Activity tracking and awareness: Sketch for a transdisciplinar automatic framework

Activity concept

- Classical **Physics** (study of Nature)
  - $E = m.c^2$ [Energy, matter, space/time]
- Quantum Physics
  - Information is limited

- **Economics**, study of:
  - How scarce resources are employed for the satisfaction of the needs of men living in society
  - Essential operations of production, distribution and consumption of goods

Activity concept

- **Evolution theory**
  - Structures and populations
- **Mathematics** (sets and logics), **Systems theory,** cognition, etc.

- Energy and matter are limited by interactions in space and time
- Decisions, information (and access) are limited
- **Activity**: Pragmatic frame [causality] for system specification
- For distributed computational devices [metaphor of societies (of mind? Computers…)]

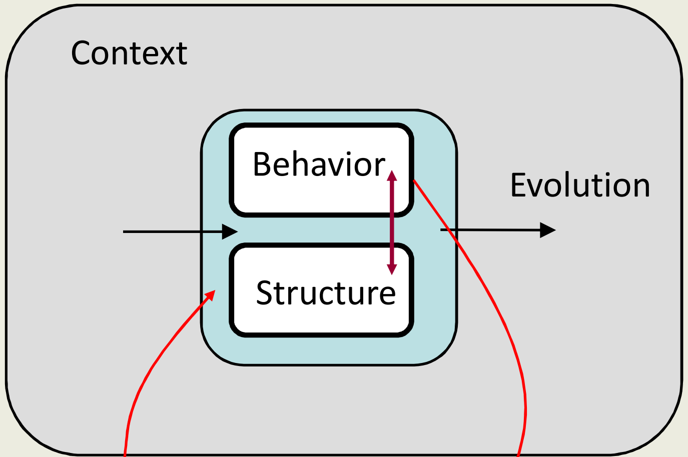
Philosophy of systems

- Evolution through laws of Nature
  - Present: Adapt to context
  - History: Selection (memory, populations…)
- Trade-off: Validity and resources
  - Engineering: Simulator resources, efficiency
  - Modeling: Dialectic between structure and behavior to meet I/O (validity)
- Limits and mappings of human (self)/natural/automatic mechanisms

Fundamental Elements

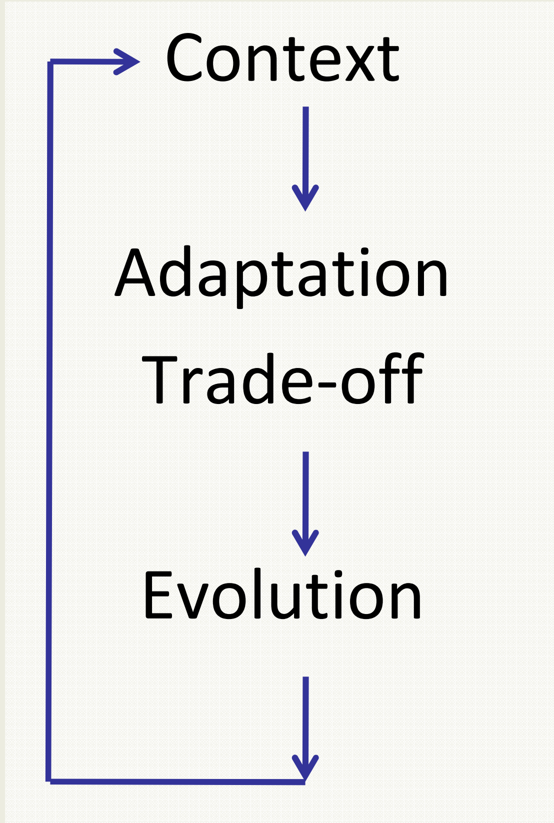
- Dynamic structure
  - Modularity
- Activity
  - Tracking & Awareness
- Automatic Modeling and Simulation
  - Validation & Verification

Dynamic Structure



Bernie, for Brain / Mind

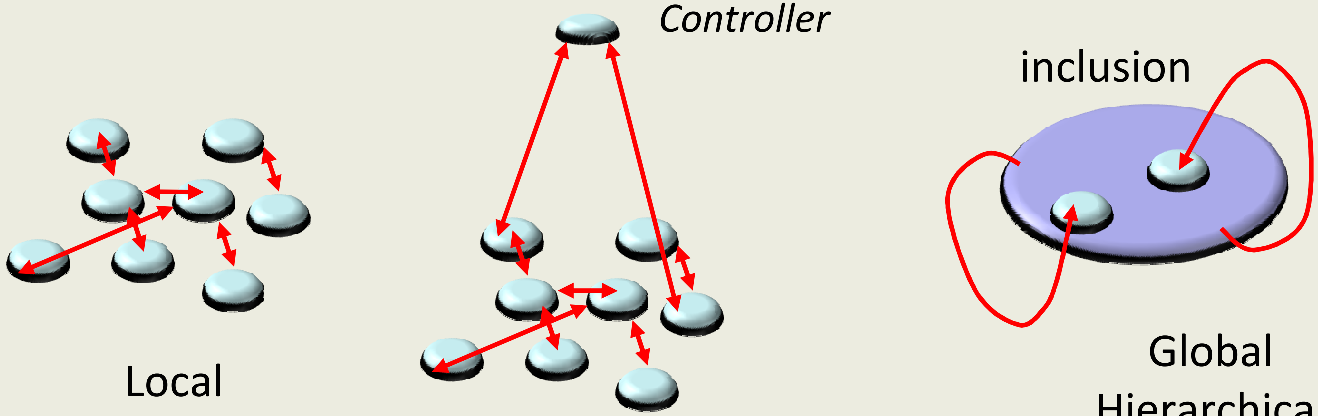
- *Learning*



Dynamic Structure

- Control
  - (No) Hierarchy of activation?
  - Local autonomy?
- (Simon, 1962) *The architecture of complexity*
  - Biological and physical systems:
    - «Flat» hierarchies: Crytal, tissues…
  - Social and symbolic systems:
    - Hierarchical: Institutions, books, music…

Autonomy



Local
No hierarchy

Global & local
Both

Global
Hierarchical

Decreasing autonomy
(perception, independence, etc.)

Immanence
emergence
Bottom-up

Multi-level
COMPLEX

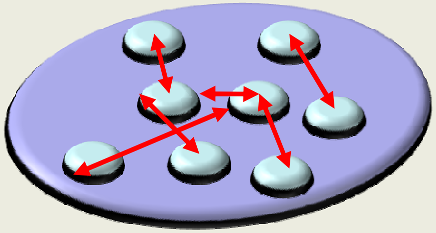
Transcendance
No emergence
Top down

Modularity degrees (cf. Mind)

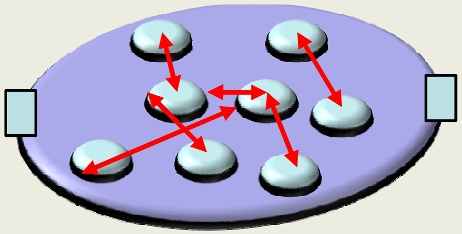
- No modularity: No specialization
  - Direct access to neighborhood transitions
  - No events
- Weak modularity
  - Direct access to neighborhood transitions
  - External events
- Strong modularity: Specialization
  - No access to influencee transitions
  - External and internal events (cost)

