

Competition in two-layer multiplex networks

Sergio Gómez

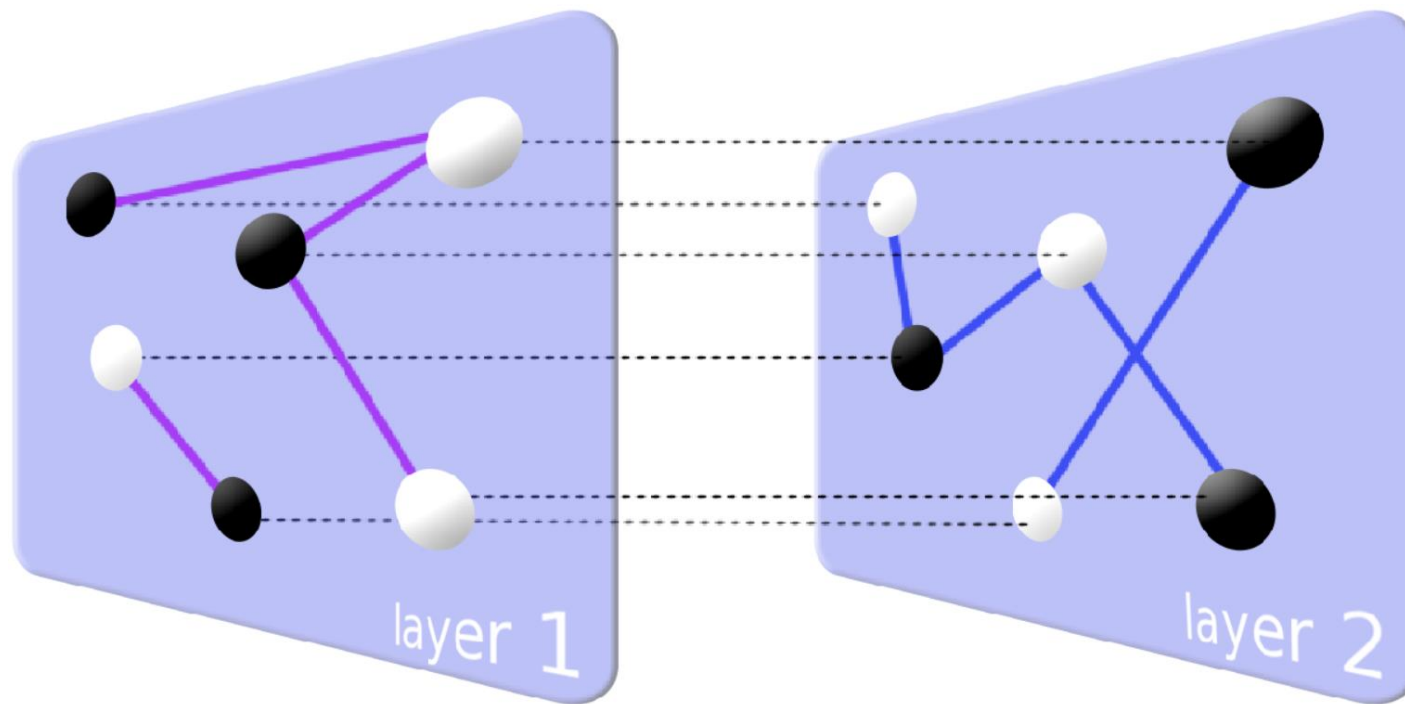
Universitat Rovira i Virgili, Tarragona (Spain)

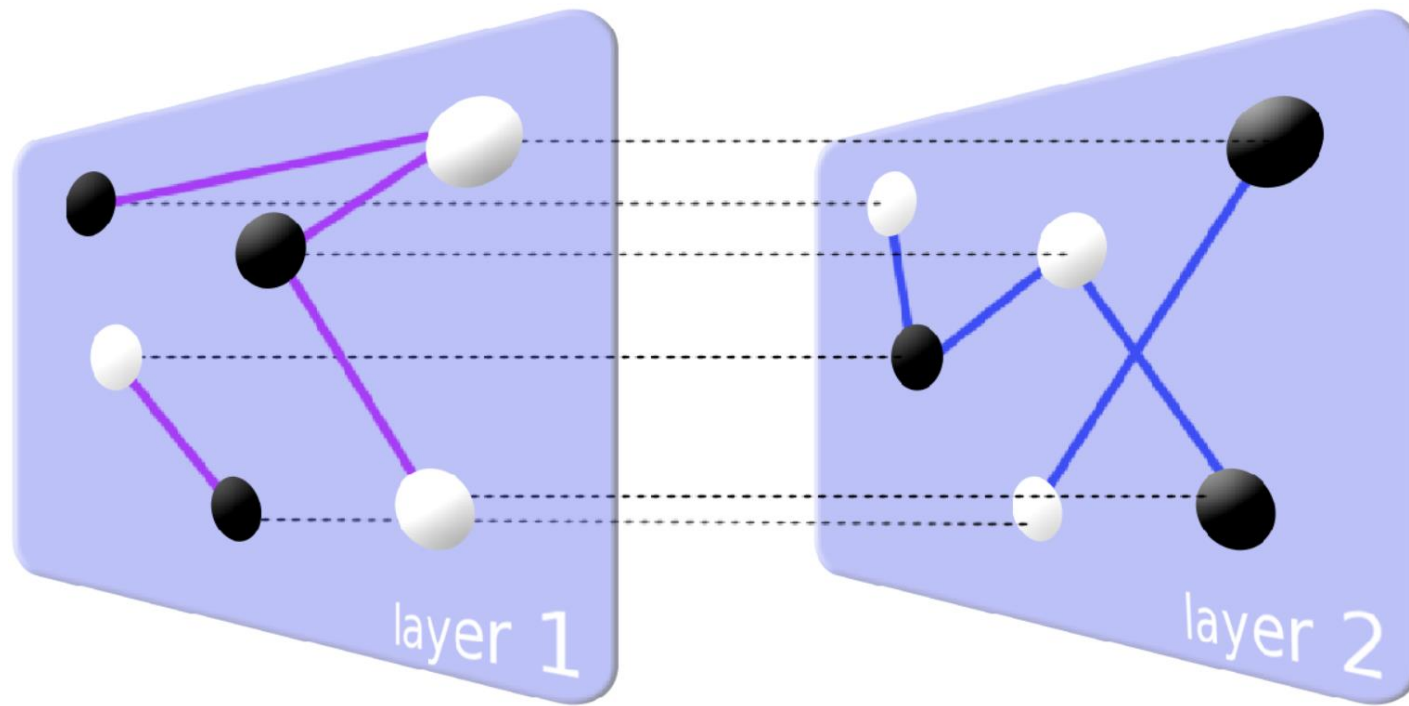
Outline

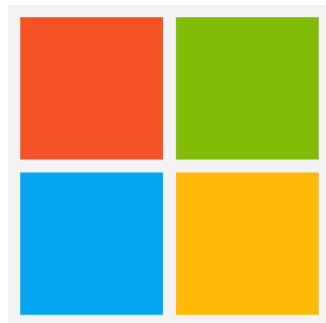
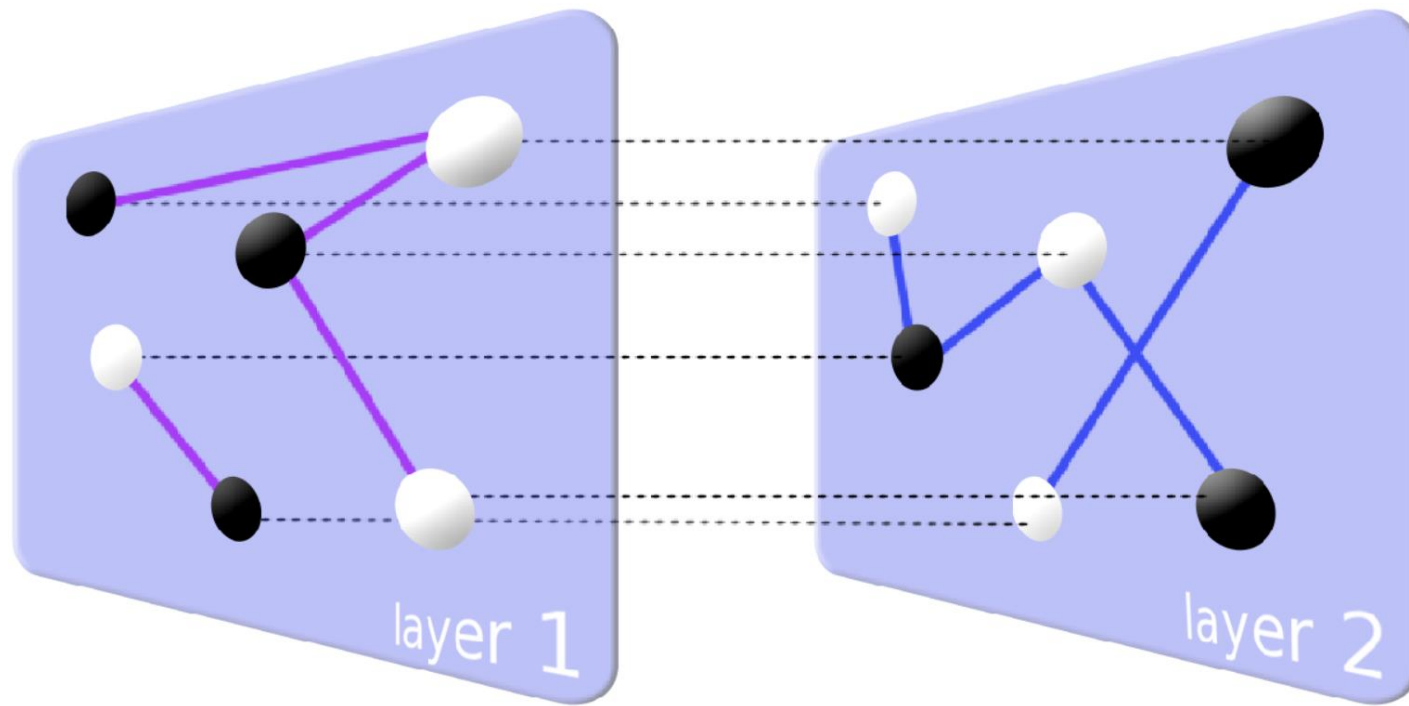
- Motivation
- Competition dynamics
- Ground State
- Optimization
- Results

