

Information Bottleneck for Optimal Prediction of Multilevel Agent-based Systems

Robin Lamarche-Perrin, Sven Banisch, Eckehard Olbrich



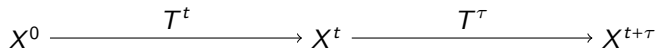
Max Planck Institute for

Mathematics

in the **Sciences**

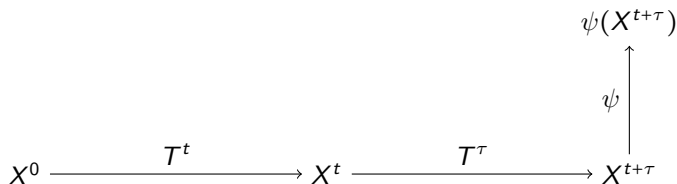


Mathematics for Multilevel
Anticipatory Complex Systems



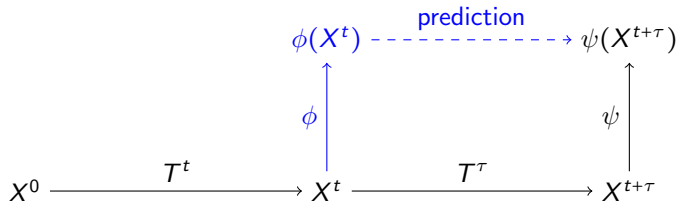
- Markovian Kernel $\mathcal{T}(X^{t+1}|X^t)$
- Initial State $X^0 \in \Sigma$
- Current State $X^t \in \Sigma$ with Current Time $t \in \mathbb{N}$
- Future State $X^{t+\tau} \in \Sigma$ with Prediction Horizon $\tau \in \mathbb{N}$

General Setting



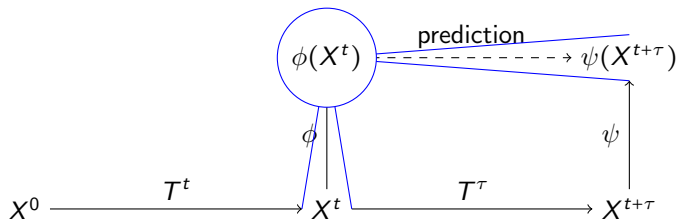
- Markovian Kernel $\mathcal{T}(X^{t+1}|X^t)$
- Initial State $X^0 \in \Sigma$
- Current State $X^t \in \Sigma$ with Current Time $t \in \mathbb{N}$
- Future State $X^{t+\tau} \in \Sigma$ with Prediction Horizon $\tau \in \mathbb{N}$
- Post-measurement $\psi : \Sigma \rightarrow \mathcal{S}_\psi$ defined by $\Pr(\psi(X)|X)$

General Setting



- Markovian Kernel $T(X^{t+1}|X^t)$
- Initial State $X^0 \in \Sigma$
- Current State $X^t \in \Sigma$ with Current Time $t \in \mathbb{N}$
- Future State $X^{t+\tau} \in \Sigma$ with Prediction Horizon $\tau \in \mathbb{N}$
- Post-measurement $\psi : \Sigma \rightarrow \mathcal{S}_\psi$ defined by $\Pr(\psi(X)|X)$
- Pre-measurement $\phi : \Sigma \rightarrow \mathcal{S}_\phi$ defined by $\Pr(\phi(X)|X)$

The Optimal Prediction Problem

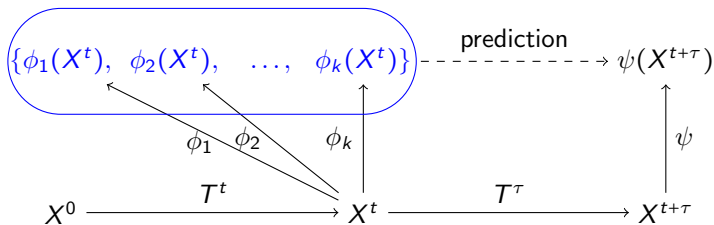


The Information Bottleneck Method [Tishby et al., 1999] :

