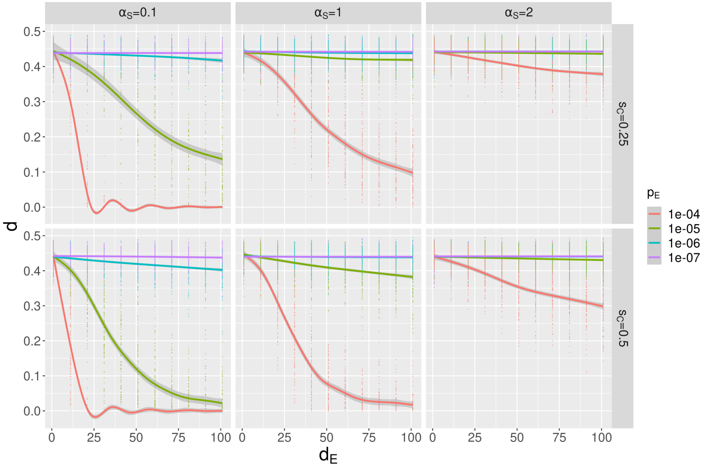
$\rightarrow$ stronger effect of mutation p_M (fixed in the following); no effect of spatial interaction on diversity but on inequality.

Parameter space exploration



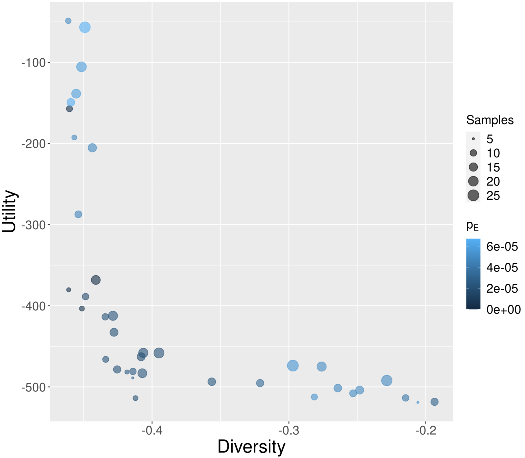
Average fitness behavior: strong but plateauing effect of informal knowledge; unequal firm sizes is less optimal.

Parameter space exploration



Diversity behavior: higher fitnesses correspond to lower diversity; qualitative regime change for low α_S when p_E increase; slight effect of s_C.

Optimisation



Pareto front between utility and the opposite of diversity obtained with a NSGA2 algorithm; U-shape behavior of interactions along the front; compromise points: long range interactions with a low probability, equal firm sizes, small product share (importance of intra-company diversity).

Discussion

Main findings: (i) important role of informal knowledge exchanges; (ii) hierarchy between firms is less optimal; (iii) trade-off between innovation fitness and diversity (compromise points correspond to equal-size regional cluster).

Link with empirics: role of spatial niche for diversity [Dionne et al., 2019]; role of local exchanges [Fitjar and Rodríguez-Pose, 2014]; no observation of "agglomeration diseconomies" on fitness but on diversity [Folta et al., 2006].

Future developments:

- More stylised facts to reproduce [Gnyawali and Srivastava, 2013]
- Multi-scale model with multiple clusters: coupling with urban evolution model [Raimbault, 2020]
- Role of telework [Bergeaud et al., 2022]
- Parametrisation on real-world data, including patent data

Conclusion

→ Simple ABM of a firm cluster with informal knowledge flows.

→ Optimal compromise systems found to be regional equal firm systems.

→ Basis for more advanced models in link with policies, other scales and dimensions of innovation and SDGs.

To use OpenMOLE (free and open software) and contribute:
`https://openmole.org`

Model code open source at
`https://github.com/JusteRaimbault/InnovationInformal`

Simulation data
`https://doi.org/10.7910/DVN/X8PWPF`

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