Modularity

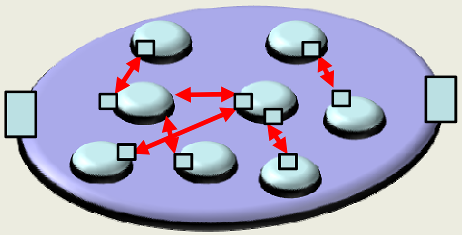
- No modularity



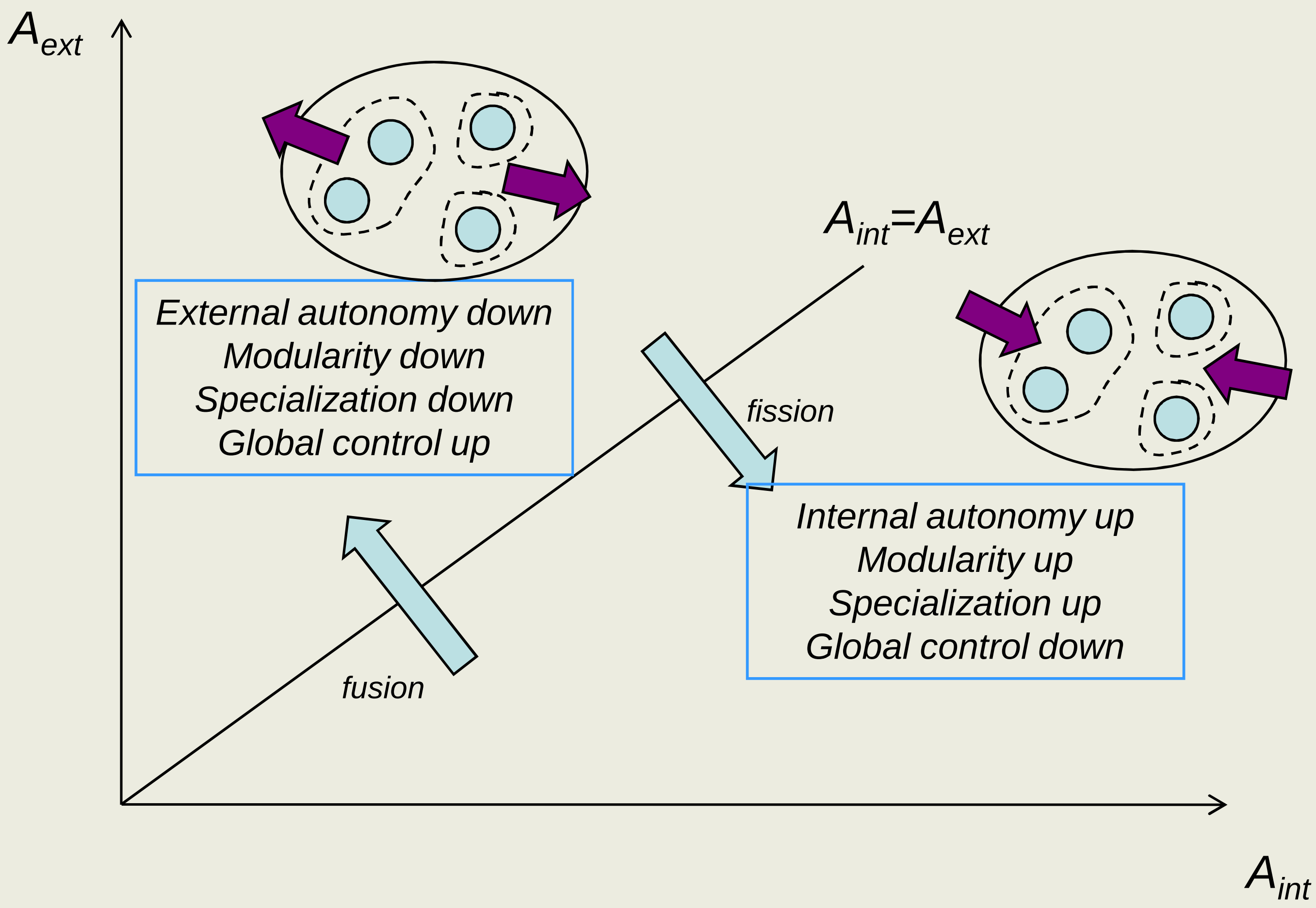
- Weak modularity



- Strong modularity



Modularity: Interface adaptation



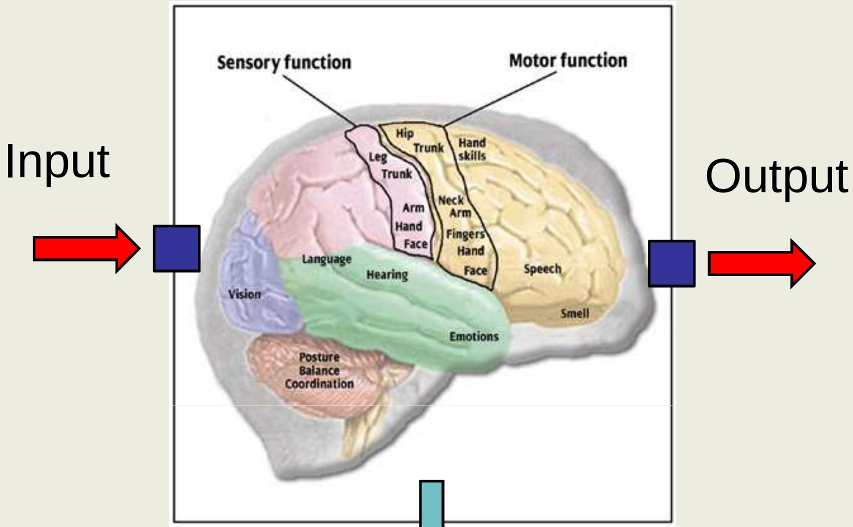
Autonomy: Energy and specialization

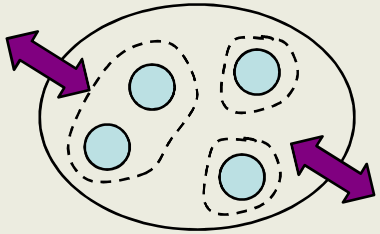
- Brain Evolution
  - Null → Weak → Strong

GF Striedter, *Précis of: Principles of brain evolution*

"Perhaps the most fascinating aspect of increasing absolute brain size is that it necessitates changes in the brain's internal connectivity. Specifically, the brain's average connection density (the likelihood that any one neuron connects to any other) must decrease with increasing brain size; otherwise the number of axons would increase explosively with neuron number, racking up enormous costs in terms of space and metabolic energy. Combined with the general tendency of brains to minimize their axon lengths, this decrease in average connection density implies that brains become more modular, both structurally and functionally, as they increase. Increasing modularity, in turn, allows for increased "division of labor," which generally improves task performance. However, decreasing connection density also reduces a brain's ability to exchange information between distant sites – even if those brains are wired as "small worlds." Overall, we can conclude that evolutionary increases in absolute brain size entail both benefits and costs."