- **Maximize** Predictive Capacity $\max_{\phi} I(\phi(X^t); \psi(X^{t+\tau}))$
- **Minimize** Measurement Complexity $\min_{\phi} I(X^t; \phi(X^t))$
- **Minimize** the IB-variational

$$\min_{\text{Pr}(\hat{X}|X)} I(X^t; \phi(X^t)) - \beta I(\phi(X^t); \psi(X^{t+\tau})) \quad \text{with } \beta \in \mathbb{R}^+$$

Constraining the Set of Feasible Measurements

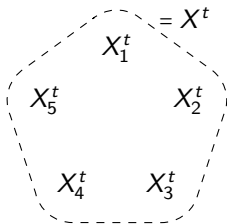


- Given a collection $\Phi = \{\phi_1, \dots, \phi_k\}$ of *feasible* pre-measurements
- **Minimize** the IB-variational

$$\min_{\phi \in \Phi} I(X^t; \phi(X^t)) - \beta I(\phi(X^t); \psi(X^{t+\tau})) \quad \text{with } \beta \in \mathbb{R}^+$$

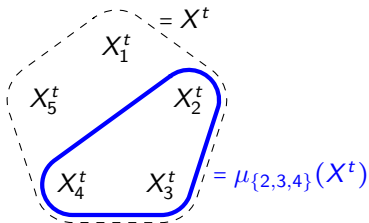
Application to Agent-based Systems

- Agent Set $\Omega = \{1, \dots, N\}$
- Agent States $X_1^t \in S, X_2^t \in S, \dots, X_k^t \in S$
- System State $X^t = (X_1^t, X_2^t, \dots, X_N^t) \in \Sigma = S^N$

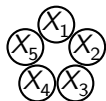
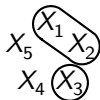
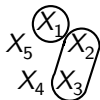
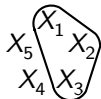


Application to Agent-based Systems

- Agent Set $\Omega = \{1, \dots, N\}$
- Agent States $X_1^t \in S, X_2^t \in S, \dots, X_k^t \in S$
- System State $X^t = (X_1^t, X_2^t, \dots, X_N^t) \in \Sigma = S^N$
- **Generic Measurement** μ
a family of measurements ($\mu_A : \Sigma \rightarrow \mathcal{S}_\mu$) for any $A \subset \Omega$
such that $\Pr(\mu_A(X)|X) = \Pr(\mu_A(X)|(X_i)_{i \in A})$



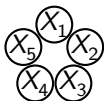
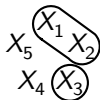
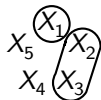
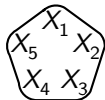
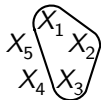
The Poset of Feasible Measurements



The Poset of Feasible Measurements



AGENT
 $\mu_{\{1\}}(X)$

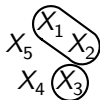
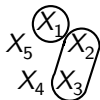
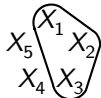


The Poset of Feasible Measurements



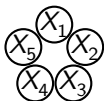
AGENT

$\mu_{\{1\}}(X)$



MICRO

$(\mu_{\{1\}}, \dots, \mu_{\{N\}})(X)$



The Poset of Feasible Measurements



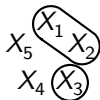
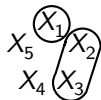
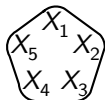
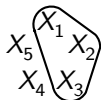
AGENT

$\mu_{\{1\}}(X)$



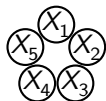
MACRO

$\mu_{\{1, \dots, N\}}(X)$



MICRO

$(\mu_{\{1\}}, \dots, \mu_{\{N\}})(X)$



The Poset of Feasible Measurements



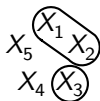
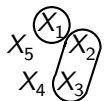
AGENT

$\mu_{\{1\}}(X)$



MACRO

$\mu_{\{1, \dots, N\}}(X)$

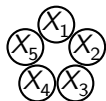


MULTI

$(\mu_{\{1\}}, \mu_{\Omega}(X))$


MICRO

$(\mu_{\{1\}}, \dots, \mu_{\{N\}})(X)$



The Poset of Feasible Measurements

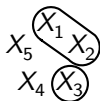
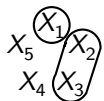
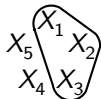
EMPTY
 $\mu_{\emptyset}(X)$



