Evolution of Neural Complexity in Division of Labor Tasks

OIST

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Motivation

2024/11/29

Social brain hypothesis (Dunbar, 2009) claims our big brains are due to the demands of our social life. However, human brain has been shrinking over Holocene (Henneberg, 1988).

Brains size of some eusocial insects is negatively correlated with social complexity (O’Donnel et al., 2015; Riveros et al., 2012).

Collective intelligence hypothesis: increased social organization lowers cognitive effort allowing for a smaller brain.

Frequently mentioned social organization trick: division of labor.

Current study aims

- set up different coordination scenarios and compare neural complexity of evolved agents
  - task specialization (specialists) vs behavioral flexibility (generalists)
  - individual agent baseline

- test a particular measure of complexity of a cognitive system
  - individual level complexity
  - dyadic level complexity

exploratory and somewhat speculative!

Hypotheses

- individual level
  - social brain hypothesis: $C_{generalists} > C_{individuals}$ & $C_{specialists} > C_{individuals}$
  - collective intelligence hypothesis: $C_{generalists} > C_{specialists}$
- dyadic level: $C_{generalists} \approx C_{specialists}$

Methods

2024/11/29

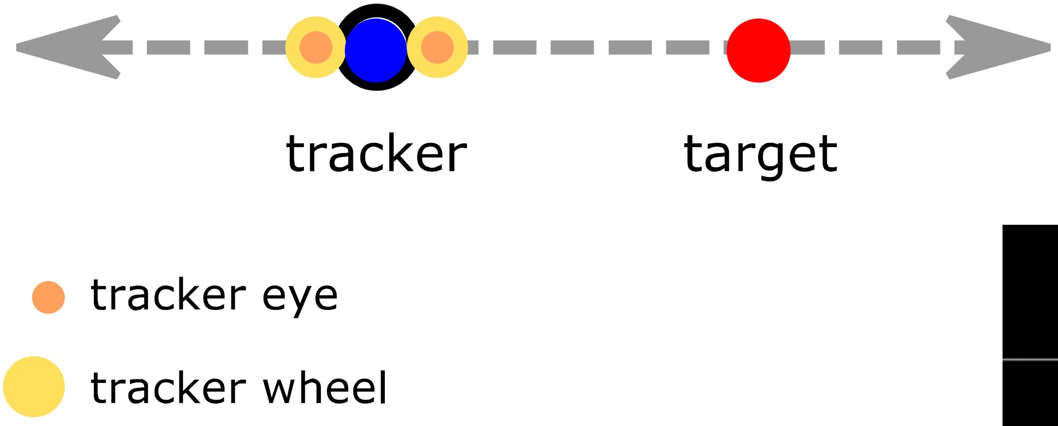
Task based on a psychological study (Knoblich & Jordan, 2003).

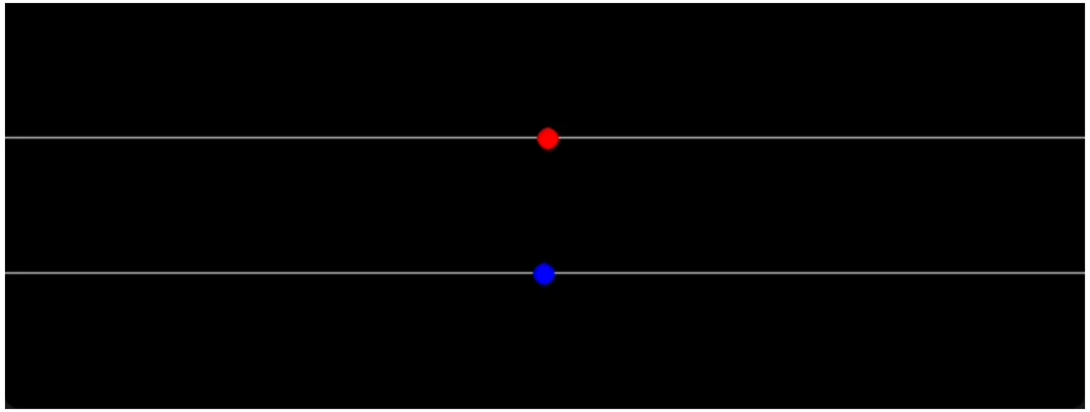
Agents implemented with CTRNN (Beer, 1995).