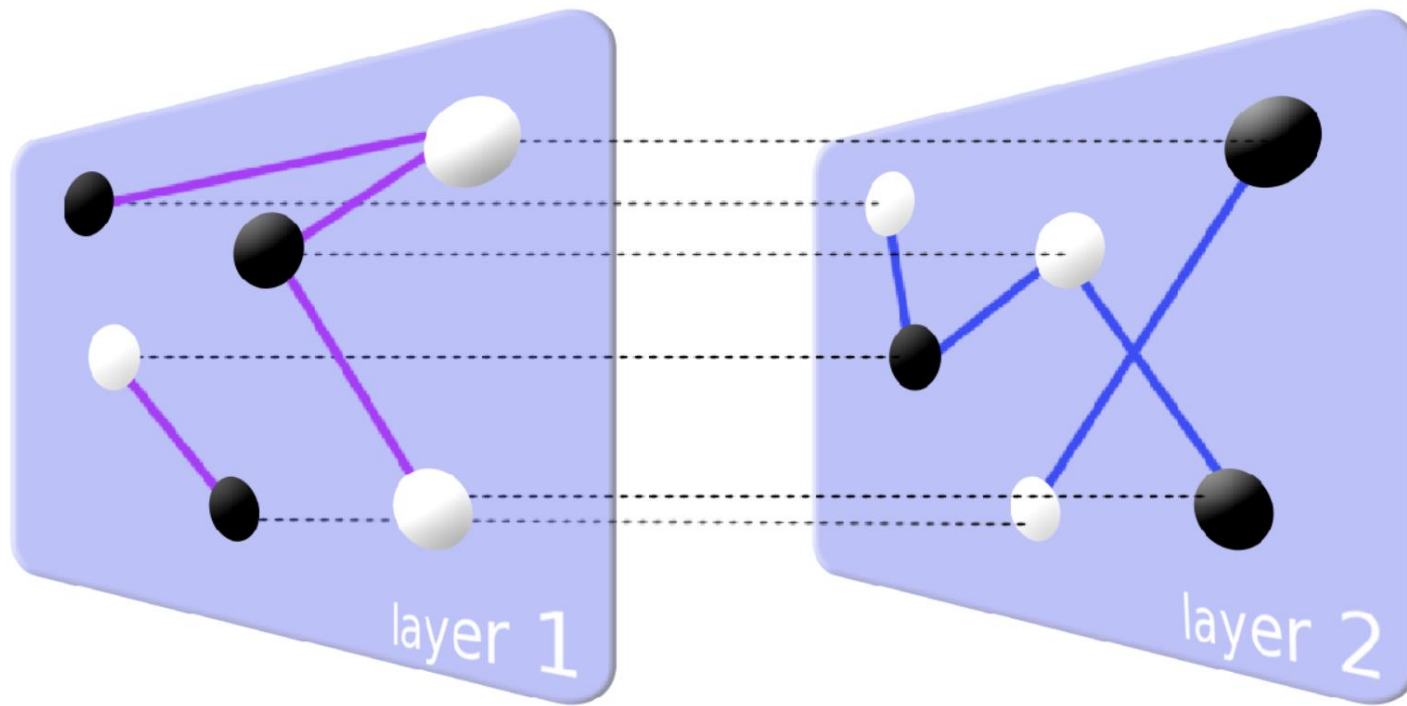
■ Structure

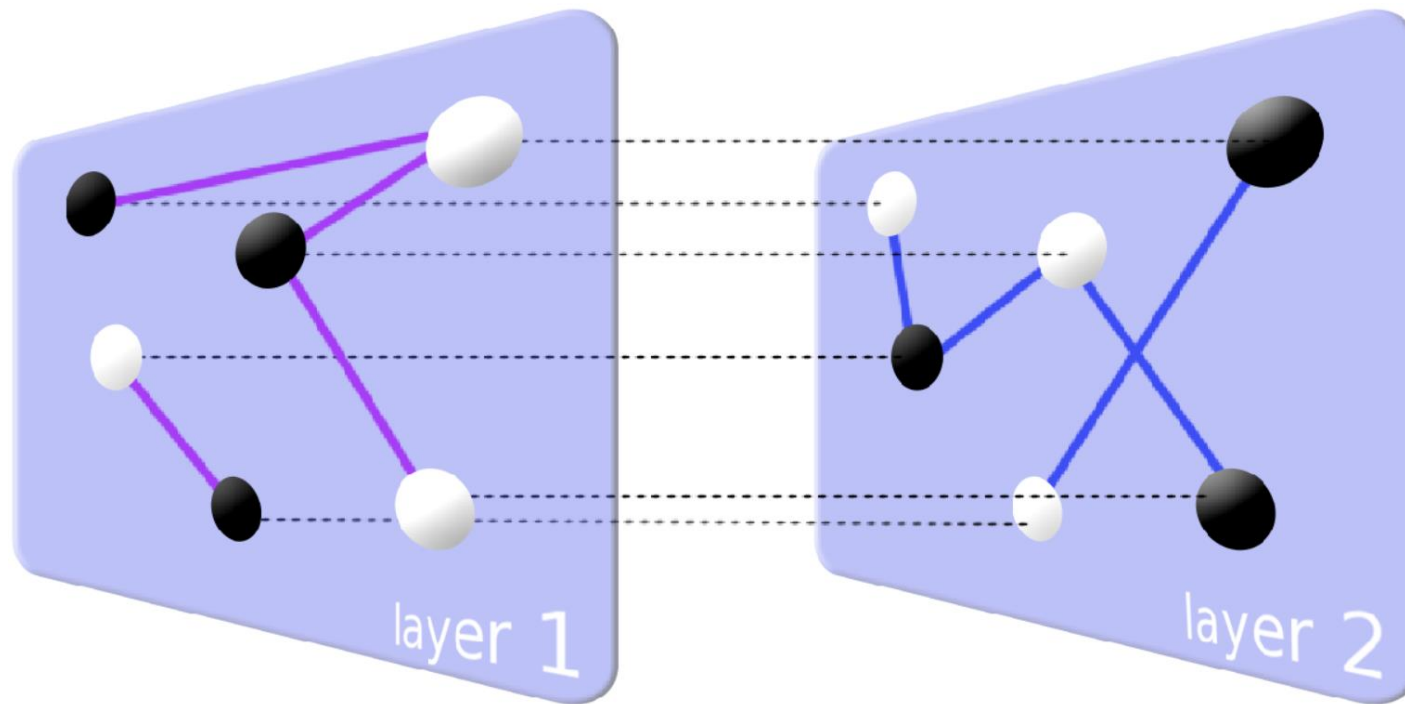
- Multiplex network





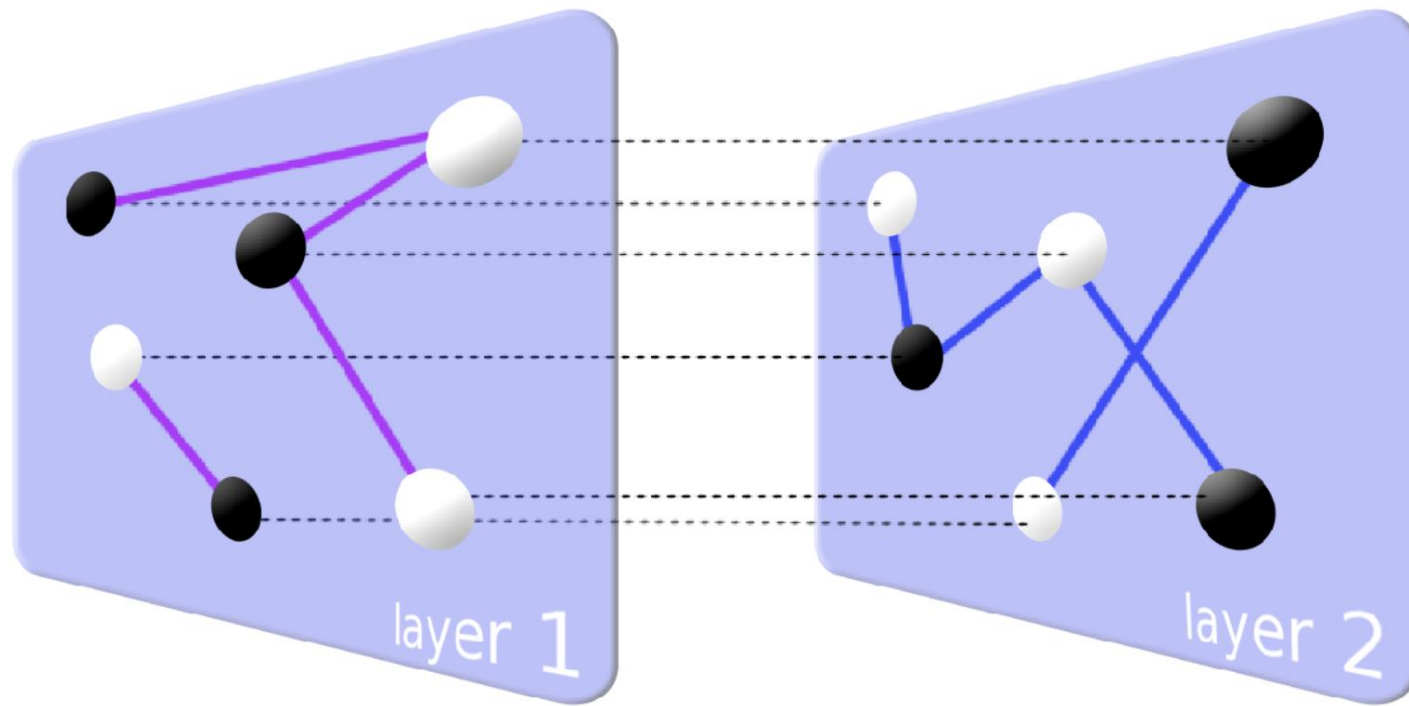






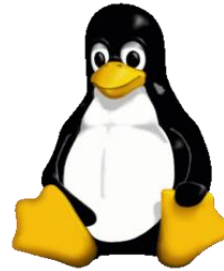
ZARA





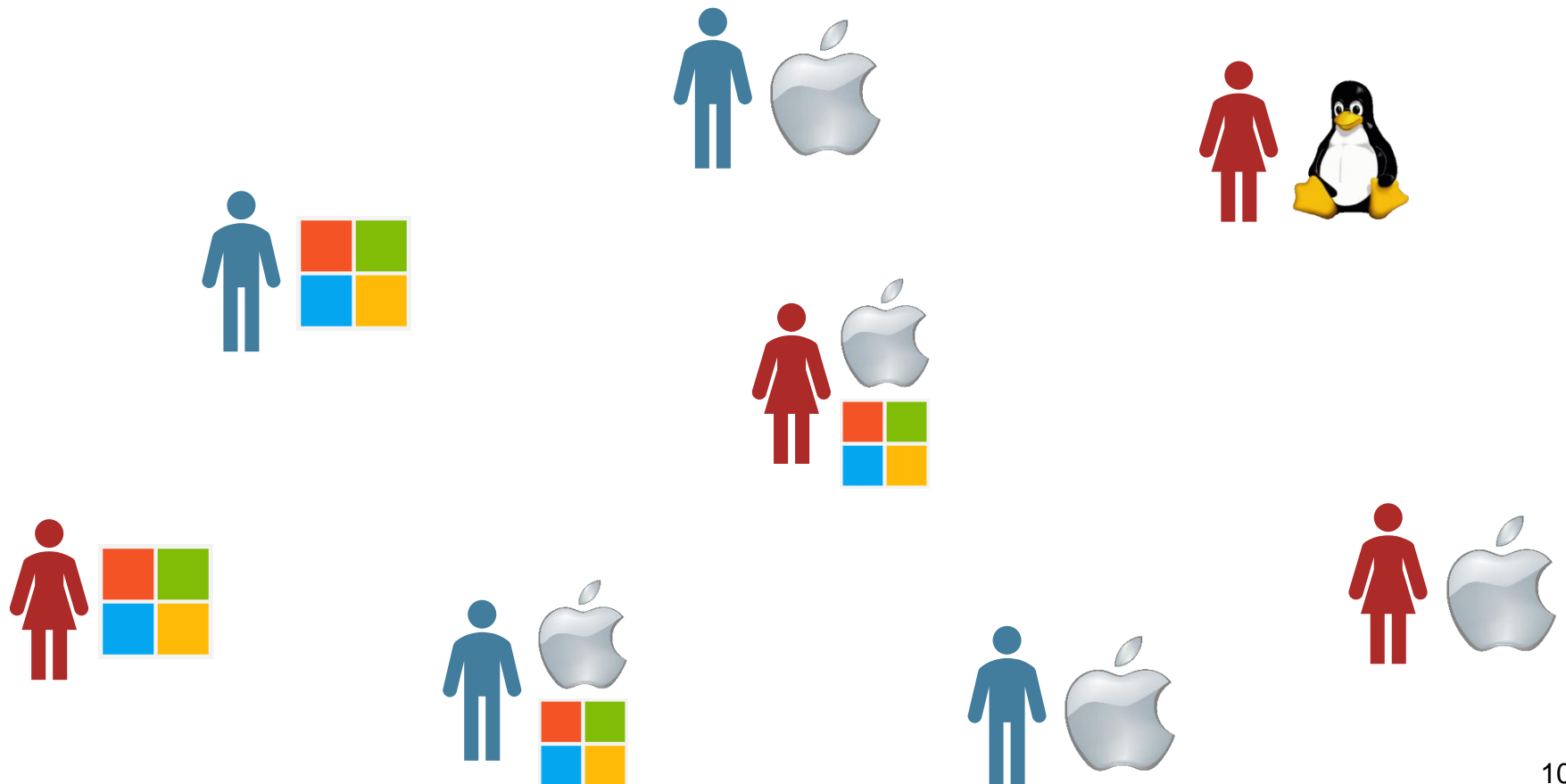
- Dynamics

- Individuals can choose between several alternatives



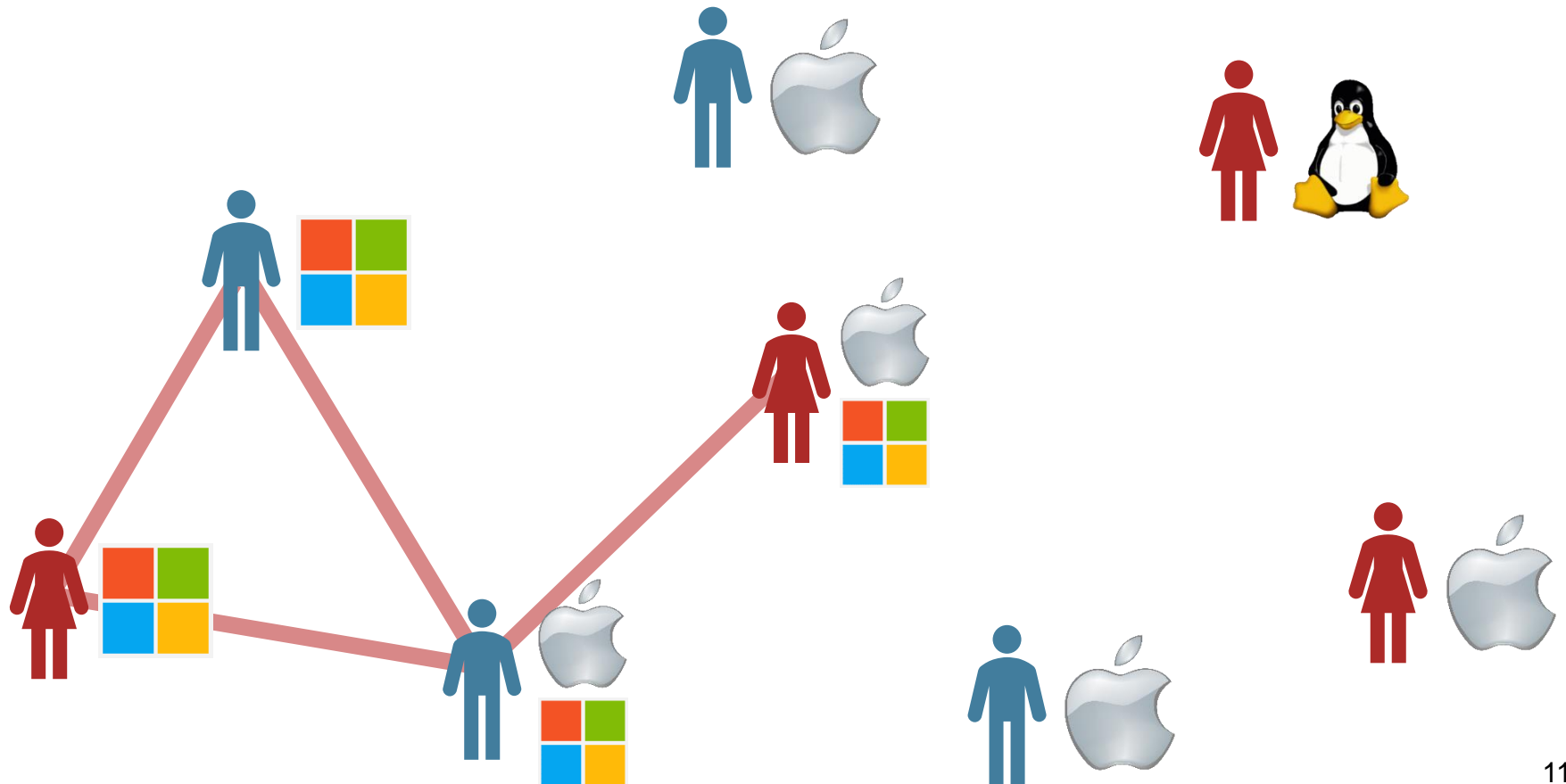
■ Dynamics

- Individuals can choose between several alternatives