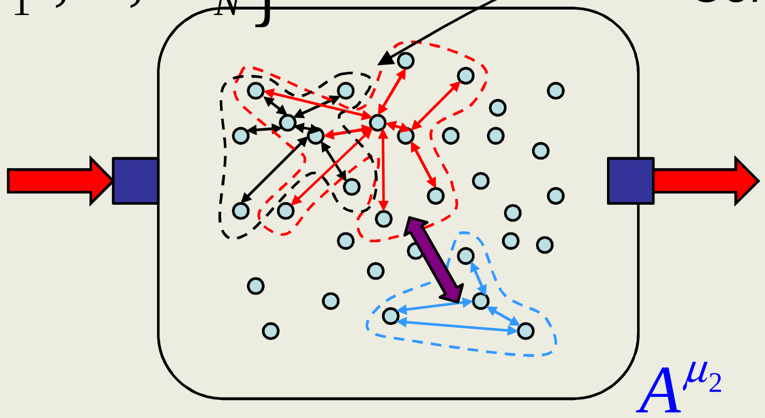
Modularity in activity environment



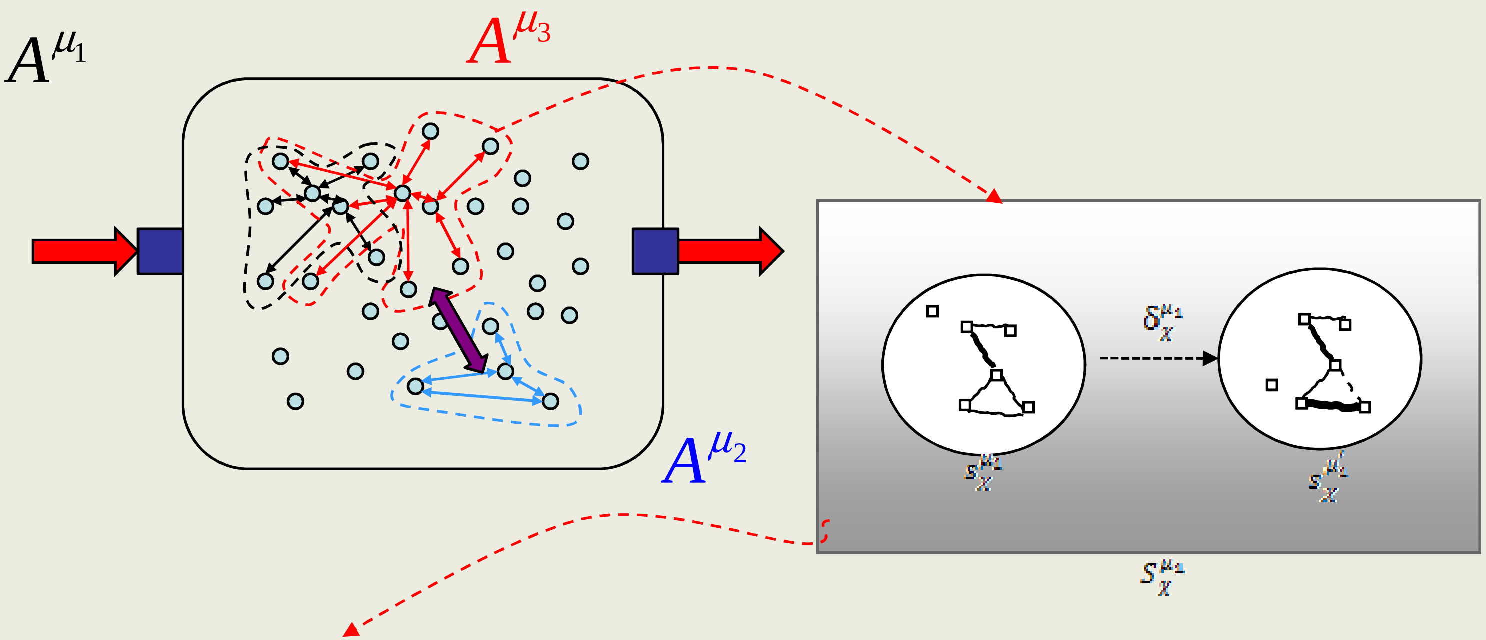


$$A^{\mu_1} = \left\{ A_1^{\mu_1}, \ldots, A_N^{\mu_1} \right\}$$

Overlapped activities: Components are multi-aspect oriented



Modularity in activity environment



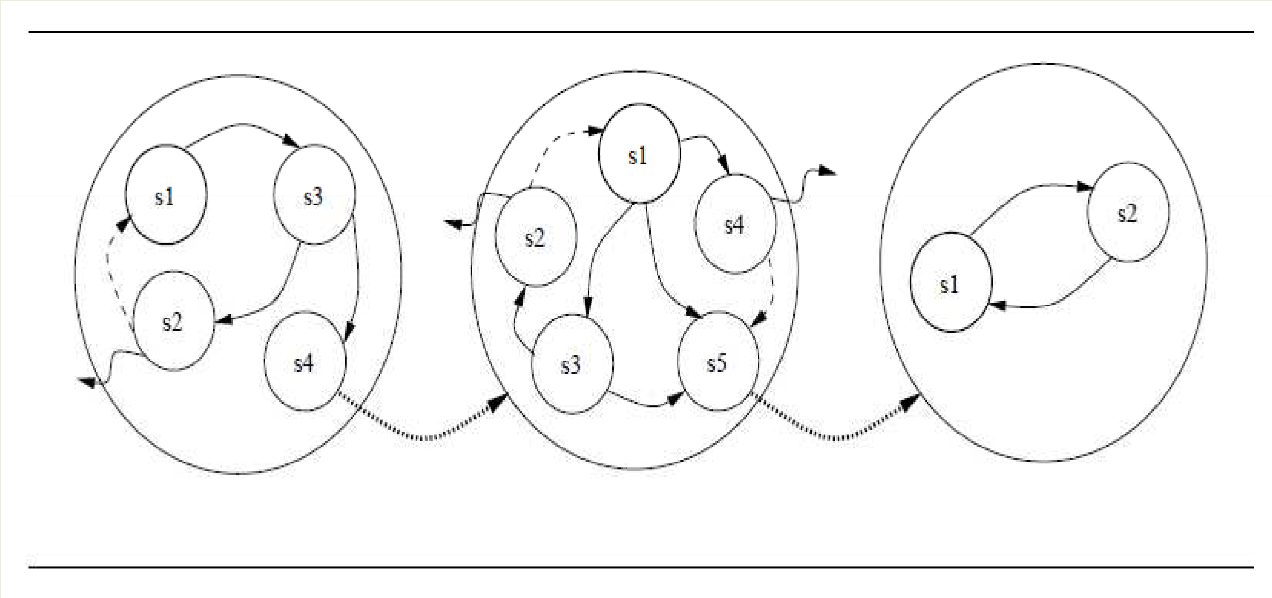
Activity-based learning leads to sensory function leg module network:

$$s_{\chi}^{\mu_1} =< D^{\mu_1}, \{C_i^{\mu_1}\}, \{I_i^{\mu_1}\}, \{Z_{i,j}^{\mu_1}\} >$$

With corresponding activity: A^{μ_1}

Modularity in activity environment

$$s_{\chi}^{\mu_n} =< D^{\mu_n}, \{C_i^{\mu_n}\}, \{I_i^{\mu_n}\}, \{Z_{i,j}^{\mu_n}\} >$$



Structural metrics

$$S_\chi = < D, \{C_i\}, \{I_i\}, \{Z_{i,j}\} >$$

$$structuralComplexity = < |D|, |C_\chi.Ports|, |C_i.Ports|, |Z_{i,j}| >$$

$$|Z_{i,j}| = |EIC| + |EOC| + |IC|$$

$$|C_i.Ports| = |C_i.InputPorts| + |C_i.OutPorts|$$

Behavioral metrics

$$Metrics = \{Value, Type\}$$

$$C_i.BehavioralMetrics =< X_i.Metrics, Y_i.Metrics, S_i.Metrics >$$

$$C_\chi.BehavioralMetrics =< X_\chi.Metrics, Y_\chi.Metrics, S_\chi.Metrics >$$

Resolution complexity

Resolution complexity: Global state space to be fully explored (cardinality of the crossproduct of local state sets)

$$S_\chi = < \underbrace{D, \{C_i\}}_{|S_i| = |S_1| \times |S_2| \times \ldots \times |S_n|}, \{I_i\}, \{Z_{i,j}\} >$$

$$\uparrow$$

$$\boxed{|S_\chi| = |S_{\chi_1}| \times |S_{\chi_2}| \times \ldots \times |S_{\chi_p}|}$$

$$\Rightarrow \begin{cases} |S_{\chi_1}| = |S_{11}| \times |S_{12}| \times \ldots \times |S_{1n}| \\ \ldots \\ |S_{\chi_p}| = |S_{p1}| \times |S_{p2}| \times \ldots \times |S_{pn}| \end{cases}$$

Resolution:
-Increases -> Improve validity
- Decreases -> improve performances

Activity-based exploratory complexity

Activity

$$S_\chi^\mu =< D^\mu, \{C_i^\mu\}, \{I_i^\mu\}, \{Z_{i,j}^\mu\} >$$

Activity network μ

$$S_\chi^\mu \subseteq S_\chi$$

$$\left|S_i^\mu\right| = \left|S_1^\mu\right| \times \left|S_2^\mu\right| \times \ldots \times \left|S_n^\mu\right|$$

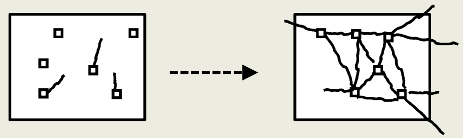
$$\uparrow$$

$$\left|S_\chi^\mu\right| = \left|S_{\chi_1}^\mu\right| \times \left|S_{\chi_2}^\mu\right| \times \ldots \times \left|S_{\chi_p}^\mu\right|$$