Standard evolutionary algorithm with fitness based on behavioral performance.

A measure of neural complexity based on Tononi-Sporns-Edelmans (TSE) metric (Tononi et al., 1994).

Task environment



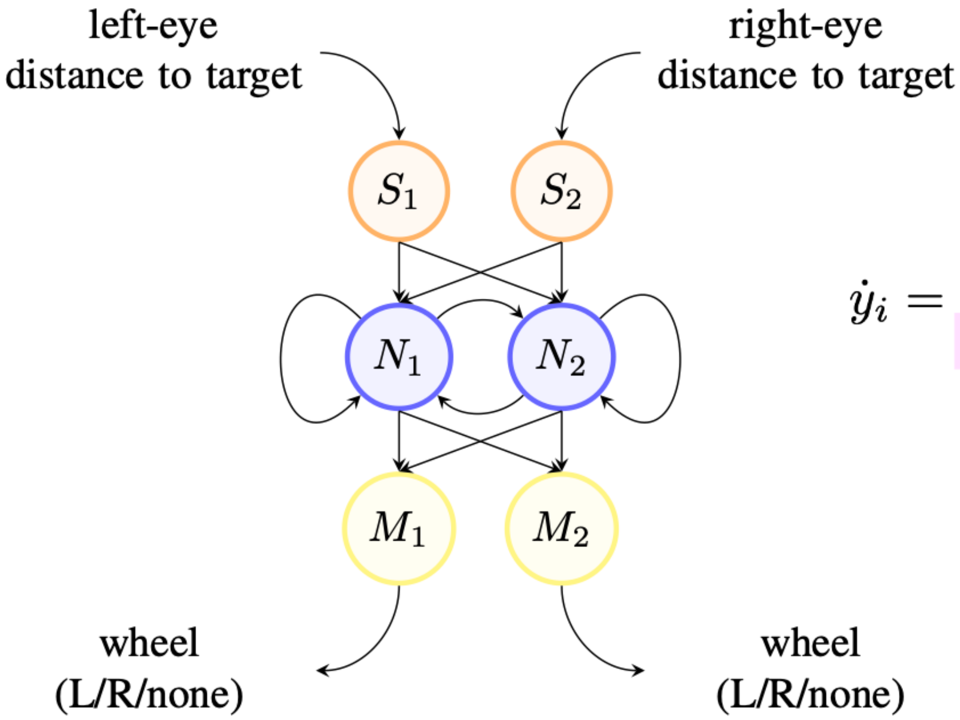


4 trials with
- 2 different starting directions of the target
- 2 different target speeds