- Using several alternatives at once has a cost



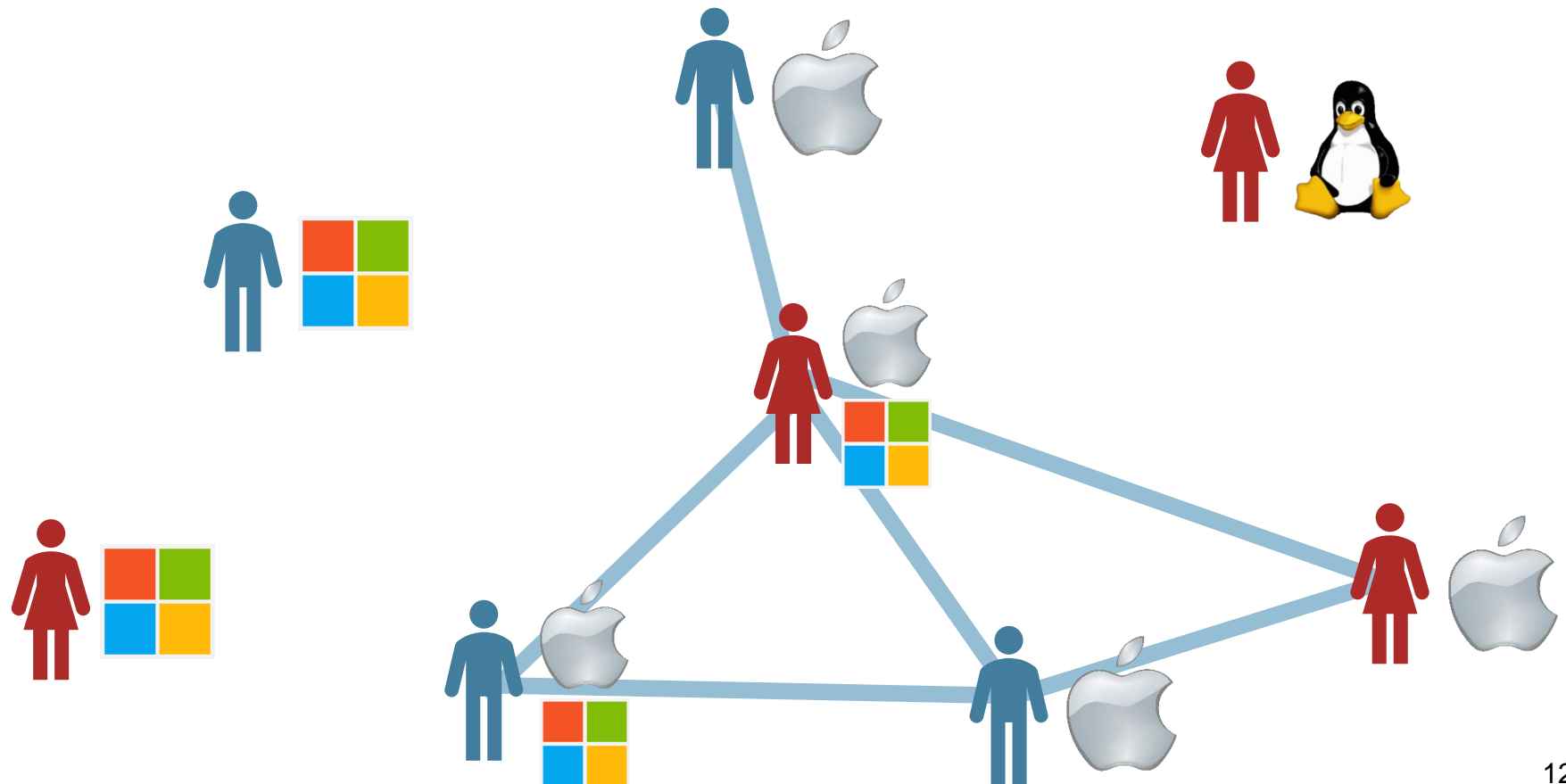
■ Dynamics

- Individuals can choose between several alternatives
- Using several alternatives at once has a cost
- Sharing an alternative with peers is beneficial



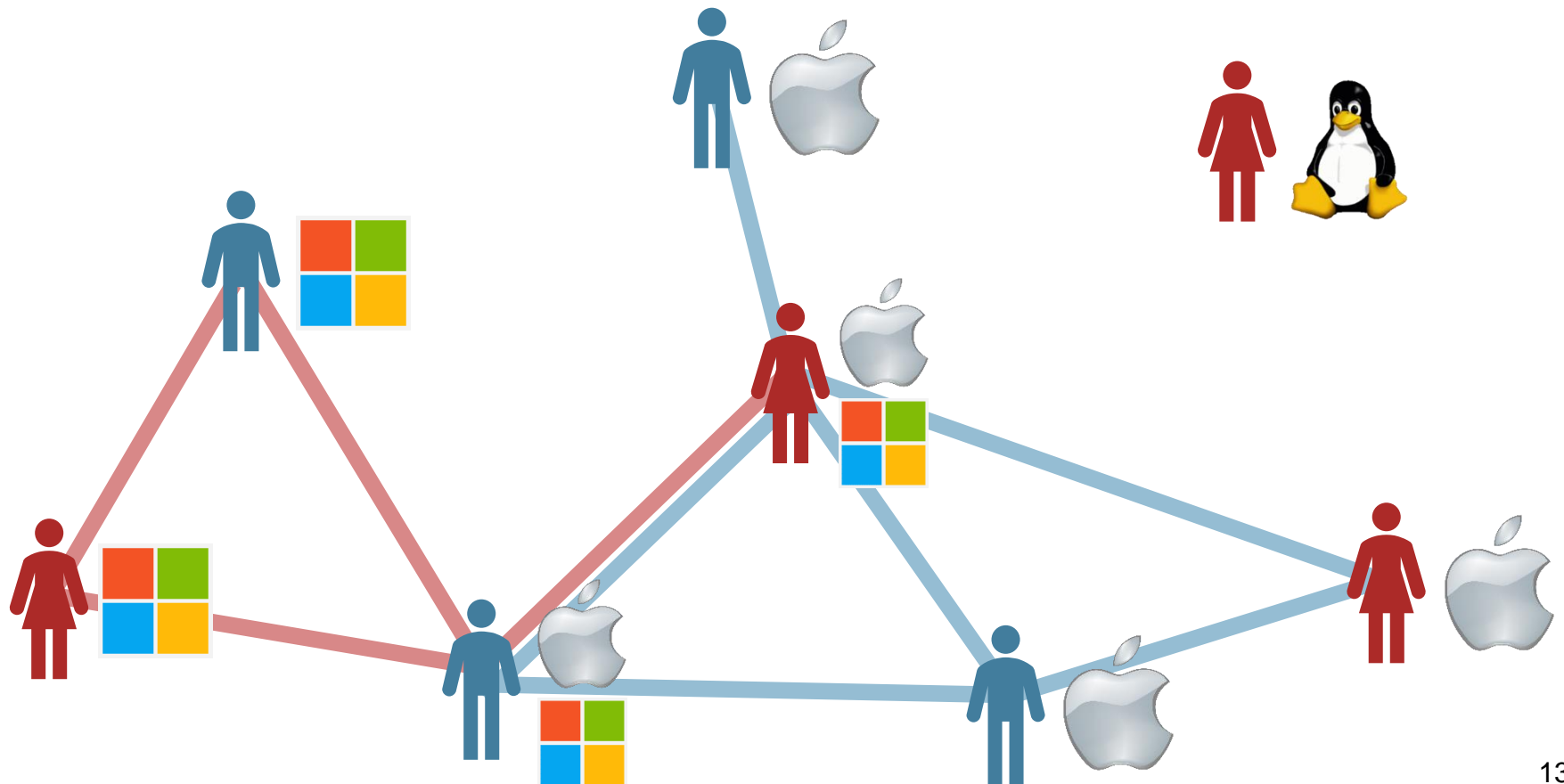
■ Dynamics

- Individuals can choose between several alternatives
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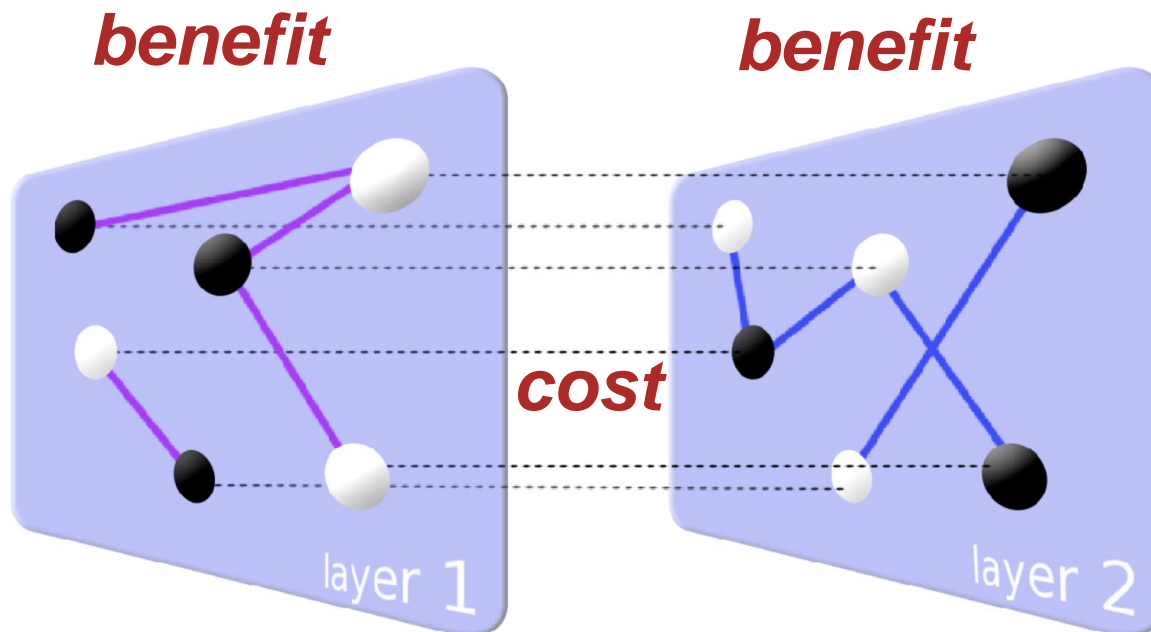
■ Dynamics