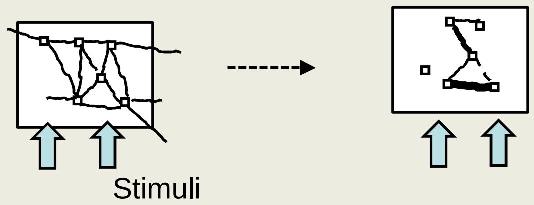
For the same precision, Activity efficiency:
$$\boxed{\begin{cases} \left|S_\chi^\mu\right| < \left|S_\chi\right| \\ A_\chi^\mu < A_\chi \end{cases}}$$

Theory of the Selection of Neuronal Groups (TSNG) Edelman

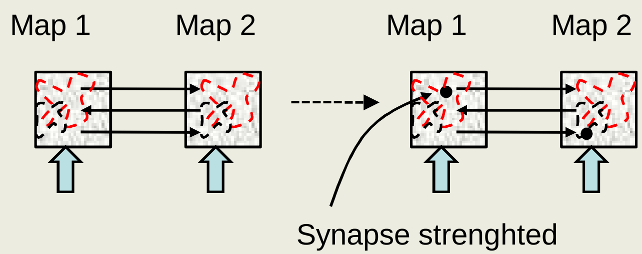
1- Development–selection
- Cells' specializations
- Extension
- Max density: 6-12 months
- Highly connected
- Deletion/death



2-Experience–selection
- Learning (synapse strength)

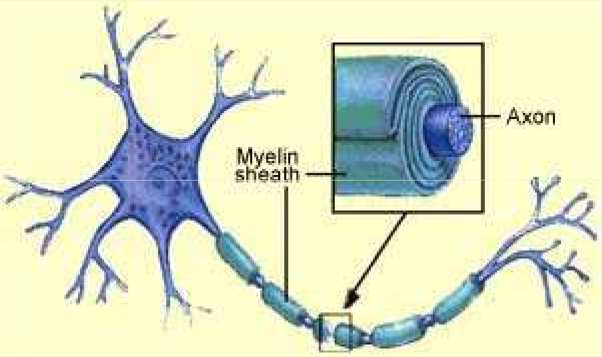


3-Reentry mapping
-Connection of modules/groups
- White matter

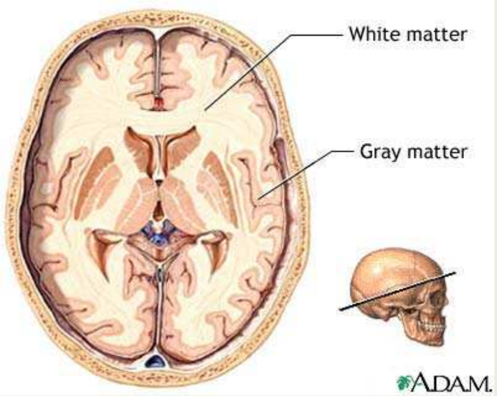


White matter channels

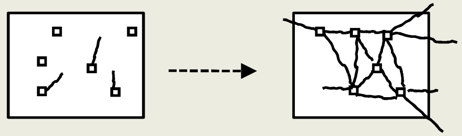
The white matter: myelin insulator that covers the axons of these same neurons to enable them to conduct nerve impulses more rapidly.



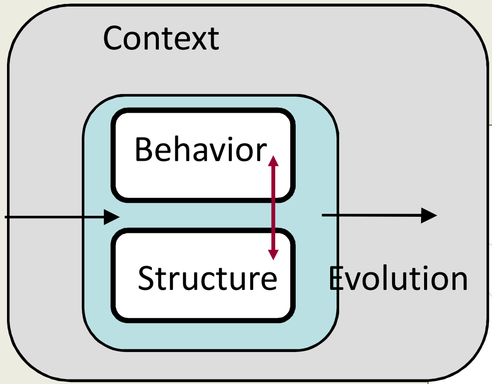
Speed up neural conduction

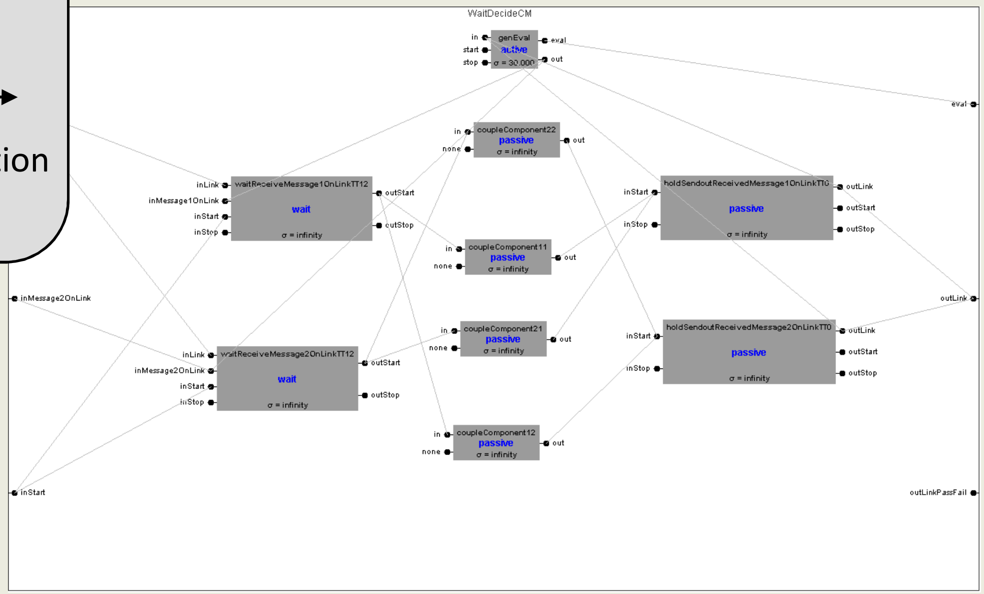


1- Development–selection

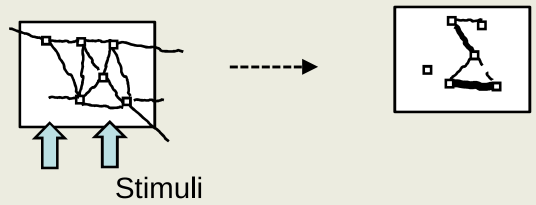


- Start with built-in (innate) modules (partial coupled models)
- Modules are units of activity credit assignment
- Highly connect them

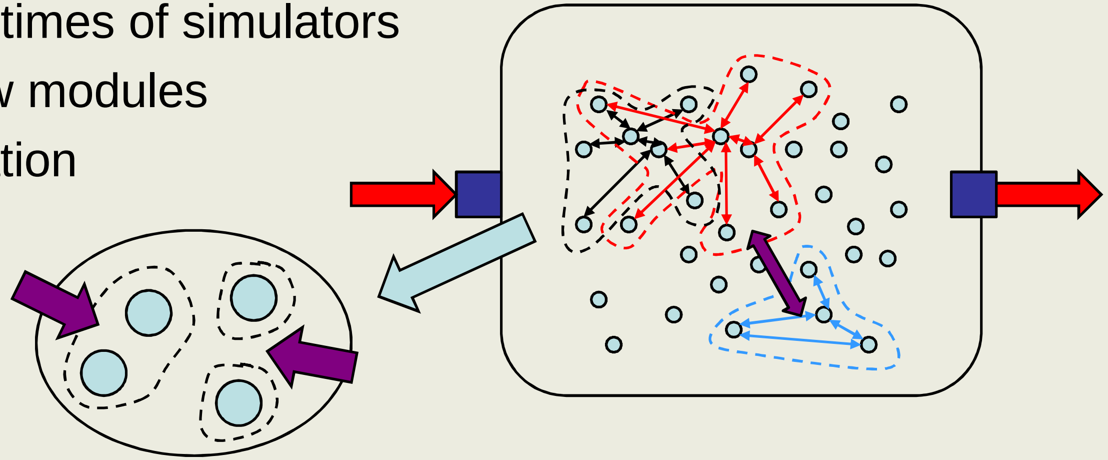




2-Experience–selection



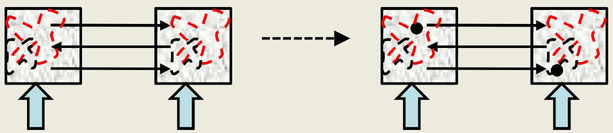
- Removing and strength connections
- Delay synchronization learning: Adapt delays of models to execution times of simulators
- Builds new modules
- Specialization