AGENT
 $\mu_{\{1\}}(X)$

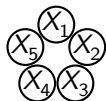


MACRO
 $\mu_{\{1, \dots, N\}}(X)$

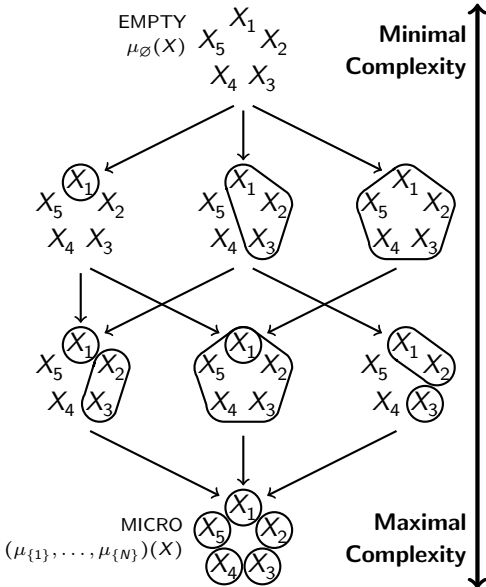


MULTI
 $(\mu_{\{1\}}, \mu_{\Omega}(X))$

MICRO
 $(\mu_{\{1\}}, \dots, \mu_{\{N\}})(X)$



The Poset of Feasible Measurements



Definition 1 (Additivity)

μ additive iff $\forall A \cap B = \emptyset$,
 $H(\mu_{A \cup B}(X) \mid \mu_A(X), \mu_B(X)) = 0$
 $H(\mu_A(X) \mid \mu_{A \cup B}(X), \mu_B(X)) = 0$

Definition 2 (Refinement)

$\phi_1 < \phi_2$
 iff $X \rightarrow \phi_1(X) \rightarrow \phi_2(X)$ is a Markov chain
 iff $I(X; \phi_2(X) \mid \phi_1(X)) = 0$

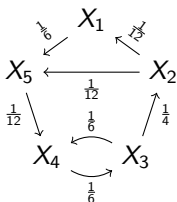
Theorem 3 (Monotonicity)

$\phi_1 < \phi_2 \Rightarrow$
 $I(\phi_1(X^t); \psi(X^{t+\tau})) \geq I(\phi_2(X^t); \psi(X^{t+\tau}))$
 and $I(X^t; \phi_1(X^t)) \geq I(X^t; \phi_2(X^t))$

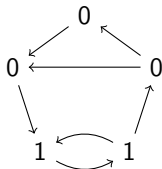
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



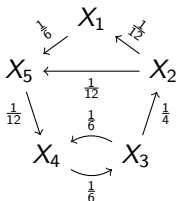
$t = 0$



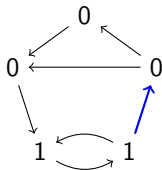
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



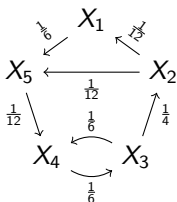
$t = 0 \rightarrow$ arc $(3, 2)$



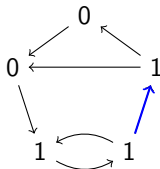
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



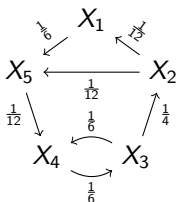
$t = 1$



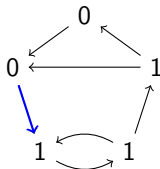
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



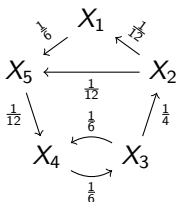
$t = 1 \rightarrow$ arc $(5, 4)$



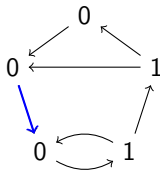
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



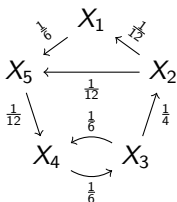
$t = 2$



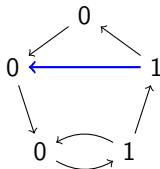
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