Agent network architecture

$$O_S = G_S\,\sigma(I_S + \theta_S)$$

$$M_i = G_M\,\sigma\left(\sum_{N=1}^{2} W_{N,i} * O_N + \theta_M\right)$$

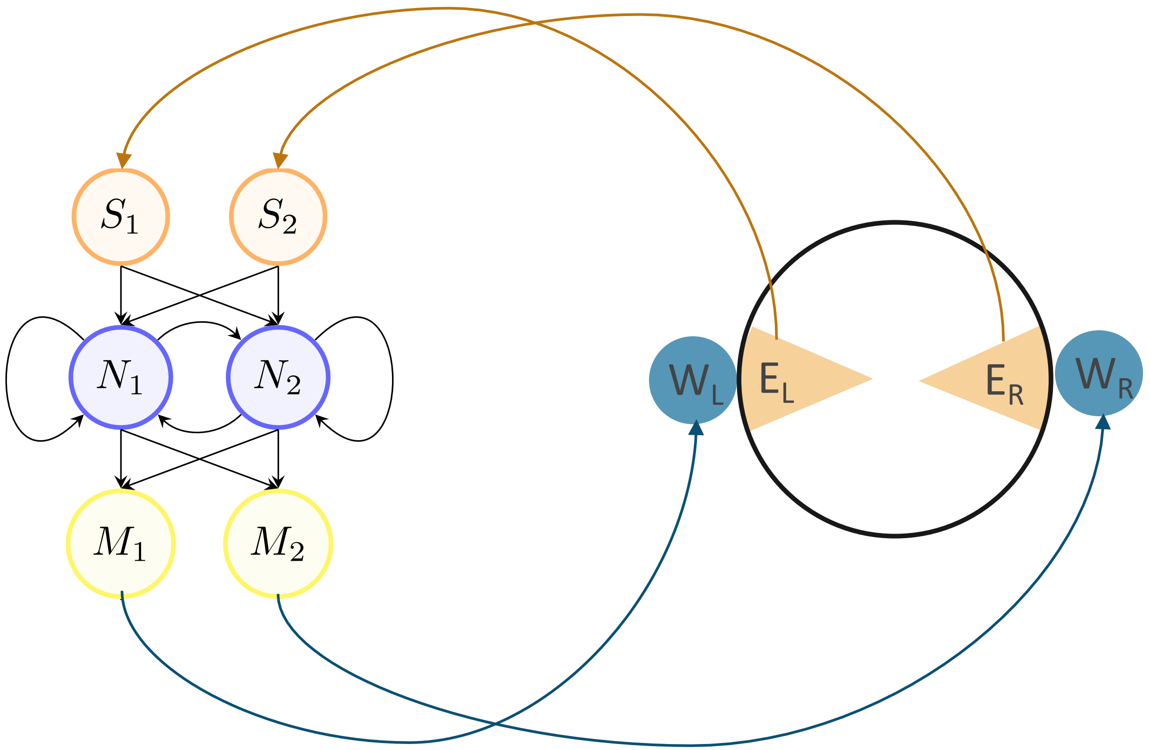


$$\dot{y}_i = \frac{1}{\tau_i}\left(-y_i + \sum_{j=1}^{N} w_{ji}\,\sigma\left(y_j + \theta_j\right) + I_i\right)$$