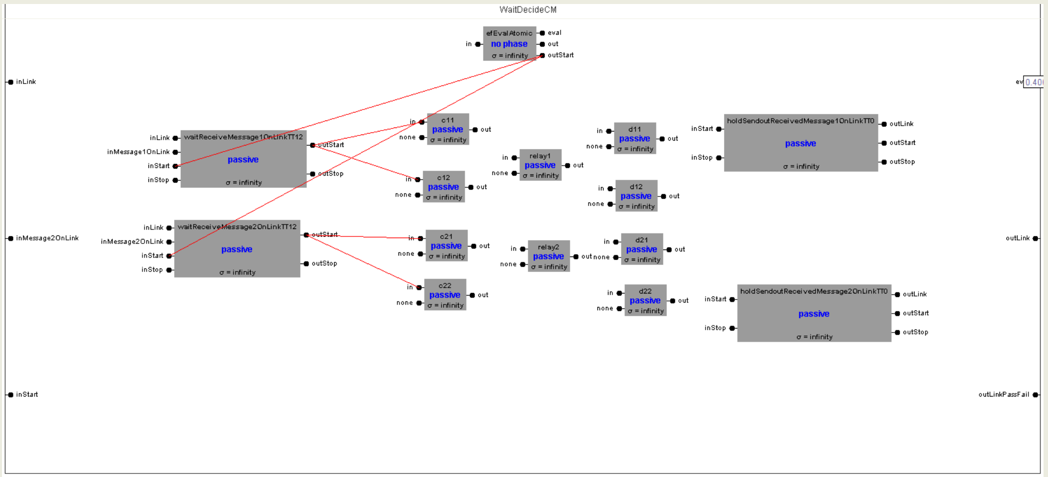
- Sender → Receiver
- Reduce external activity
- Comparatively less increase internal activity
- Specialize: Increase performances, decrease adaptability.

Internal autonomy up
Modularity up
Specialization up
Global control down

3-Reentry mapping

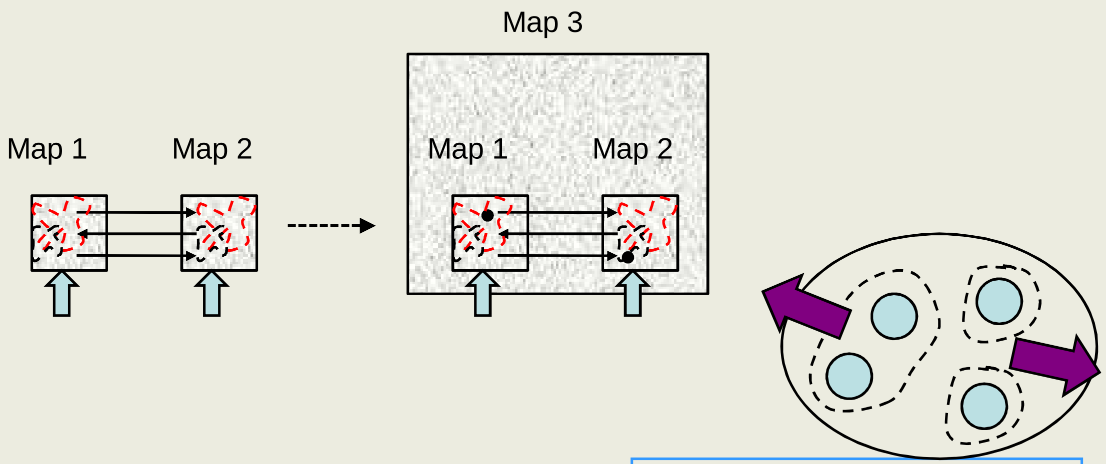


- White matter: External activity
- Relay’s delay synchronization between neurons of maps



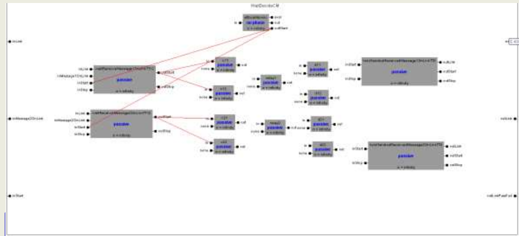
4-Hierarchical modular learning

- Successive evolution/learning stages
- Package components into new modules
  with internal components that can be activated all at once
  and be assigned credit as a whole



External autonomy down
Modularity down
Specialization down
Global control up

Infrastructure

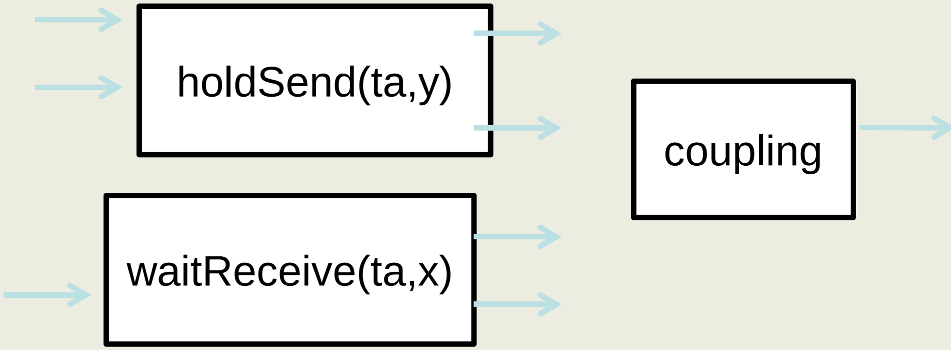


Construction & Testing tools

innate modules, hierarchical composition,... EF, ...

activity measurement, feedback, credit assignment,..

Primitives



Modeling & simulation framework

- Analytical modeling
  - Phenomenon (physical: Gravitation, convection, etc.)
- Computation
  - Computations & PRNG (ENIAC, 1946)
- Simulation of analytical models
- Spatial modeling and simulation

? Random

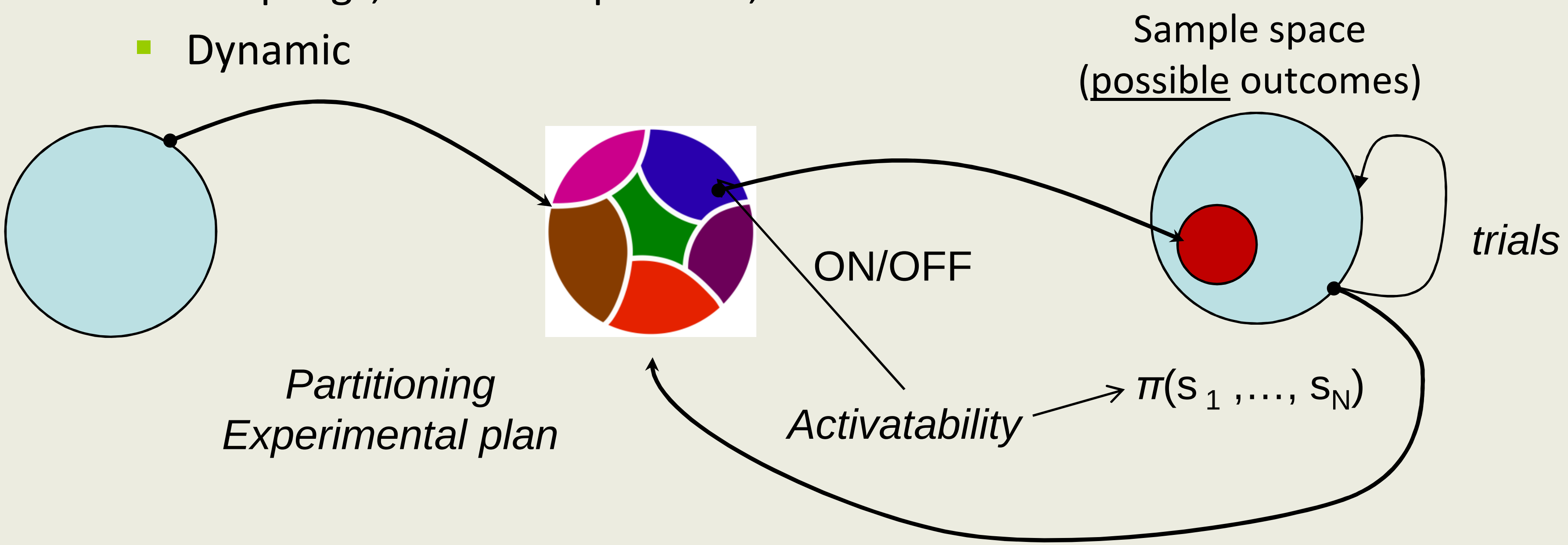
  - Large -> fine grain
  - Population, large-scale systems

Large --> Fine grain M&S?