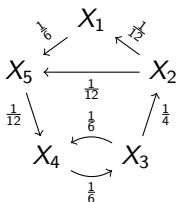
$t = 2 \rightarrow$ arc $(2, 5)$



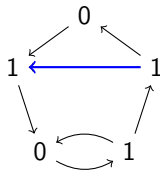
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



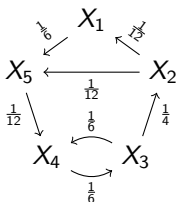
$t = 3$



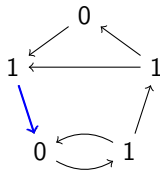
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



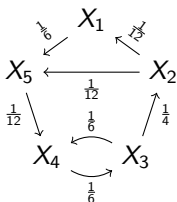
$t = 3 \rightarrow$ arc $(5, 4)$



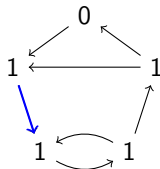
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



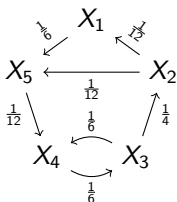
$t = 5$



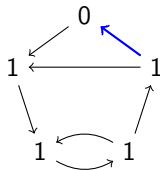
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



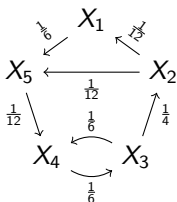
$t = 5 \rightarrow$ arc $(2, 1)$



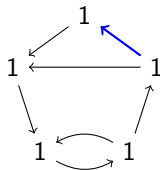
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



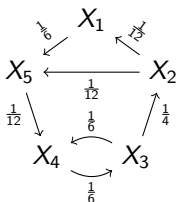
$t = 6$



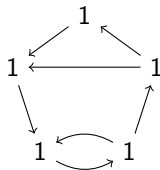
The Voter Model [Banisch & Lima, 2012]

- Set of Agents $\Omega = \{1, \dots, N\}$
- State of i th Agent $X_i^t \in \{0, 1\}$
- System State $X^t = (X_1^t, \dots, X_N^t) \in \{0, 1\}^N$
- Transitions Kernel $T(X^{t+1}|X^t)$ determined by an interaction graph :

arc (i, j) selected $\Rightarrow X_j^{t+1} = X_i^t$ and $\forall k \neq j, X_k^{t+1} = X_k^t$



$t = 6$

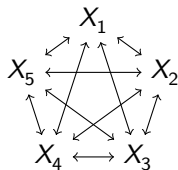


Aggregated-states in the Complete Graph

- All arcs are equally likely
- Uniform Initial State

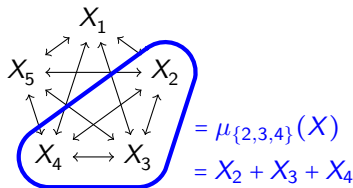
$$\forall (i, j) \in \Omega^2, \quad \Pr(\text{arc } (i, j)) = \frac{1}{N(N-1)}$$

$$\forall x \in \{0, 1\}^N, \quad p(X^0 = x) = 2^{-N}$$

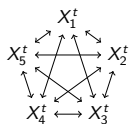


Aggregated-states in the Complete Graph

- All arcs are equally likely $\forall (i,j) \in \Omega^2, \quad \Pr(\text{arc } (i,j)) = \frac{1}{N(N-1)}$
- Uniform Initial State $\forall x \in \{0,1\}^N, \quad p(X^0 = x) = 2^{-N}$
- Aggregated-state Measurement $\forall A \subset \Omega, \quad \eta_A(x) = \sum_{i \in A} x_i$