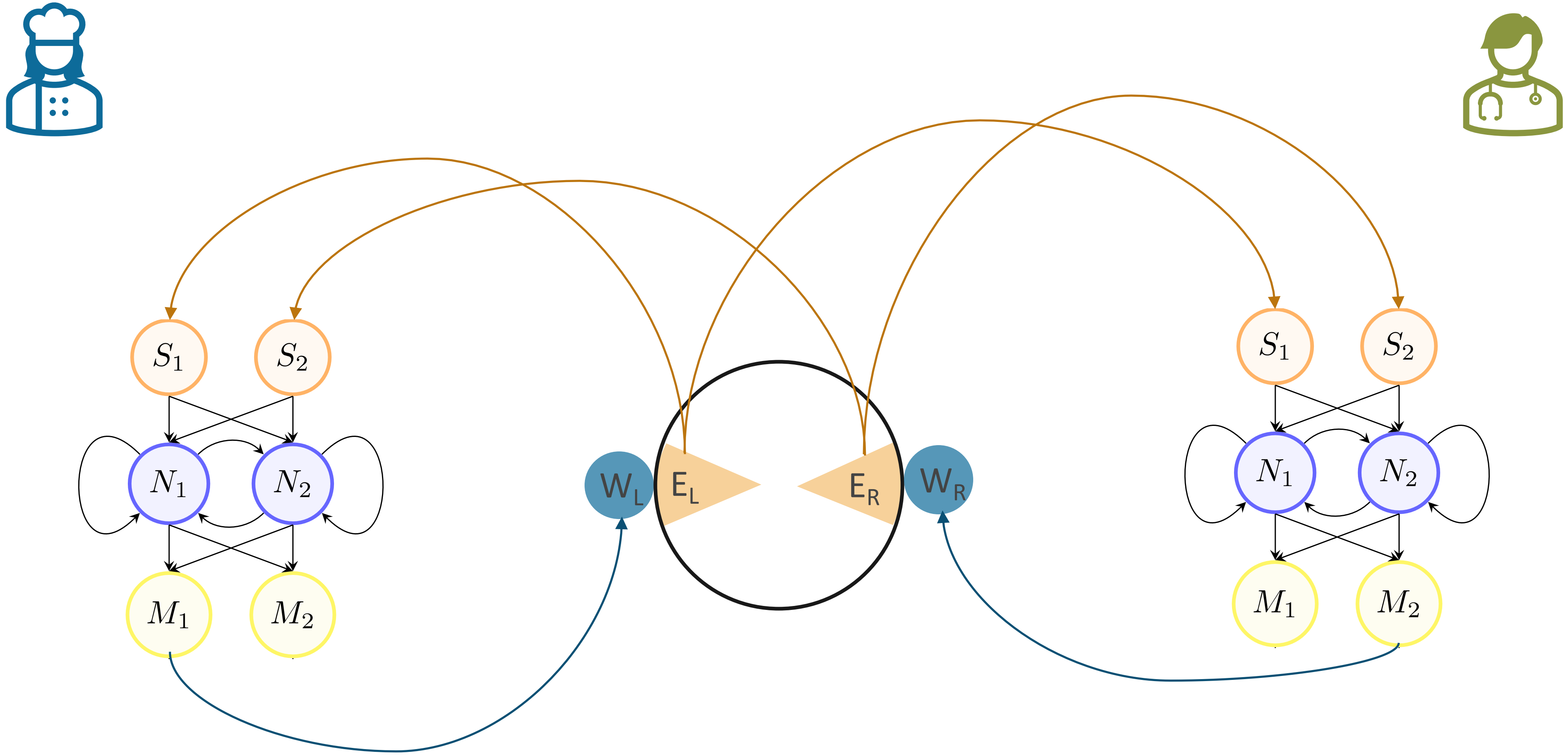
$$-\sum_{S=1}^{2} W_{i,S}\,O_S$$

Gain [1, 20]
Bias [-3, 3]
Weights [-8, 8]

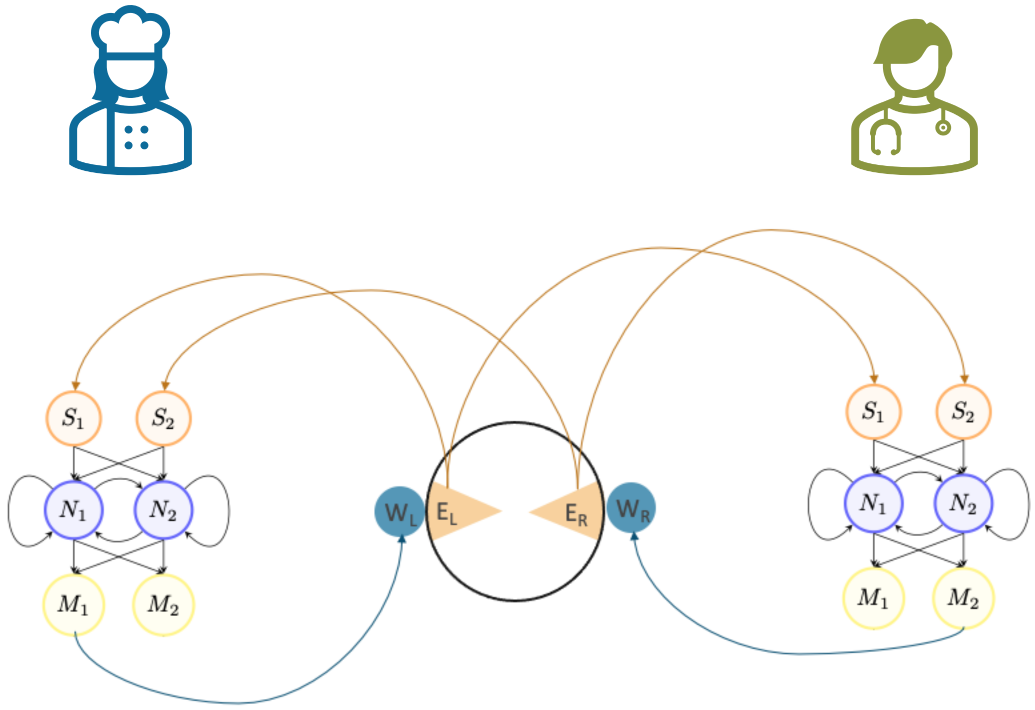
Isolated condition (single agent)