- Individuals can choose between several alternatives
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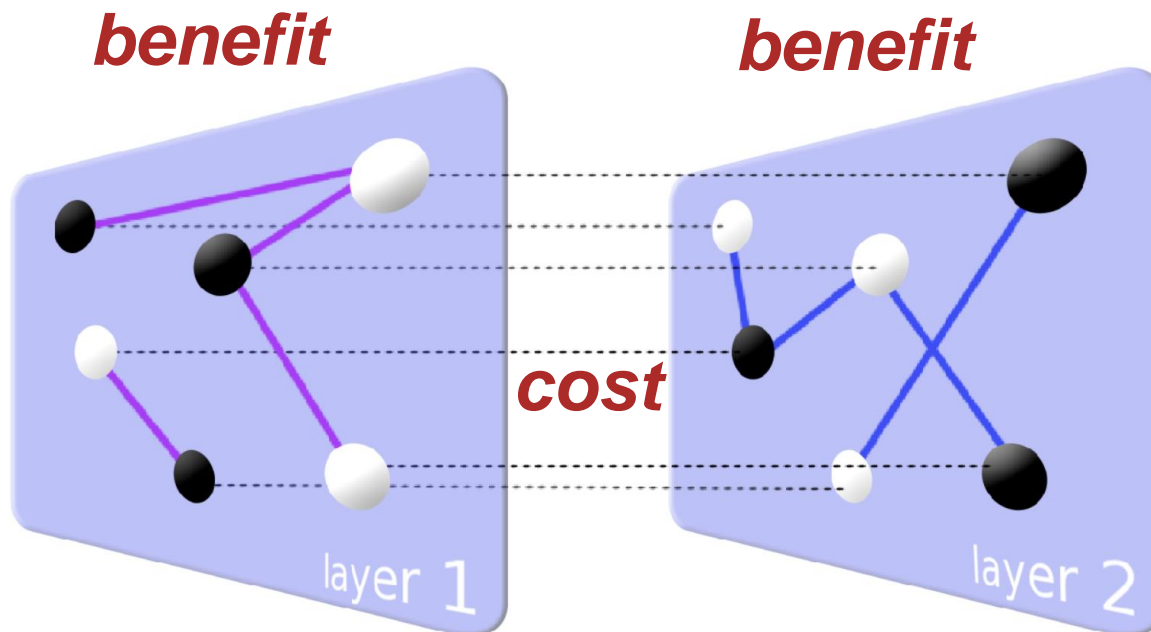
■ Dynamics

- Individuals can choose between several alternatives
- Using several alternatives at once has a **cost**
- Sharing an alternative with peers is **beneficial**



■ Dynamics

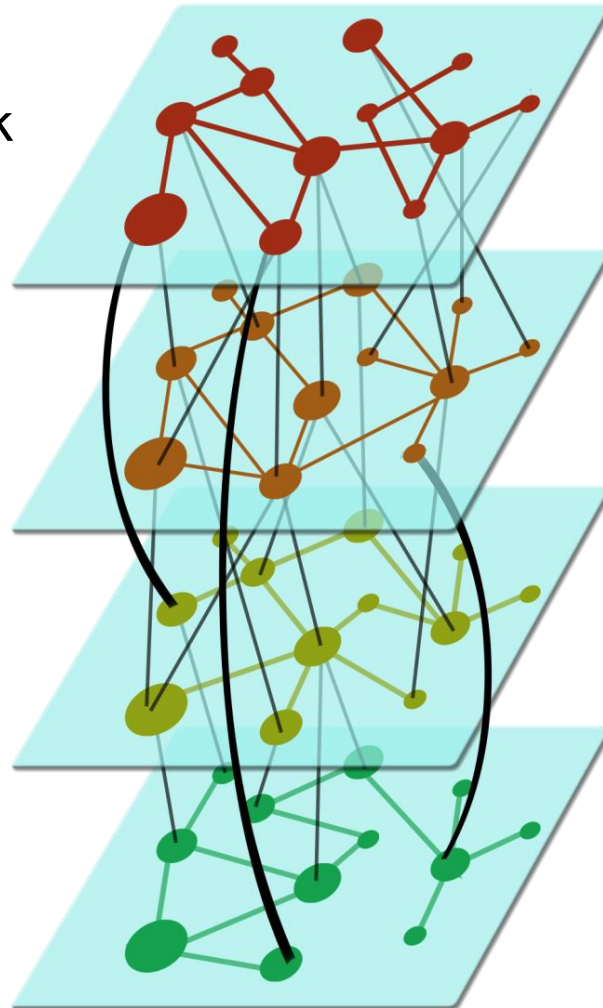
- Individuals can choose between several alternatives
- Using several alternatives at once has a **cost**
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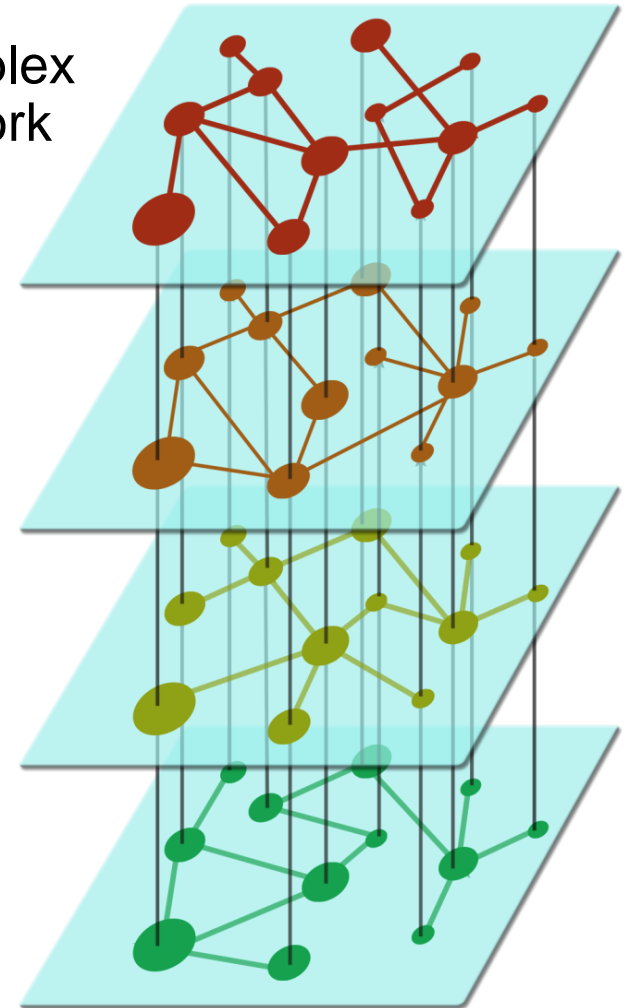
Competition between layers

Structure

Interconnected multilayer network



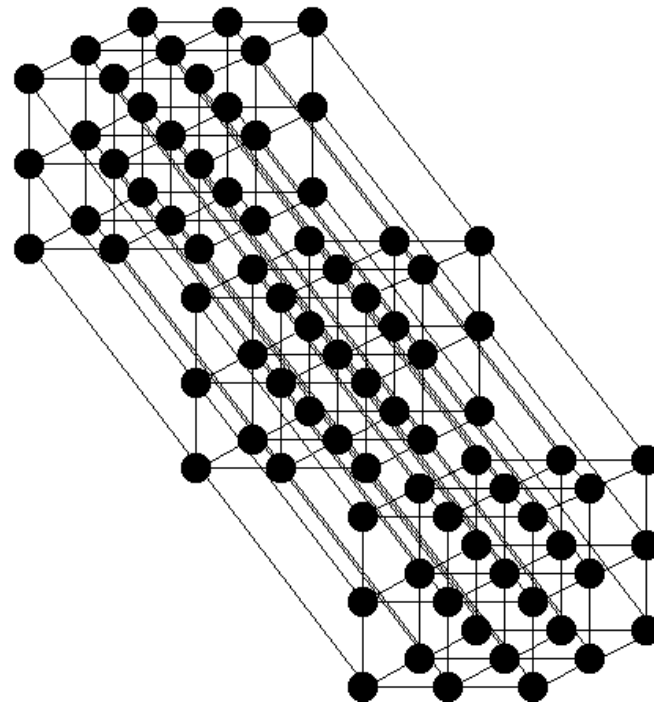
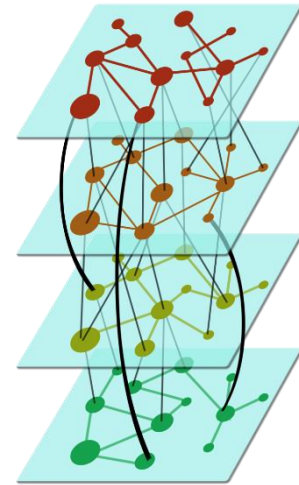
Multiplex network



■ Mathematical description

□ Adjacency (or weights) tensor

- $M_{j\beta}^{i\alpha}$ node i in layer α connects to node j in layer β

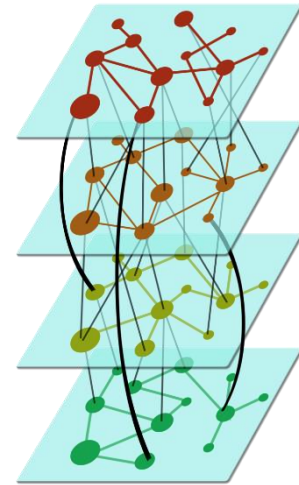


$$\mathbb{R}^{N \times L \times N \times L}$$

■ Mathematical description

□ Supra-adjacency matrix

- $\mathbf{W}^{(\alpha)}$ adjacency (or weights) matrix of layer α
- $\mathbf{D}^{(\alpha\beta)}$ interaction matrix between layers α and β

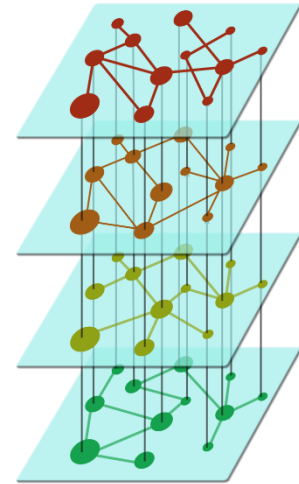


$$\mathcal{J} = \begin{pmatrix} \mathbf{W}^{(1)} & 0 & \dots & 0 \\ 0 & \mathbf{W}^{(2)} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \mathbf{W}^{(L)} \end{pmatrix} + \begin{pmatrix} \mathbf{D}^{(11)} & \mathbf{D}^{(12)} & \dots & \mathbf{D}^{(1L)} \\ \mathbf{D}^{(21)} & \mathbf{D}^{(22)} & \dots & \mathbf{D}^{(2L)} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{D}^{(L1)} & \mathbf{D}^{(L2)} & \dots & \mathbf{D}^{(LL)} \end{pmatrix}$$

$$\mathcal{J} = \bigoplus_{\alpha=1}^L \mathbf{W}^{(\alpha)} + \mathcal{D}$$

■ Mathematical description

- Supra-adjacency matrix ***multiplex network***
 - $\mathbf{W}^{(\alpha)}$ adjacency (or weights) matrix of layer α
 - $D^{(\alpha\beta)}$ interaction strength between layers α and β