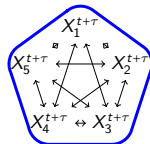
Predicting the Macroscopic Measurement



pre-measurement \longrightarrow

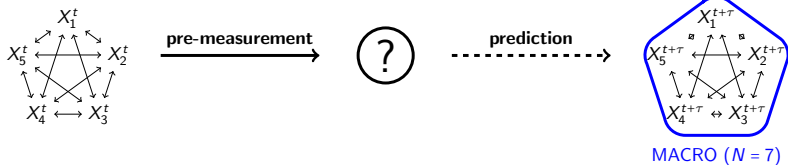


prediction \dashrightarrow

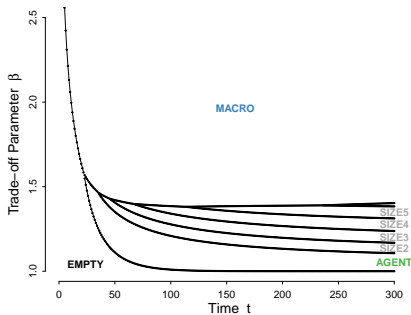


MACRO ($N = 7$)

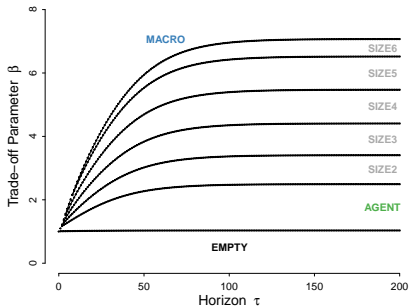
Predicting the Macroscopic Measurement



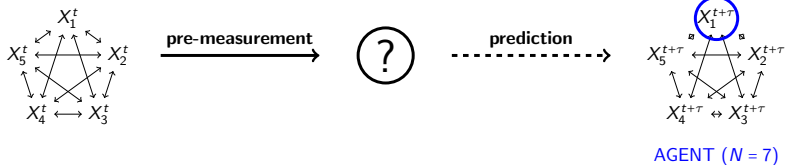
Fixed horizon $\tau = 3$



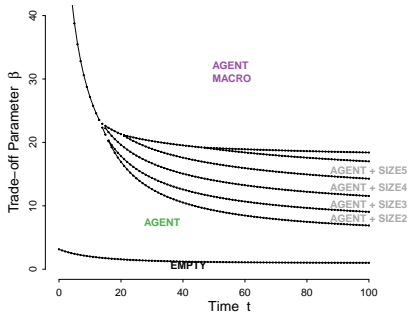
Fixed time $t = 100$



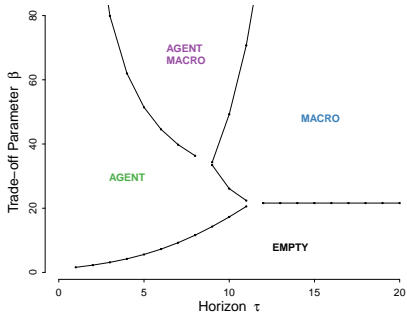
Predicting the Agent Measurement



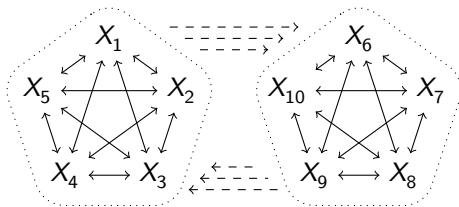
Fixed horizon $\tau = 3$



Fixed time $t = 0$



The Two-community Graph

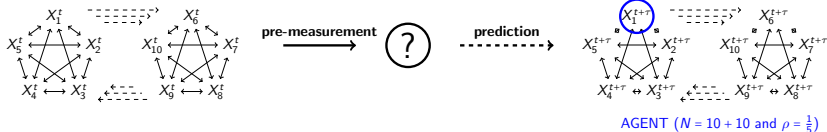


First Community Ω_1

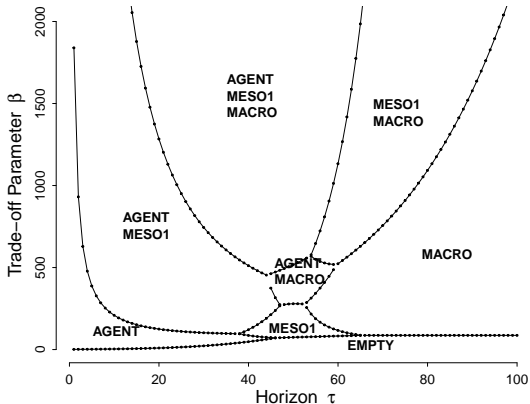
Second Community Ω_2

Coupling Parameter $\rho = \frac{\text{Pr}(\text{inter edge})}{\text{Pr}(\text{intra edge})} < 1$