- Spatial, real phenomena
  - Population, prey-predator, Web, etc.
- Theoretical phenomena in most scientific discipline models are analytical
- Gap
  - Experiments
  - **Vs.** Usual mathematical methods (ODEs, PDEs, optimal control, etc.)
  - **And** Implementation
  - Engineering problems
  - Validation & Analysis vs. Modeling & Automation (what is the goal?)
- Exploring the large state space of (spatial) reality?
- Why? How?

Formal and Automated M&S framework

- Partitioning
  - Activatability: Initialization & exploration range
  - Activity-based searching heuristics
- Structural
  - Couplings, set of components, active sub-sets
  - Dynamic

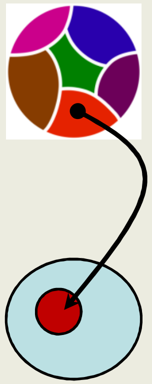


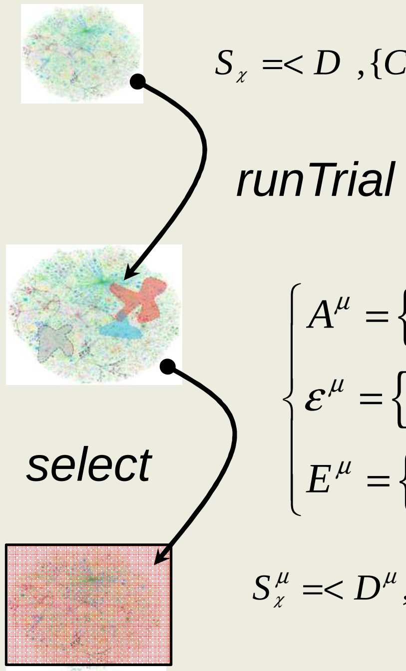
Structural state set

- Population / Set analogy
  - Metamathematics through structure sets
  - Piloting simulator
- Activity-based selection of sub-set solutions
  - Define IO objectives
  - Define initial structure set $S_{\chi} =< D ,\{C_i\},\{I_i\},\{Z_{i,j}\}>$
  - Define activatability
  - Activity-based selection $S_{\chi}^{\mu} =< D^{\mu},\{C_i^{\mu}\},\{I_i^{\mu}\},\{Z_{i,j}^{\mu}\}>$
  - Run trials

Structural state set

- Population / Set analogy
  - Define initial structure set
  - Define activatability (for activity-based selection)
  - Run trials

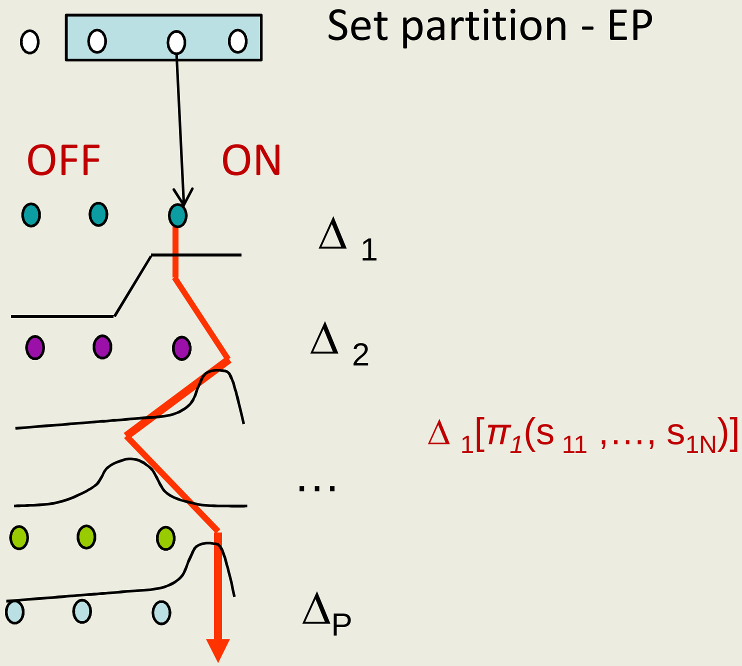




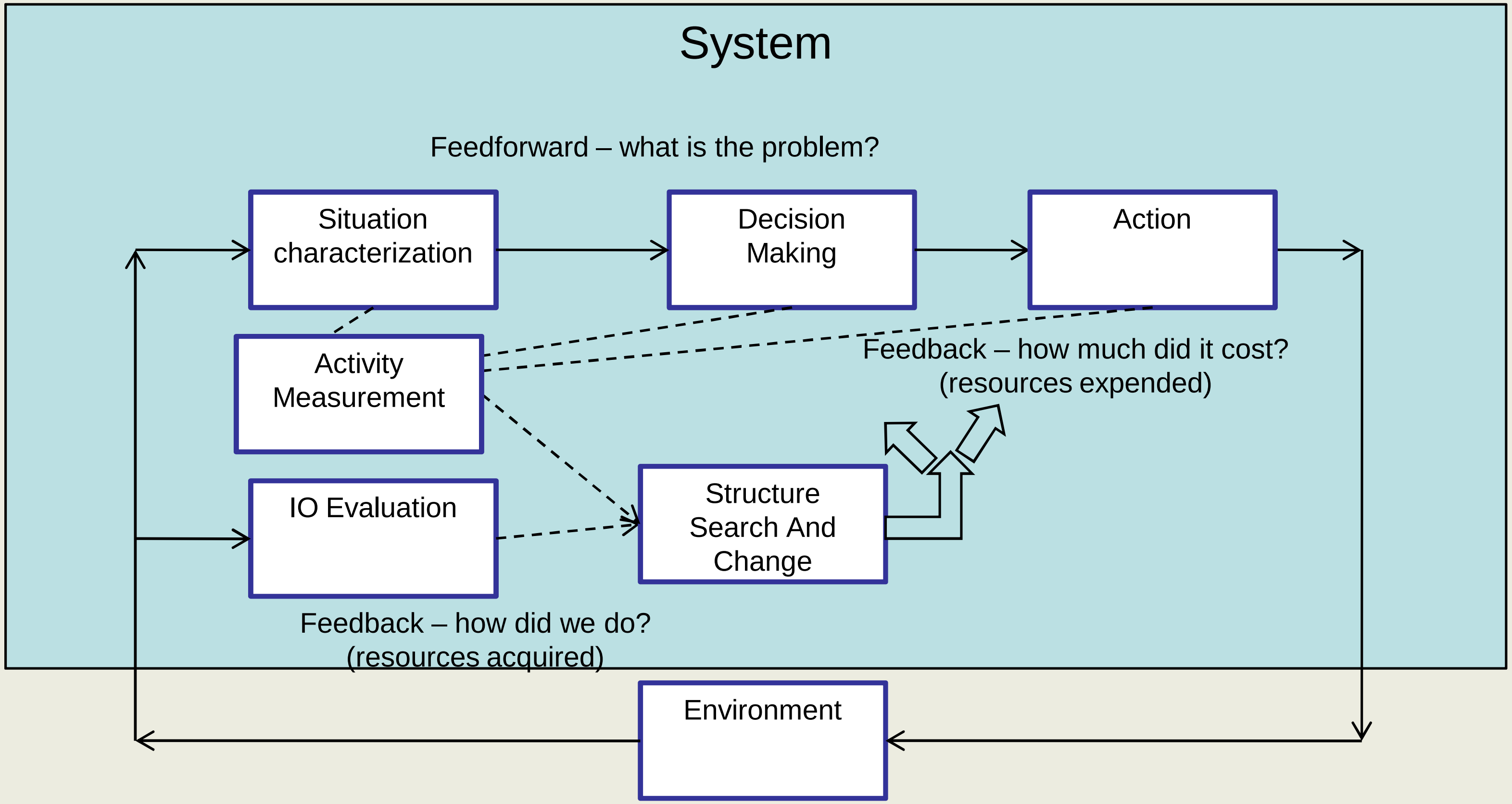
$$S_\chi = < D, \{C_i\}, \{I_i\}, \{Z_{i,j}\} >$$