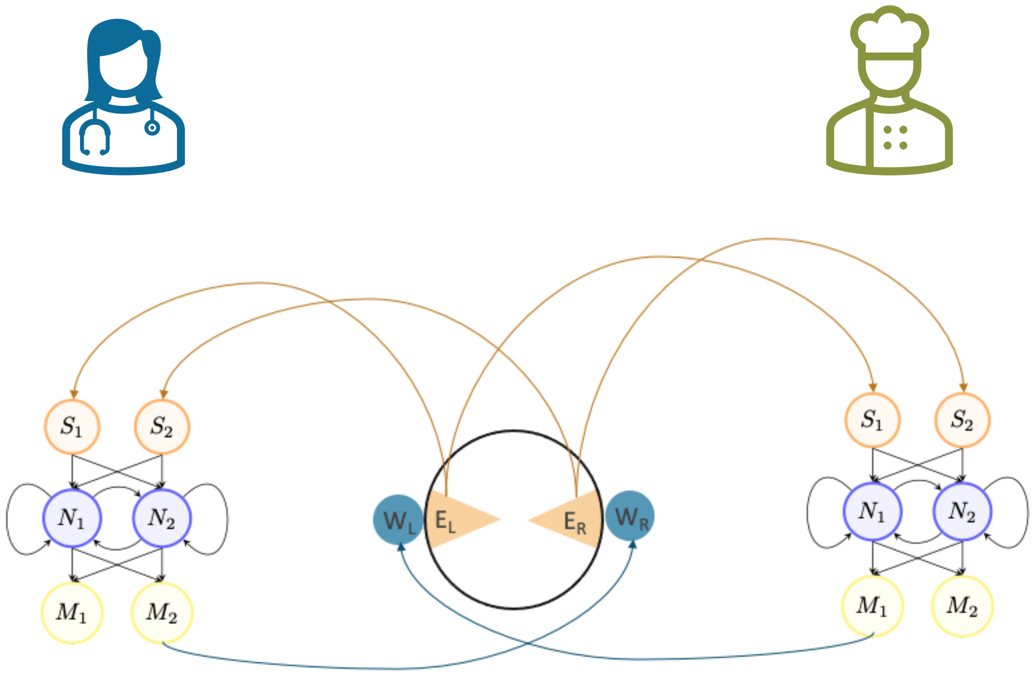
Specialist condition (two agents, all trials)



Generalist condition (two agents)



trials 1 and 3



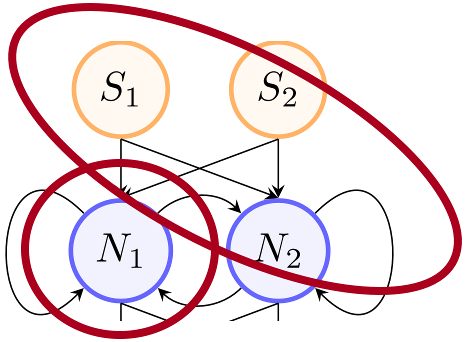
trials 2 and 4

Evolutionary algorithm

- genetic algorithm on network parameters
- 96 individuals/pairs (conditions evolved separately; **specialists evolved separately**)
- **3 random pairings for each agent in social conditions**
- 4 trials with 4 target velocities
- 20 random seeds for 2,000 generations
- **fitness: minimize the average distance between the position of the tracker and the target**
- Fitness Proportionate Selection
- 5% elite copied without modification
- mating pool with Roulette Wheel Selection, uniform crossover with probability 0.1 and zero-mean Gaussian mutation noise with variance of 0.05