Predicting the Agent Measurement

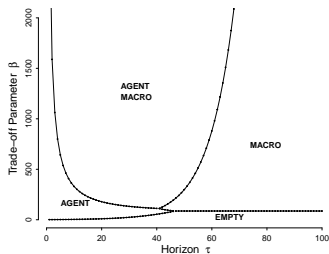


Fixed time $t = 0$

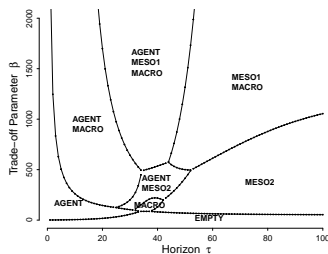


Some Other Heterogeneous Interaction Graphs

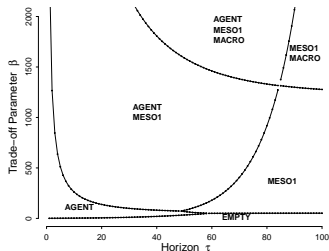
Homogeneous Case : $\rho_{1 \rightarrow 2} = \rho_{2 \rightarrow 1} = 1$



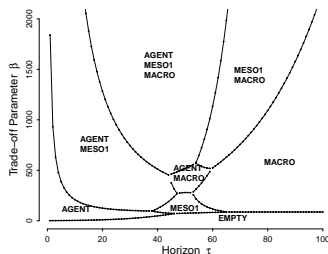
Follower Case : $\rho_{1 \rightarrow 2} = 1/5$ and $\rho_{2 \rightarrow 1} = 1$



Leader Case : $\rho_{1 \rightarrow 2} = 1$ and $\rho_{2 \rightarrow 1} = 1/5$



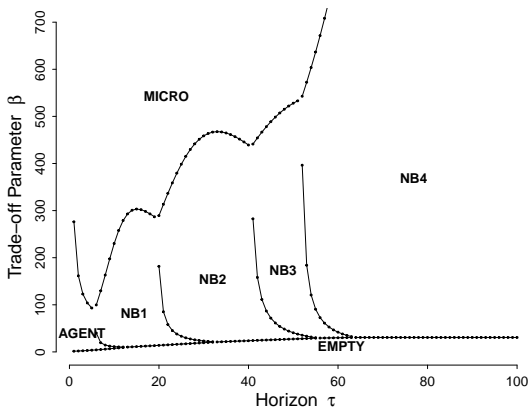
Symmetrical Case : $\rho_{1 \rightarrow 2} = \rho_{2 \rightarrow 1} = 1/5$



Predicting the Agent Measurement in the Ring



Fixed time $t = 0$

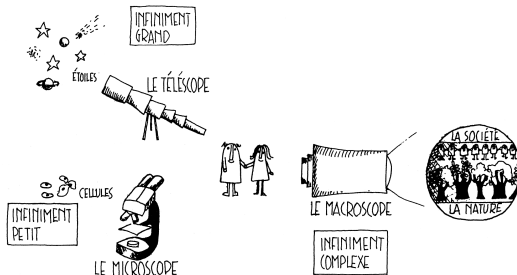


- Application to efficient prediction of national **economic indicators** from the structure of the **trade network** :
 - Countries exchange products on a global scale
 - Multilevel measurements regarding the network of international trade (related to graph theory and community modelling)
 - Multilevel measurements regarding the structure of products (production chains, productions stages, economic fields, etc.)
 - Complexity should also be used to model data collection costs

Thank you for your attention

Mail : Robin.Lamarche-Perrin@mis.mpg.de

Web : www.mis.mpg.de/jjost/members/robin-lamarche-perrin.html



"Aujourd'hui nous sommes confrontés à un autre infini : l'infiniment complexe. Mais cette fois, plus d'instrument."

Joël de Rosnay, *Le macroscopie*, 1975