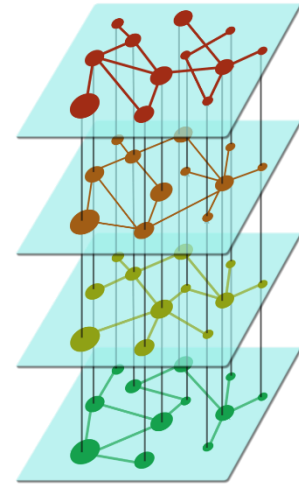


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$$\mathcal{J} = \bigoplus_{\alpha=1}^L \mathbf{W}^{(\alpha)} + \mathbf{D} \otimes \mathbf{I}$$

■ Mathematical description

- Supra-adjacency matrix ***multiplex network***
 - $\mathbf{W}^{(\alpha)}$ adjacency (or weights) matrix of layer α
 - $D^{(\alpha\beta)}$ interaction strength between layers α and β

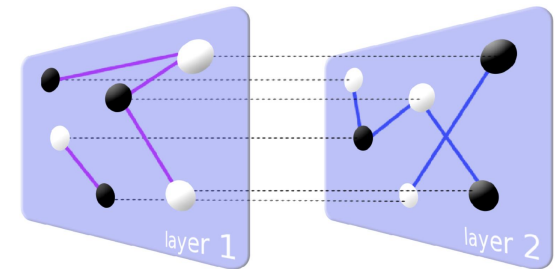


$$\mathcal{J} = \begin{pmatrix} \mathbf{W}^{(1)} & 0 & \dots & 0 \\ 0 & \mathbf{W}^{(2)} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \mathbf{W}^{(L)} \end{pmatrix} + \begin{pmatrix} D^{(11)}\mathbf{I} & D^{(12)}\mathbf{I} & \dots & D^{(1L)}\mathbf{I} \\ D^{(21)}\mathbf{I} & D^{(22)}\mathbf{I} & \dots & D^{(2L)}\mathbf{I} \\ \vdots & \vdots & \ddots & \vdots \\ D^{(L1)}\mathbf{I} & D^{(L2)}\mathbf{I} & \dots & D^{(LL)}\mathbf{I} \end{pmatrix}$$

■ Hypotheses

- All nodes same interlayer strength $\mathbf{D}^{(\alpha\beta)} = D^{(\alpha\beta)}\mathbf{I}$
- No self-loops $D^{(\alpha\alpha)} = 0$
- Symmetry $D^{(\alpha\beta)} = D^{(\beta\alpha)}$

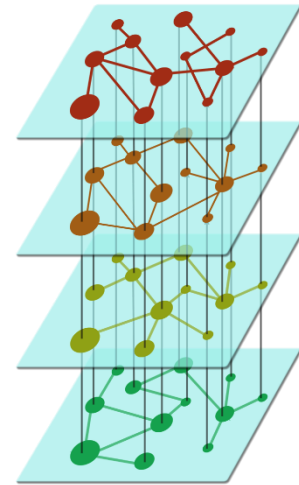
- Mathematical description
 - Two-layer multiplex networks



$$\mathcal{J} = \begin{pmatrix} \mathbf{W}^{(1)} & 0 \\ 0 & \mathbf{W}^{(2)} \end{pmatrix} + J_x \begin{pmatrix} 0 & \mathbf{I} \\ \mathbf{I} & 0 \end{pmatrix}$$

Related dynamics

■ Diffusion in multiplex networks



$$\dot{x}_i^{(\alpha)} = \sum_{j=1}^N w_{ij}^{(\alpha)} (x_j^{(\alpha)} - x_i^{(\alpha)}) + \sum_{\beta=1}^L D^{(\alpha\beta)} (x_i^{(\beta)} - x_i^{(\alpha)})$$

Laplacian

$$\mathcal{L} = \mathcal{L}^L + \mathcal{L}^I$$

$$\mathcal{L}^L = \bigoplus_{\alpha=1}^M L^{(\alpha)}$$

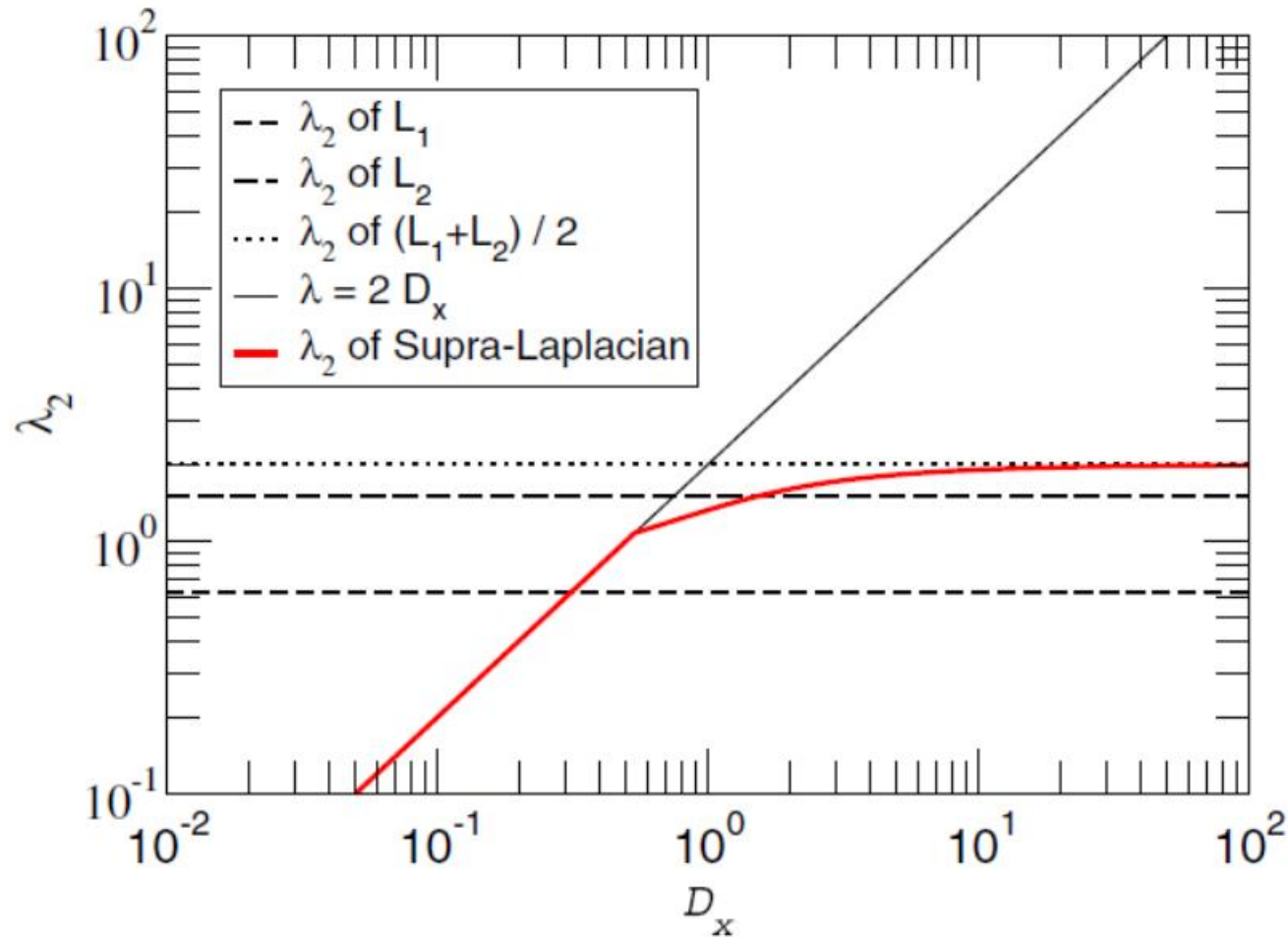
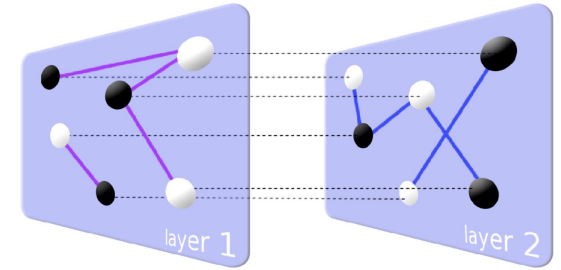
$$\mathcal{L}^I = L^I \otimes I$$

Diffusion time

$$\tau \sim \frac{1}{\lambda_2(\mathcal{L})}$$

■ Results

□ Superdiffusion! $\tau < \tau_1 < \tau_2$

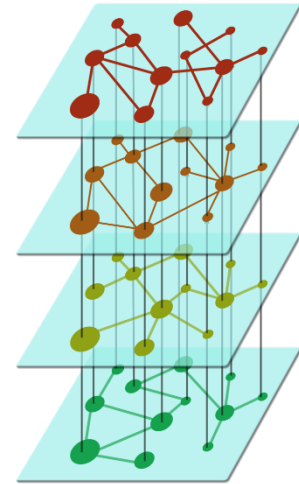
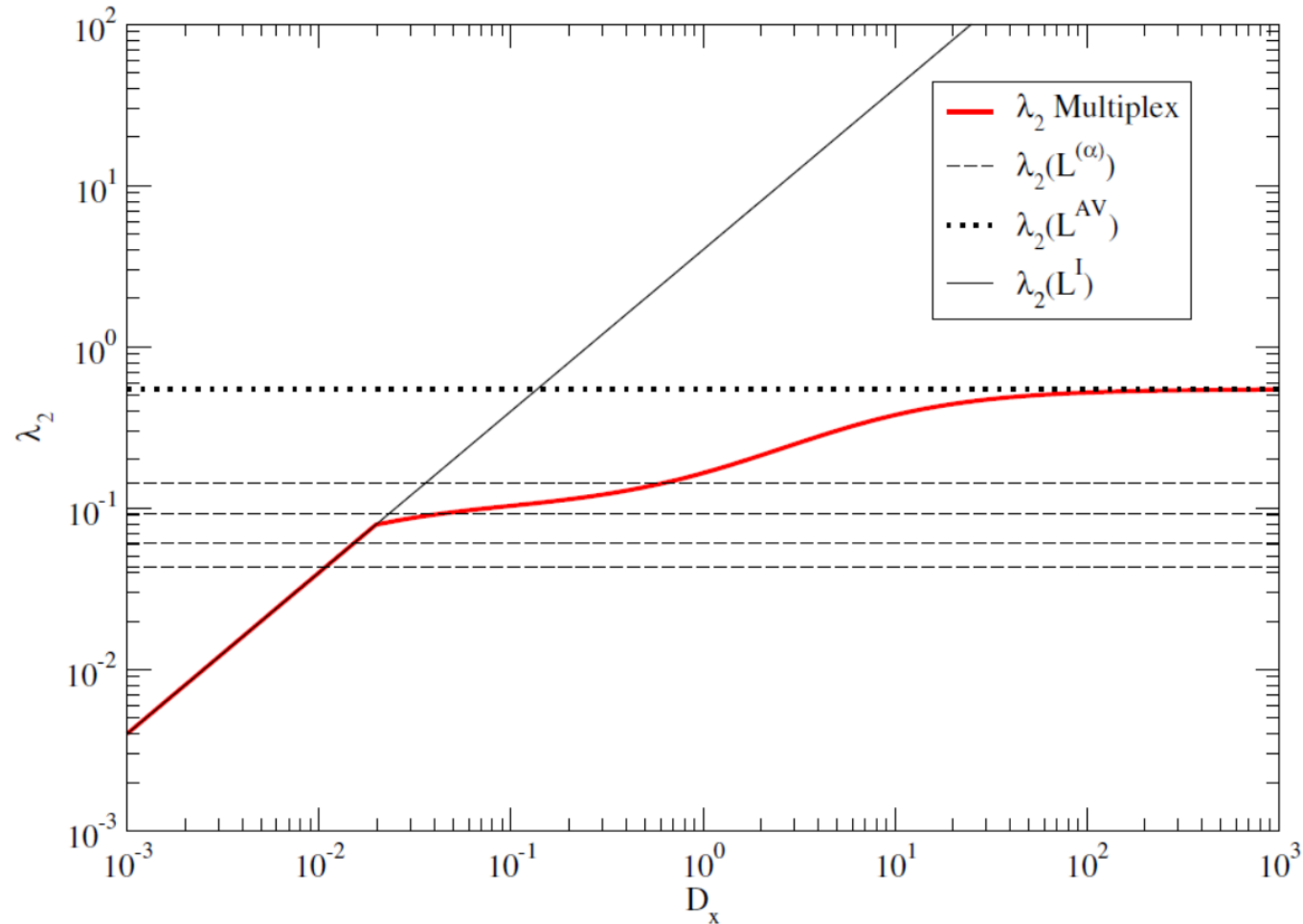


$$L = 2$$

$$D_x \equiv D^{(12)}$$

■ Results

□ Superdiffusion! $\tau < \tau_1 < \tau_2$



$$L = 4$$

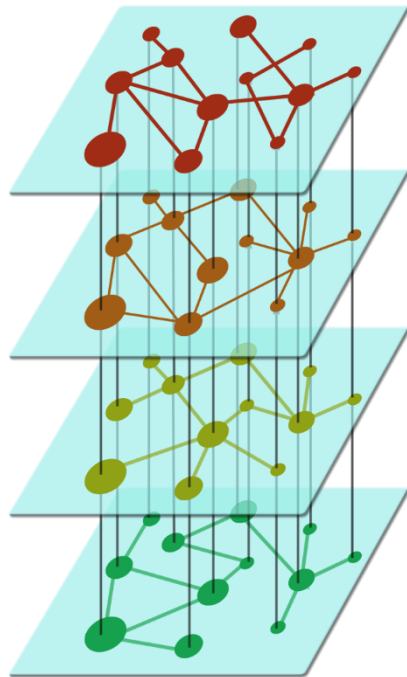
$$D_x \equiv D^{(\alpha\beta)}$$

Solé-Ribalta et al: Spectral properties of the Laplacian of multiplex networks
Physical Review E **88** (2013) 032807