Neural complexity

Individual Complexity

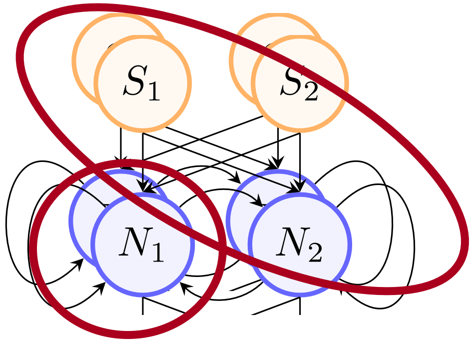


$$\mathrm{MI1} = \mathrm{MI}(N_1; S_1 S_2 N_2)$$
$$\mathrm{MI2} = \mathrm{MI}(N_2; S_1 S_2 N_1)$$
$$C = (\mathrm{MI1} + \mathrm{MI2})/2$$

$$\mathrm{MI}(N_1; S_1 S_2 N_2) = H(N_1) + H(S_1 S_2 N_2) - H(N_1 N_2 S_1 S_2)$$

$$H(X) = \frac{1}{2} \ln((2\pi e)^{\mathcal{N}} |\mathrm{cov}(X)|)$$

Joint Complexity



$$\mathrm{MI1}_{AB} = \mathrm{MI}_{AB}(N_1; S_1 S_2 N_2)$$
$$\mathrm{MI2}_{AB} = \mathrm{MI}_{AB}(N_2; S_1 S_2 N_1)$$
$$C_{AB} = (\mathrm{MI1}_{AB} + \mathrm{MI2}_{AB})/2$$

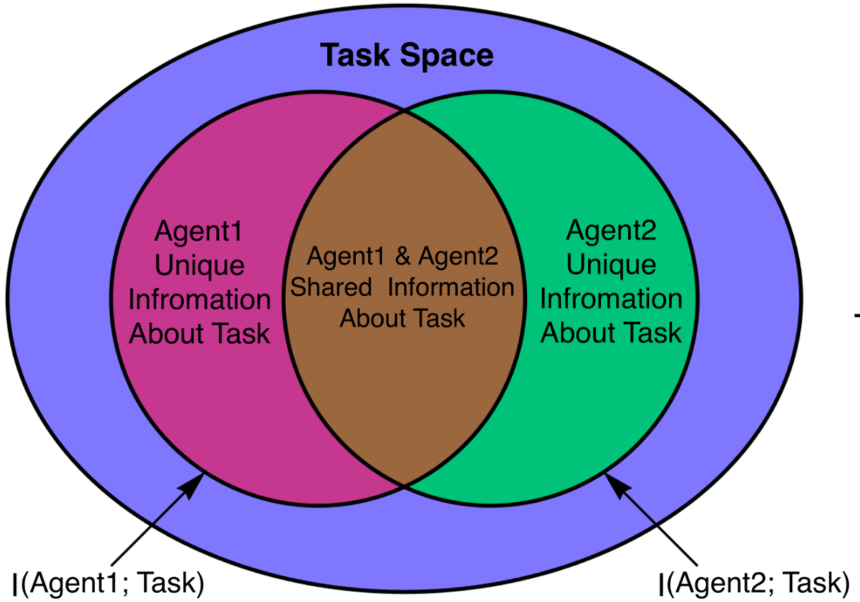
$$\mathrm{MI}_{AB}(N_1; S_1 S_2 N_2) = H_{AB}(N_1) + H_{AB}(S_1 S_2 N_2) - H_{AB}(N_1 N_2 S_1 S_2)$$

$$H_{AB}(X) = \frac{1}{2} \ln((2\pi e)^{\mathcal{N}} |\mathrm{cov}(X_A) + \mathrm{cov}(X_B)|)$$

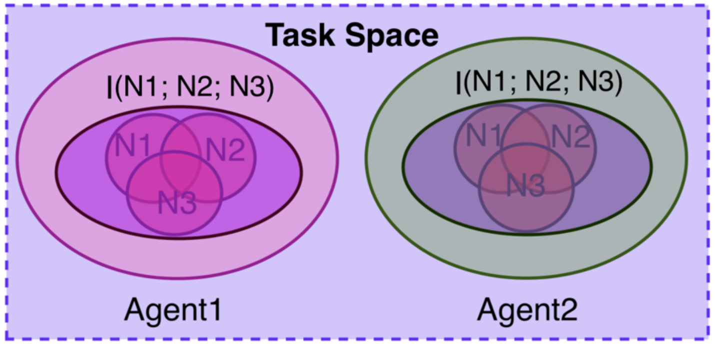
(Seth & Edelman, 2004)
(Cover & Thomas, 1991)