$$\begin{cases} A^\mu = \{A_1^\mu, \ldots, A_N^\mu\} \\ \varepsilon^\mu = \{\varepsilon_1^\mu, \ldots, \varepsilon_N^\mu\} \\ E^\mu = \{E_1^\mu, \ldots, E_N^\mu\} \end{cases}$$

$$S_\chi^\mu = < D^\mu, \{C_i^\mu\}, \{I_i^\mu\}, \{Z_{i,j}^\mu\} >$$



Activity awareness



- Metamathematics [(endo, iso, meta?)morphisms]

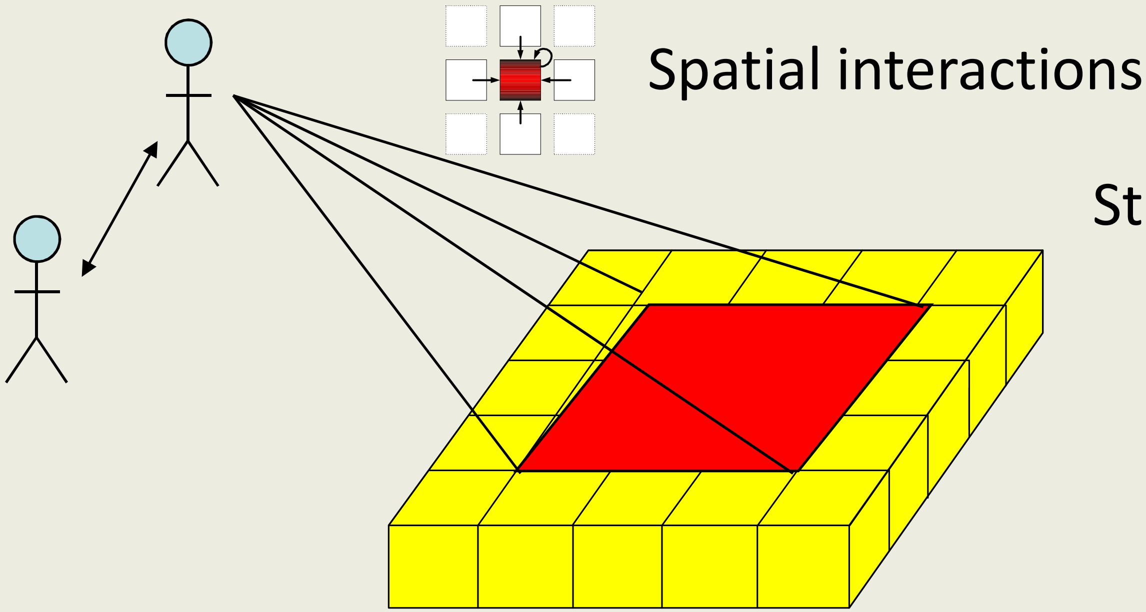
Common Applications? Evolutionnary Game

- Price in "The Logic of Animal Conflict." In this game, two individuals compete for a **resource of a fixed value *V***.
- Each individual follows exactly one of two strategies:
  - **Hawk** Initiate aggressive behaviour, not stopping until injured or until one's opponent backs down.
  - **Dove** Retreat immediately if one's opponent initiates aggressive behaviour.
- Assumptions:
  - (1) whenever two individuals both initiate aggressive behaviour, conflict eventually results and the two individuals are equally likely to be injured,
  - (2) the cost of the **conflict** reduces individual fitness by some **constant value *C***,
  - (3) when a Hawk meets a Dove, the Dove immediately retreats and the Hawk obtains the resource, and (4) when two Doves meet the resource is shared equally between them, the fitness payoffs for the Hawk-Dove game can be summarized according to the following matrix:

	Hawk	**Dove**
Hawk	$\frac{1}{2}(V - C)$	V
Dove	0	$V/2$

Common agent-based structure

- Cellular models interacting with interacting agents



Structural evolutions:

- Vegetation
- Populations (ecology, genetics)
- Decisions (economics)
- Moving (crowds)
- Anticipation
- Theory of mind
-…

Common activity-based structure

- Adaptative structure/goal
- Common limited internal/external resources
- Activity cost counting (C)
- Subjective value of solutions (V)
- Decision according to (V/C) trade-off

Activity detector: Example

10 45 37
28 33 2
2 5 8

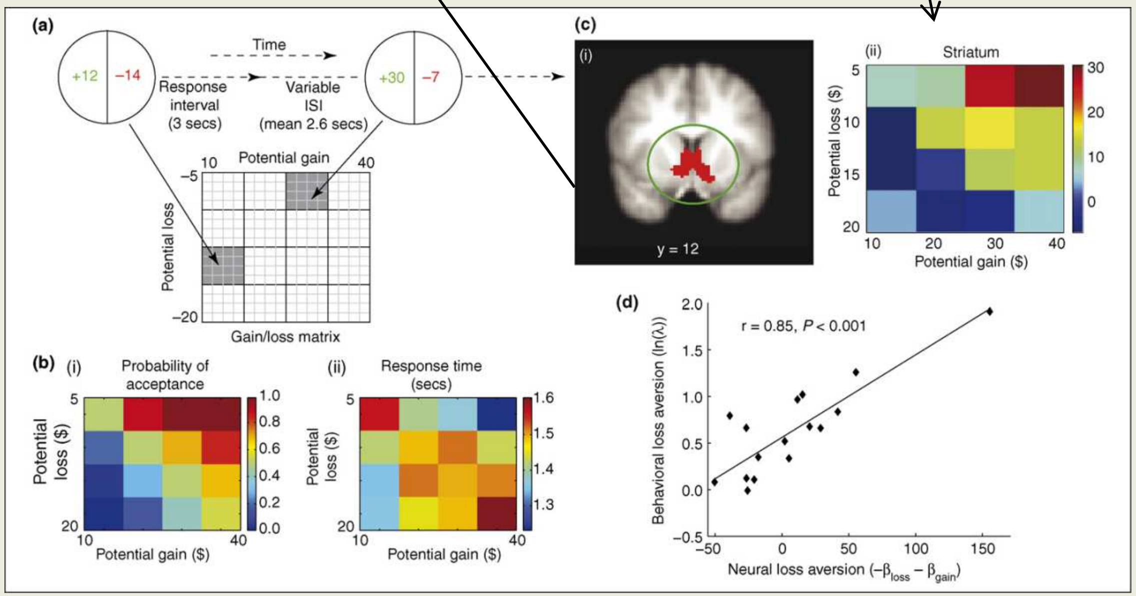
Robot vision
Brain activity
Combustible mass…

Data
activity
extraction

1 0 2
28 0 3
2 7 8

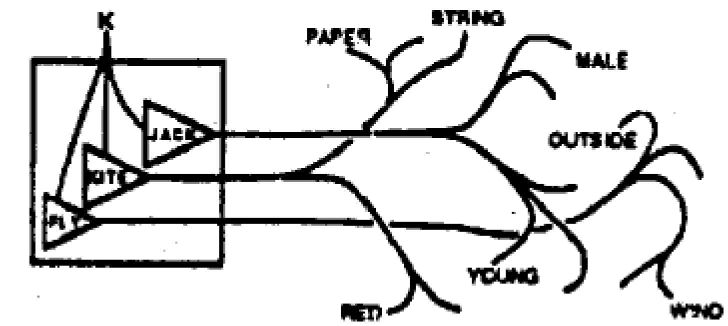
Loss/gain
characterization

Decision



Activity concept

- Activity measures
  - Problem-solving: Model
  - Engineering: Simulator (active/inactive executions)
- Activity paths
  - Sender/receiver
    (filter: continuous, physical, psychological, social)



K-line attached to three K-lines.