Competition dynamics

■ Variables

- $p_i^{(\alpha)}$ probability of node i being active in layer α



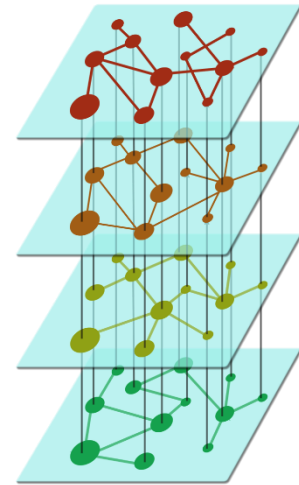
$$\sum_{\alpha=1}^L p_i^{(\alpha)} = 1$$

- Competition
 - Hamiltonian

$$H(\mathbf{P}) = - \sum_{\alpha, \beta=1}^L \sum_{i, j=1}^N J_{ij}^{(\alpha\beta)} p_i^{(\alpha)} p_j^{(\beta)}$$

where

$$\mathcal{J} = \bigoplus_{\alpha=1}^L \mathbf{W}^{(\alpha)} + \mathbf{D} \otimes \mathbf{I}$$



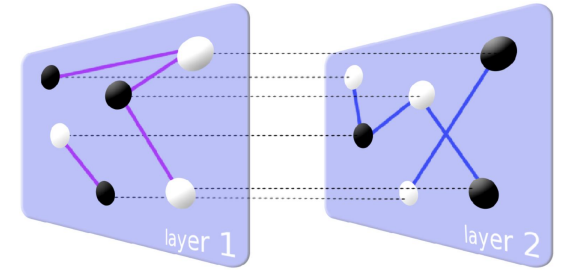
■ Competition in two-layer multiplex

□ Variables

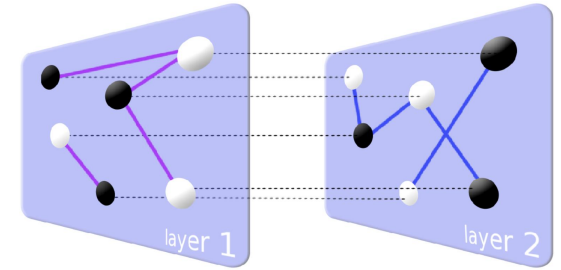
$$p_i^{(1)} = p_i \quad p_i^{(2)} = 1 - p_i$$

□ Hamiltonian

$$H(\vec{p}) = - \sum_{i,j=1}^N W_{ij}^{(1)} p_i p_j - \sum_{i,j=1}^N W_{ij}^{(2)} (1 - p_i)(1 - p_j) \\ - 2J_x \sum_{i=1}^N p_i (1 - p_i)$$

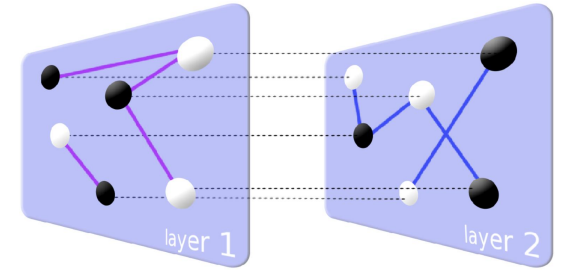


■ Competition in two-layer multiplex



$$H(\vec{p}) = - \sum_{i,j=1}^N W_{ij}^{(1)} p_i p_j - \sum_{i,j=1}^N W_{ij}^{(2)} (1 - p_i)(1 - p_j) - 2J_x \sum_{i=1}^N p_i (1 - p_i)$$

■ Competition in two-layer multiplex

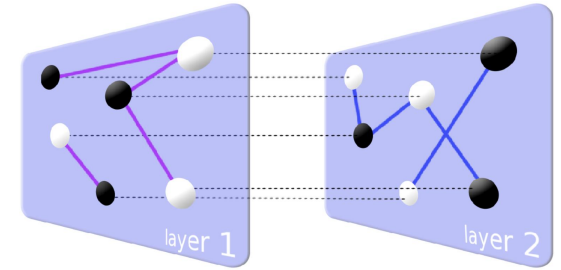


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Minimum value when
all $p_i = 1$

■ Competition in two-layer multiplex

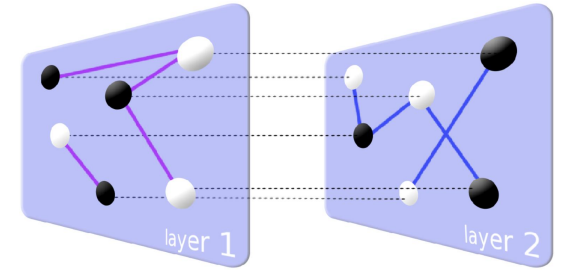


$$H(\vec{p}) = - \sum_{i,j=1}^N W_{ij}^{(1)} p_i p_j - \sum_{i,j=1}^N W_{ij}^{(2)} (1 - p_i)(1 - p_j) - 2J_x \sum_{i=1}^N p_i (1 - p_i)$$



Minimum value when
all $p_i = 0$

■ Competition in two-layer multiplex



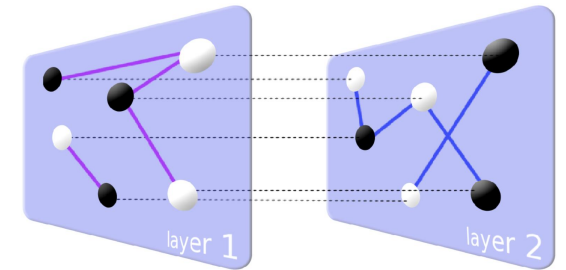
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Minimum value when
all $p_i = 0.5$

■ Magnetization

$$M(\vec{p}) = \frac{1}{N} \sum_{i=1}^N (2p_i - 1)$$



- All $p_i = 1$ ➡ $M = +1$ ➡ All nodes in first layer
- All $p_i = 0.5$ ➡ $M = 0$ ➡ All nodes equally in all layers
- All $p_i = 0$ ➡ $M = -1$ ➡ All nodes in second layer

Ground state

■ Minimize

$$H(\vec{p}) = - \sum_{i,j=1}^N W_{ij}^{(1)} p_i p_j - \sum_{i,j=1}^N W_{ij}^{(2)} (1 - p_i)(1 - p_j) \\ - 2J_x \sum_{i=1}^N p_i (1 - p_i)$$

with the constraints

$$0 \leq p_i \leq 1 \quad \rightarrow \quad \text{solution inside the } [0, 1]^N \text{ hypercube}$$

Ground state

Quadratic programming problem

■ Minimize

$$H(\vec{p}) = - \sum_{i,j=1}^N W_{ij}^{(1)} p_i p_j - \sum_{i,j=1}^N W_{ij}^{(2)} (1 - p_i)(1 - p_j) - 2J_x \sum_{i=1}^N p_i (1 - p_i)$$

with the constraints

$$0 \leq p_i \leq 1 \quad \rightarrow \quad \text{solution inside the } [0, 1]^N \text{ hypercube}$$

■ Gradient

$$\frac{\partial H}{\partial p_i} = -2 \sum_{j=1}^N W_{ij}^{(1)} p_j + 2 \sum_{j=1}^N W_{ij}^{(2)} (1 - p_j) - 2J_x(1 - 2p_i)$$

■ Zero gradient equation

$$[2J_x \mathbf{I} - (\mathbf{W}^{(1)} + \mathbf{W}^{(2)})] \vec{p} = J_x \vec{1} - \vec{s}^{(2)} \quad \rightarrow \quad \vec{p}^*$$

■ Hessian

$$\frac{\partial^2 H}{\partial p_i \partial p_j} = 2 \left(2J_x \delta_{ij} - W_{ij}^{(1)} - W_{ij}^{(2)} \right)$$

■ Ground state conditions

□ If \vec{p}^* inside $[0, 1]^N$ and Hessian positive definite

- \vec{p}^* is feasible solution
- \vec{p}^* is the ground state

□ Else

- Ground state lies in one side of the hypercube $[0, 1]^N$
- If Hessian not positive definite → **NP-hard** problem

■ Asymptotic limits

□ When $J_x \gg 1$

□ When $J_x = 0$

■ Asymptotic limits

□ When $J_x \gg 1$

$$H(\vec{p}) = - \sum_{i,j=1}^N W_{ij}^{(1)} p_i p_j - \sum_{i,j=1}^N W_{ij}^{(2)} (1 - p_i)(1 - p_j) - 2J_x \sum_{i=1}^N p_i(1 - p_i)$$



Other terms negligible

■ Asymptotic limits

□ When $J_x \gg 1$

$$H(\vec{p}) = - \sum_{i,j=1}^N W_{ij}^{(1)} p_i p_j - \sum_{i,j=1}^N W_{ij}^{(2)} (1 - p_i)(1 - p_j) - 2J_x \sum_{i=1}^N p_i(1 - p_i)$$

$$M = 0$$

Minimum value when
all $p_i = 0.5$

Other terms negligible

■ Asymptotic limits

□ When $J_x = 0$

$$H(\vec{p}) = - \sum_{i,j=1}^N W_{ij}^{(1)} p_i p_j - \sum_{i,j=1}^N W_{ij}^{(2)} (1 - p_i)(1 - p_j) - 2J_x \sum_{i=1}^N p_i (1 - p_i)$$



Other term negligible

■ Asymptotic limits

□ When $J_x = 0$

$$H(\vec{p}) = - \sum_{i,j=1}^N W_{ij}^{(1)} p_i p_j - \sum_{i,j=1}^N W_{ij}^{(2)} (1 - p_i)(1 - p_j) - 2J_x \sum_{i=1}^N p_i (1 - p_i)$$



$$s^{(\alpha)} = \sum_{i,j=1}^N W_{ij}^{(\alpha)}$$

If $s^{(1)} > s^{(2)}$ → $M = +1$

If $s^{(1)} < s^{(2)}$ → $M = -1$

■ Asymptotic limits

$$J_x = 0$$

$$J_x \gg 1$$



Localized activity in
first layer

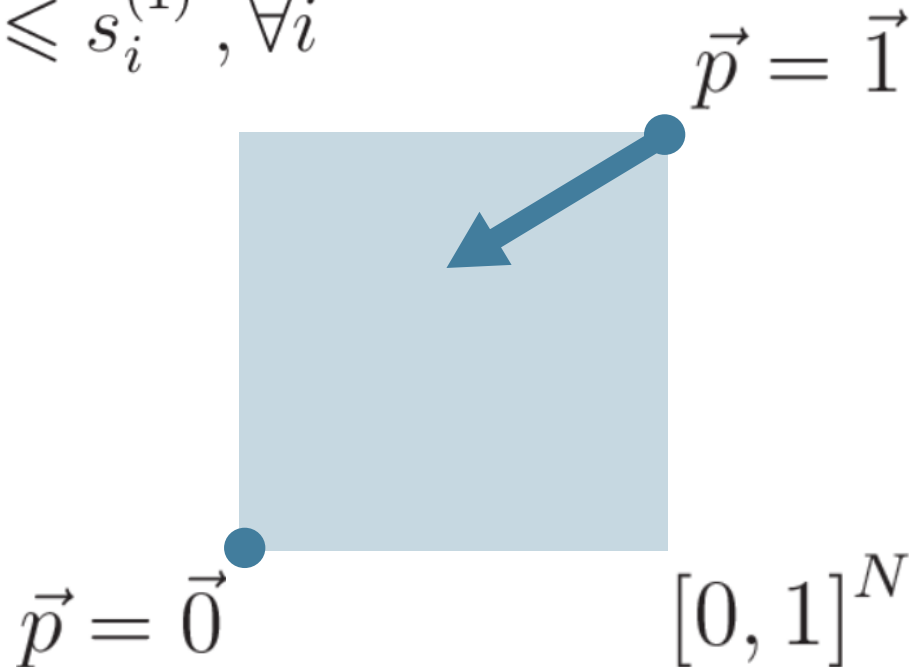
Mixed activity in
all layers

(supposing $s^{(1)} > s^{(2)}$)