Neural complexity

Actual Problem: a Bird-Eye-View



Our Current Simplified Version



From Co-Information **To** Independently Integrated Information

I(x,y): Information Shared by x & y

Results

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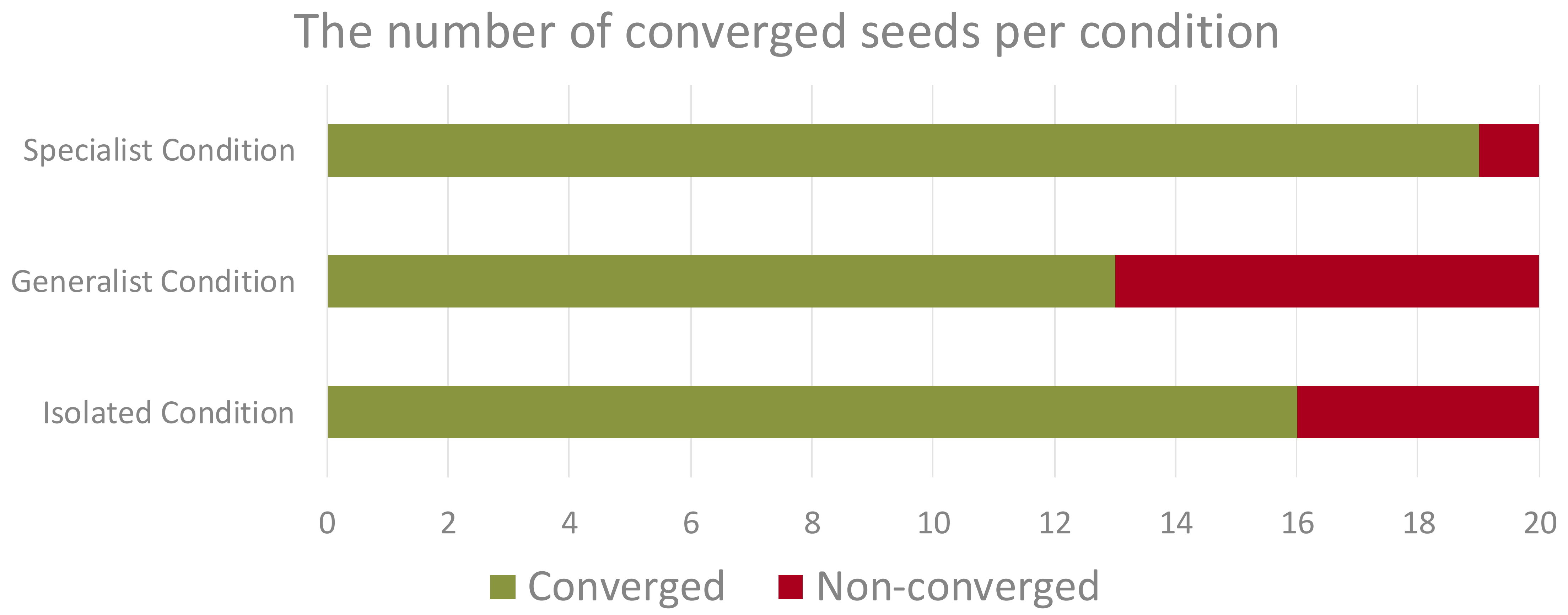
Behavioral analysis