Experimental frame

IO Evaluation

Given $f : X \rightarrow Y$

Define $evaluate(f, x, S)$ with range in [0 ,1]

by

$$evaluate(f, x, S) = 1 \quad \text{if} \quad S = \{f(x)\}$$

$$= \frac{val}{|S|} \quad \text{if} \quad f(x) \in S \quad \text{and} \, |S| > 1$$

$$= 0 \text{ otherwise}$$

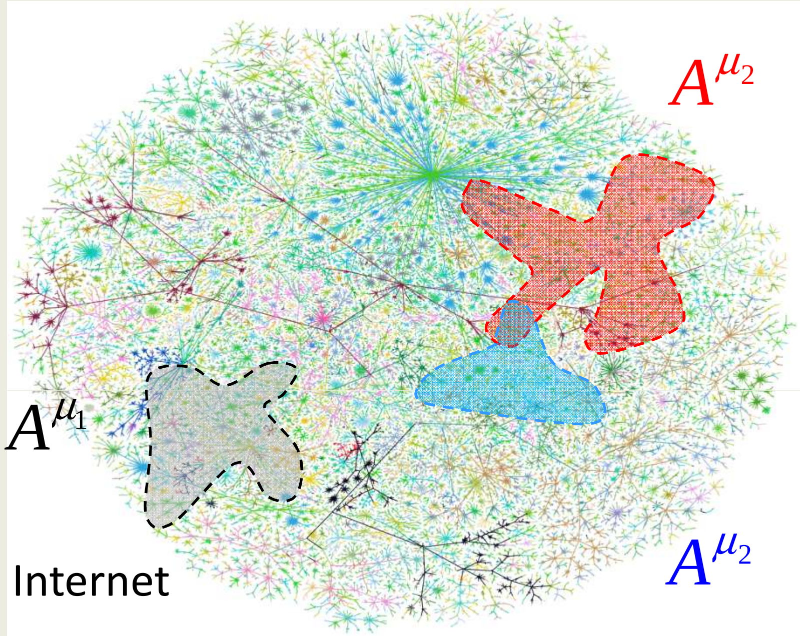
Ω_M: Admissible input segments of the plug-in component

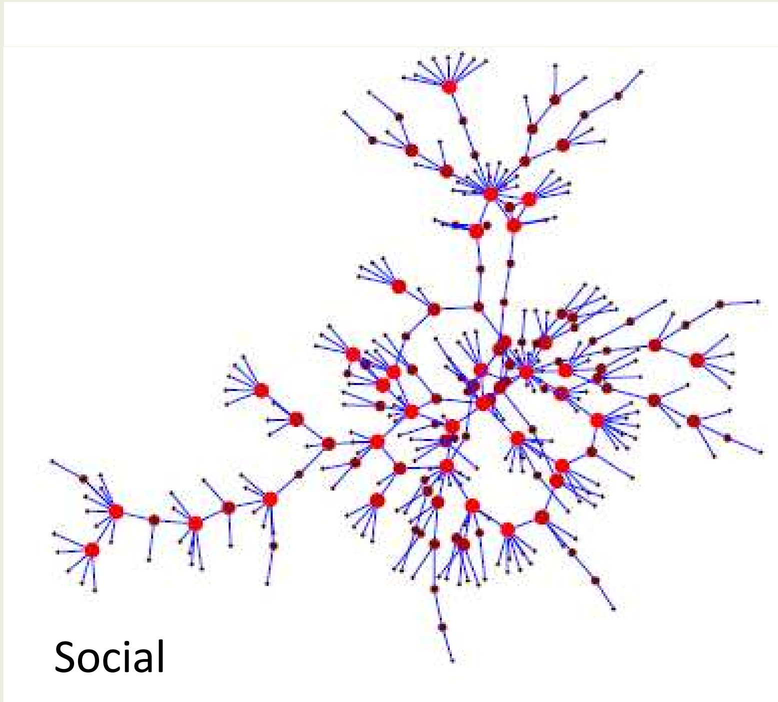
Ω_E= {(start, t_{init}),(stop, t_{end})}, Admissible input segments for experiment control

Ω_C = {f(x)} Admissible output segments expected from the plug-in component

SU = {(I_1,O_1),…, (I_N,O_N)}, Summary mapping from the control input set to the summary set depending on the plug-in inputs and outputs

Infrastructure





Activity-based search

$$score = \{0, val, 1\}, val \in \left]0,1\right[$$

$\max Score = |D| * 1$ (all components provide the right output)

Credit of a component:

Individual component credit assignment
$$\frac{\sum_{trials} evaluate(f, x, S)}{\overline{A_i^{\mu}}}$$

All set: D

Search candidate sub-sets: $\{D^{\mu}\}$

totalActivityResult of candidates: $\overline{A^{\mu}(t, t')} = \sum_{i=1}^{d \in D^{\mu}} A_i^{\mu}$

Activity-based search

Starting full network: $\left| S_{\chi} \right|$

Define activity structural maps: $S_{\chi}^{\mu} \subseteq S_{\chi}$

Using:

Global cost/benefit function: $$\frac{evaluate(f, x, S)}{\overline{A_{\chi}^{\mu}}}$$

From EF-Eval

From Simulator

Global cost of a solution

Local cost/benefit function:

$$evaluate_i(.) = \frac{\sum_{trials} evaluate(f, x, S)}{\overline{A_i^{\mu}}}$$

Local cost

Control search algorithm

Initialization call:

$$s_\chi^\mu \leftarrow s_\chi$$

$$All \quad c_i.phase \leftarrow active$$

Control search algorithm:

$$while(evaluate(.) < globalEvalThreshold)$$

$$\quad trials++$$

$$\quad \text{call} \quad \text{Simulator}$$

$$\delta_\chi^\mu(s_\chi^\mu):$$

$$if\left(\frac{evaluate(.,t')}{\overline{A_i^\mu}} \le \frac{evaluate(.,t)}{\overline{A_i^\mu}}\right)$$

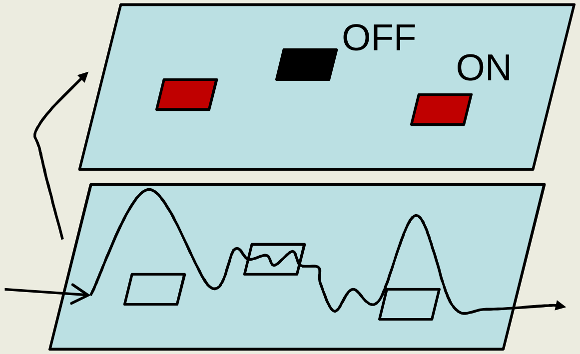
$$\quad c_i.phase \leftarrow inactive$$

$$if\,(trials \ge trialsThreshold \quad \&\& \quad c_i.phase == inactive)$$

$$\quad if\,(evaluate_i(.) \le localEvalThreshold))$$

$$\quad\quad remove\ i \in D\ \ from\ D'$$

$$\quad\quad remove\ Z_{ij}$$



Simulator:

Search algorithm call:

$$for \quad d = 1\,to\ N\ do$$

$$s_d^\mu \leftarrow \delta_d^\mu(s_d^\mu)$$

$$s_\chi^\mu \leftarrow \delta_\chi^\mu(s_\chi^\mu)$$

- Each component accumulates credit equal to its activity correlated with the global score after each trial.
- Selection of new subsets is made by adding up the individual component credits.
- The subset at the current stage with the highest total is selected for simulation.
- If its evaluation is not better than the current best, we go on to the next ranked subset. (It turns out the first ranked set is usually the best or near best, thus saving us to look at the lower ranked ones.)