- Gradient at $\vec{p} = \vec{1}$

$$\left. \frac{\partial H}{\partial p_i} \right|_{\vec{p}=\vec{1}} = 2 \left(J_x - s_i^{(1)} \right)$$

- If $J_x \leq s_i^{(1)}, \forall i$



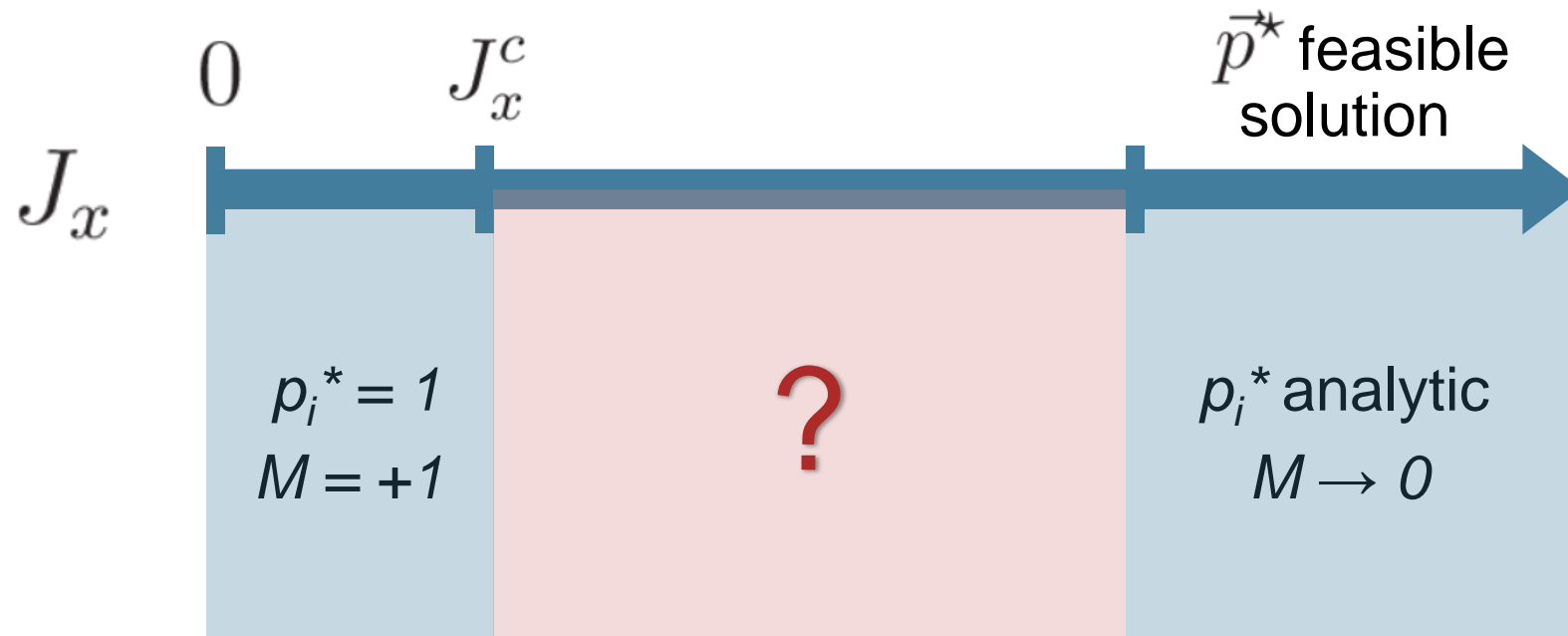
- Gradient at $\vec{p} = \vec{1}$

$$\left. \frac{\partial H}{\partial p_i} \right|_{\vec{p}=\vec{1}} = 2 \left(J_x - s_i^{(1)} \right)$$

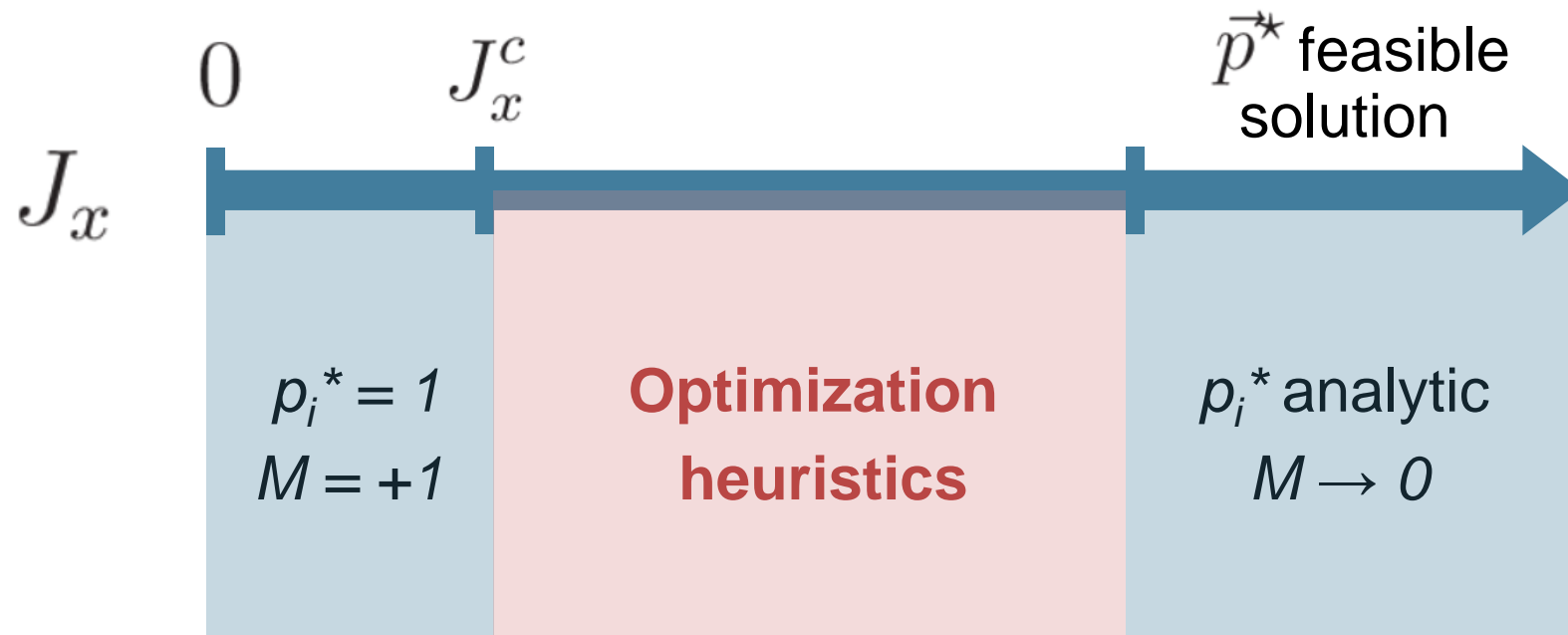
- If J_x below $J_x^c = \min_{i=1, \dots, N} (s_i^{(1)}) = s_{\min}^{(1)}$

- $\vec{p}^* = \vec{1}$

■ Solutions diagram



■ Solutions diagram



Combinatorial optimization

- NP-complete / NP-hard optimization problems
 - Many variables
 - Huge search space
 - No known polynomial time algorithms

- Algorithms
 - Local search
 - Collective search
 - Hybrid search

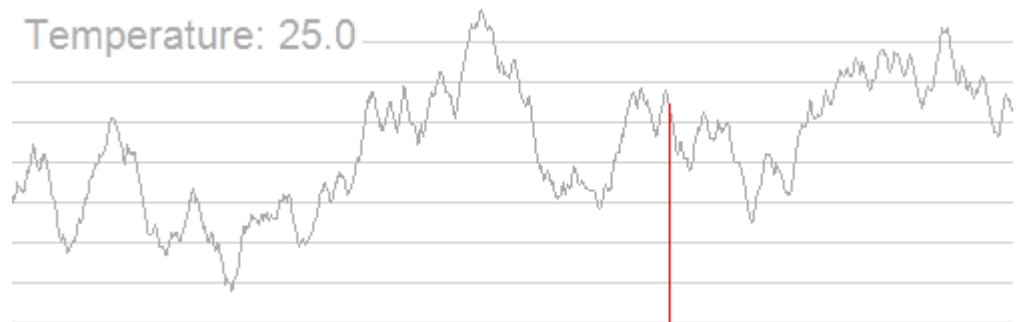
■ Local search

□ Characteristics

- One individual moves in the search state
- Travel guided by local information
- Short-term memory
- Try to avoid local optima

□ Some methods

- Gradient descent
- Simulated annealing
- Tabu search
- Extremal optimization



■ Local search methods

□ Gradient descent

- Continuous variables
- Needs the gradient
- Easily stuck in local minima
- Add noise or inertia to improve search

□ Simulated annealing

- Inspired by physics at equilibrium
- Adequate for discrete variables
- Explore neighbors
- Allow uphill moves with certain probability (temperature)



■ Local search methods

□ Tabu search

- Adequate for discrete variables
- Explore neighbors
- Forbid uphill moves in a certain tabu list

□ Extremal optimization

- Inspired by physics out of equilibrium
- Adequate for discrete variables
- Explore neighbors
- Objective function sum of one-variable terms
- Improve the worst contribution

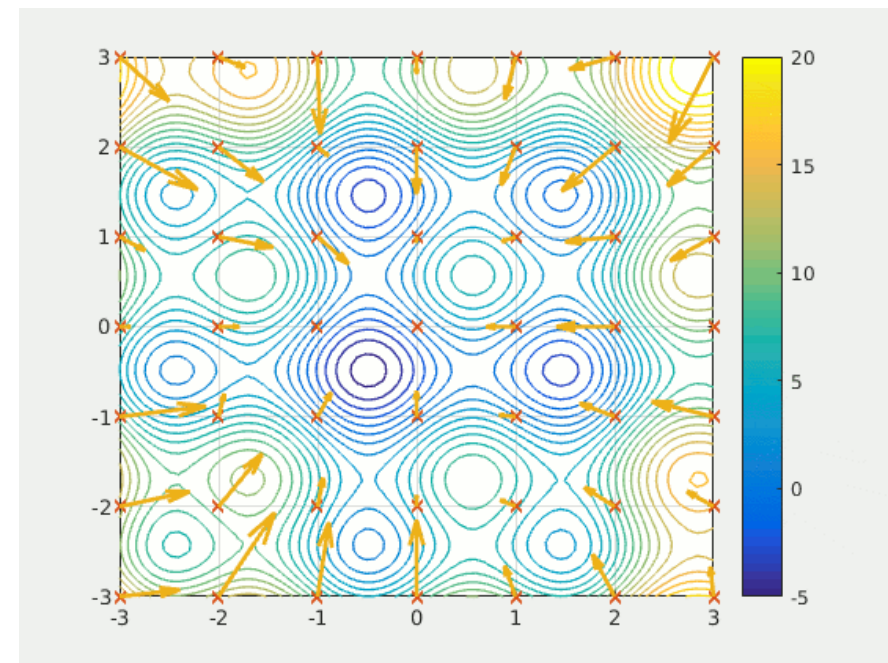
■ Collective search

□ Characteristics

- Several individuals move in the search state
- Communication between individuals
- Travel guided by local and global information
- Long-term memory, swarm intelligence, diversity

□ Some methods

- Evolutionary computation
 - Genetic algorithms
 - Evolution strategies
- Swarm intelligence
 - Particle swarm optimization
 - Ant colony systems
 - Artificial bee colony



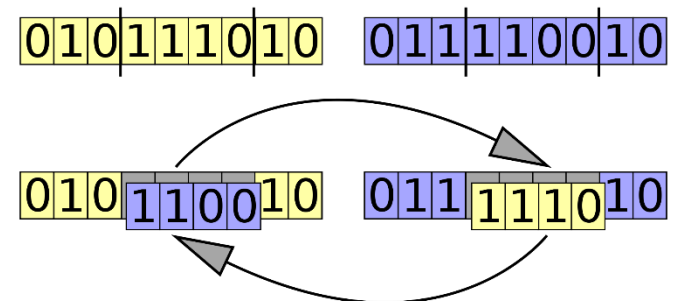
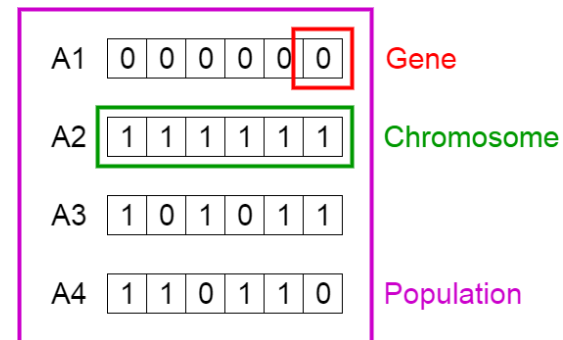
■ Collective search methods

□ Genetic algorithms

- Inspired by evolution and natural selection
- Adequate for discrete binary variables

- Population of individuals, each with a chromosome
- Iteration over generations

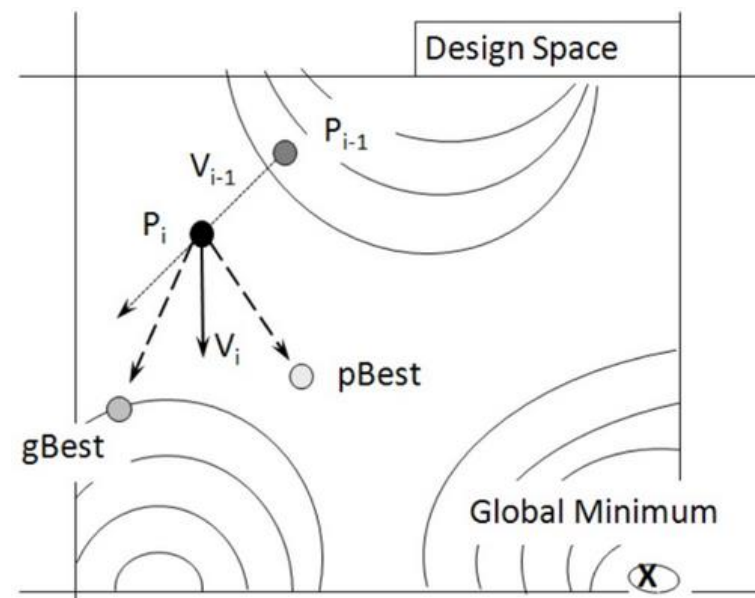
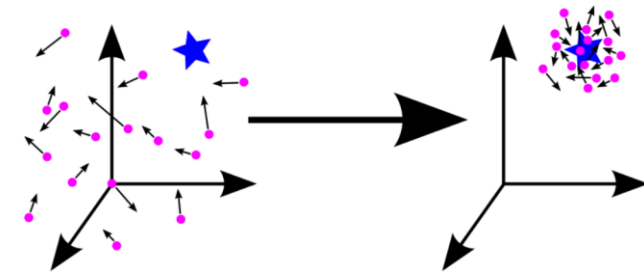
- Selection
- Reproduction (crossover)
- Mutation
- Elitism



■ Collective search methods

□ Particle swarm optimization (PSO)

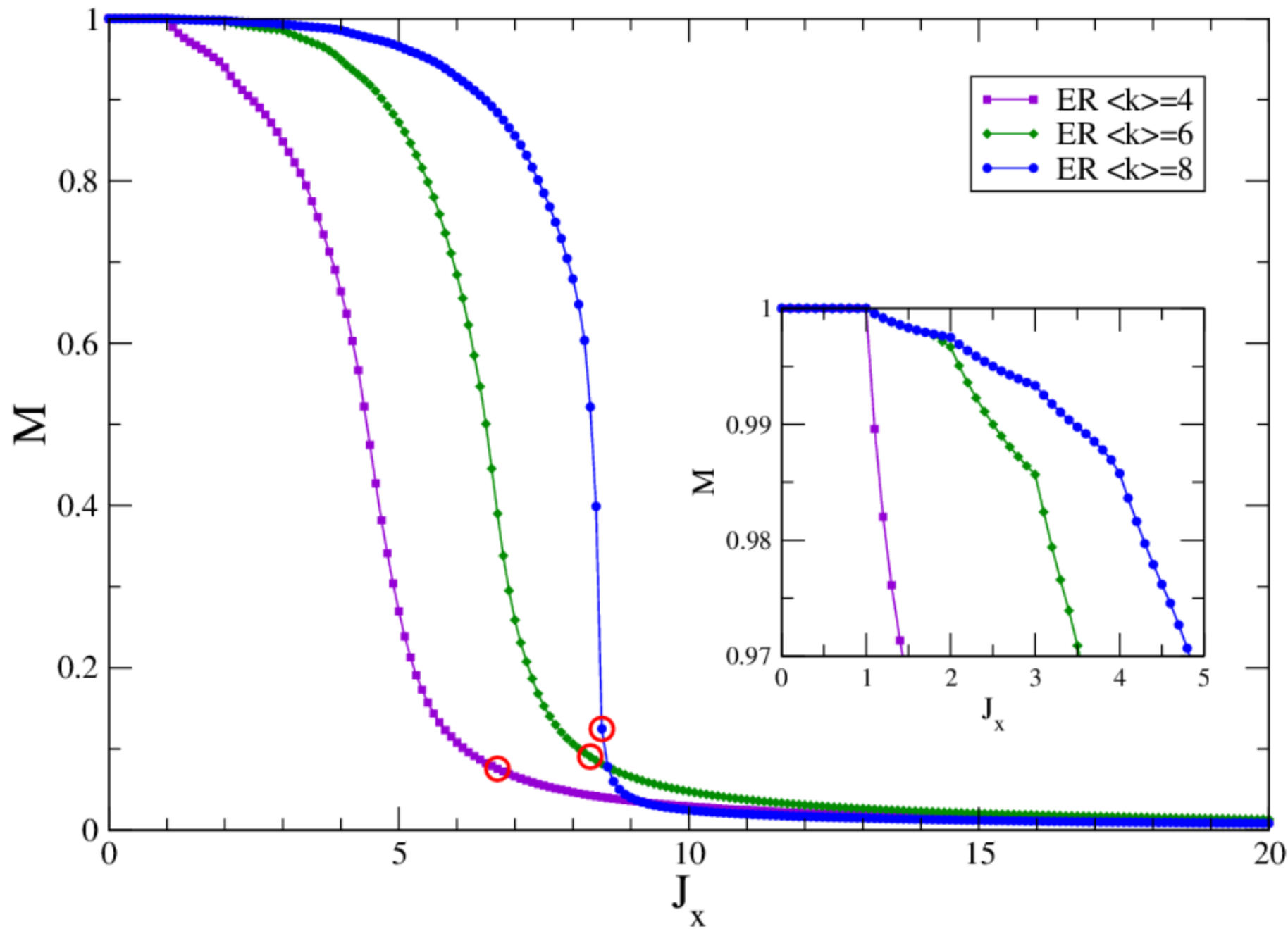
- Inspired by bird flocks and fish schools
- Adequate for continuous variables
- Set of particles
- Each particle has position and velocity
- Each particle remembers its best position
- Inertia
- Approach local best
- Approach global best

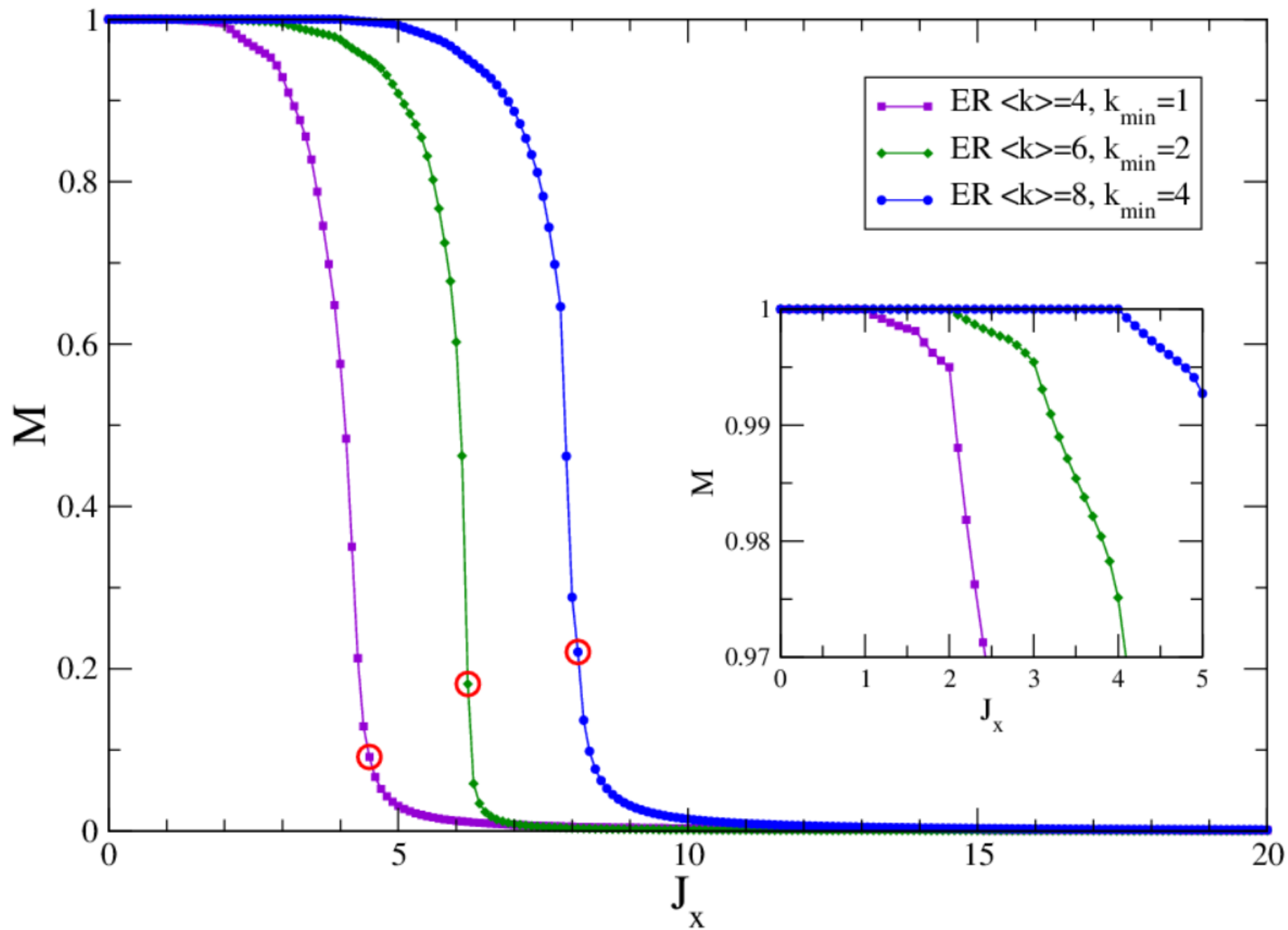


- Hybrid search
 - Collective search + Local optimization
 - Memetic algorithms

Results

- Ground state search
 - Standard optimization package
 - METIS, **failed**
 - Local search
 - Simulated annealing, **failed**
 - Collective search
 - Particle swarm optimization, **success** → selected





Concluding remarks

- Model of competition between layers
- Analytically tractable in part of the phase diagram
- Optimization heuristics required
 - There is life beyond simulated annealing!
 - Use the most appropriate
 - Try several
 - Check always the natural candidate solutions

Thank you for your attention!

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■ References

- **J Gómez-Gardeñes, M De Domenico, G Gutiérrez, A Arenas, S Gómez**
Layer-layer competition in multiplex complex networks
Philosophical Transactions of the Royal Society A **373** (2015) 20150117

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Antoine Allard



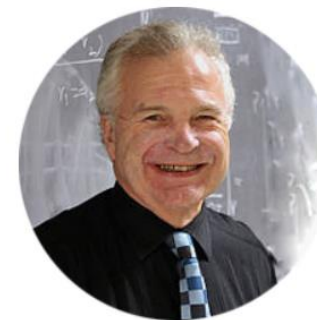
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