Neural complexity analysis

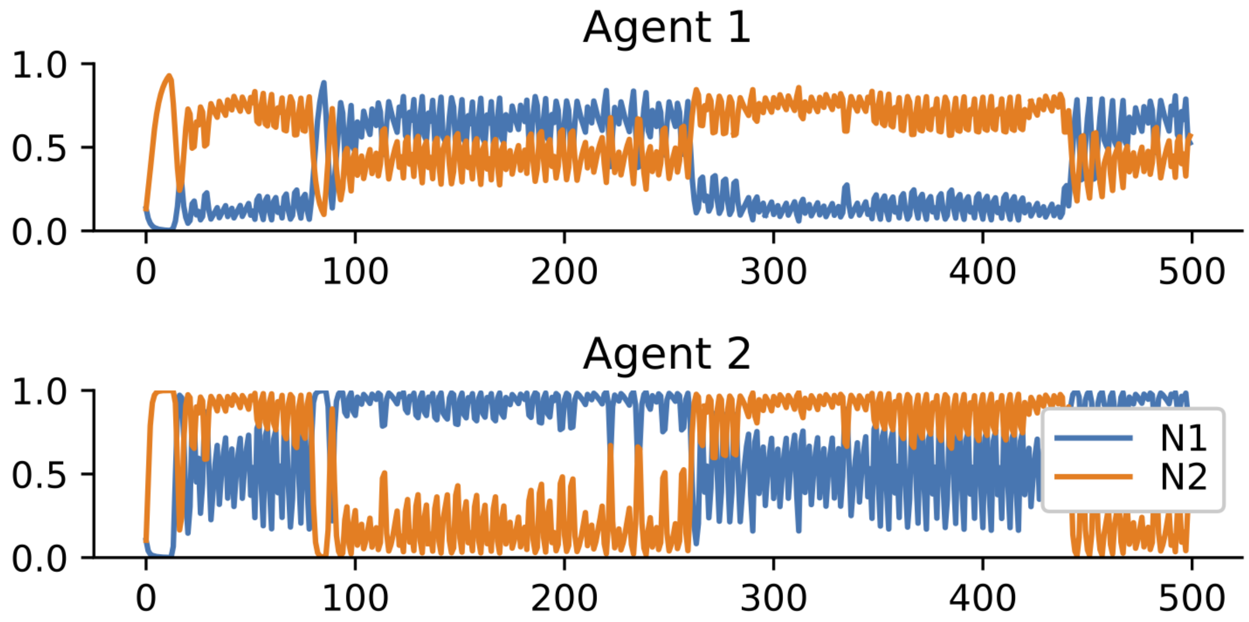
Evolved behavior



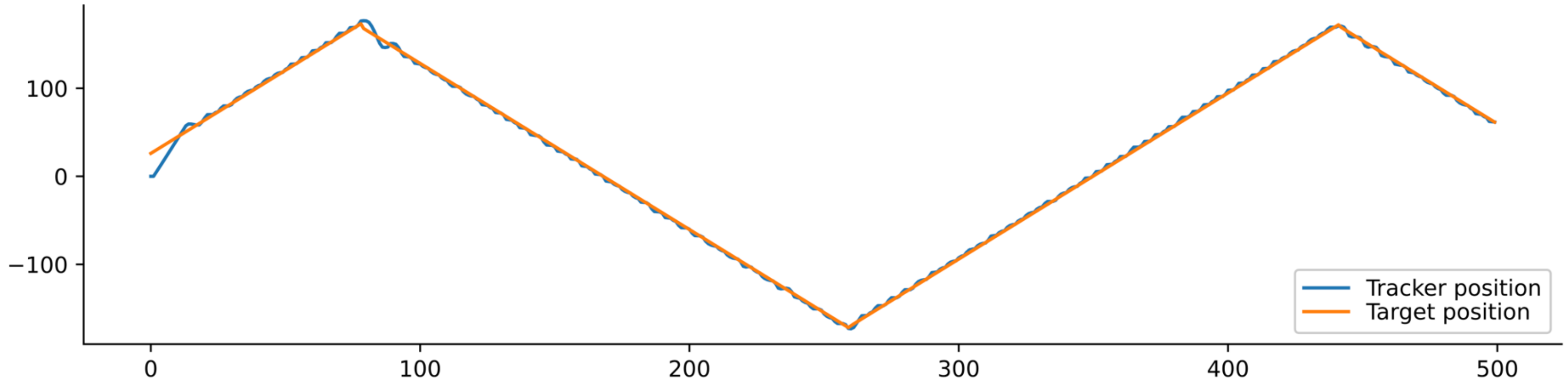
Evolved behavior

Generalist example:

Neural output

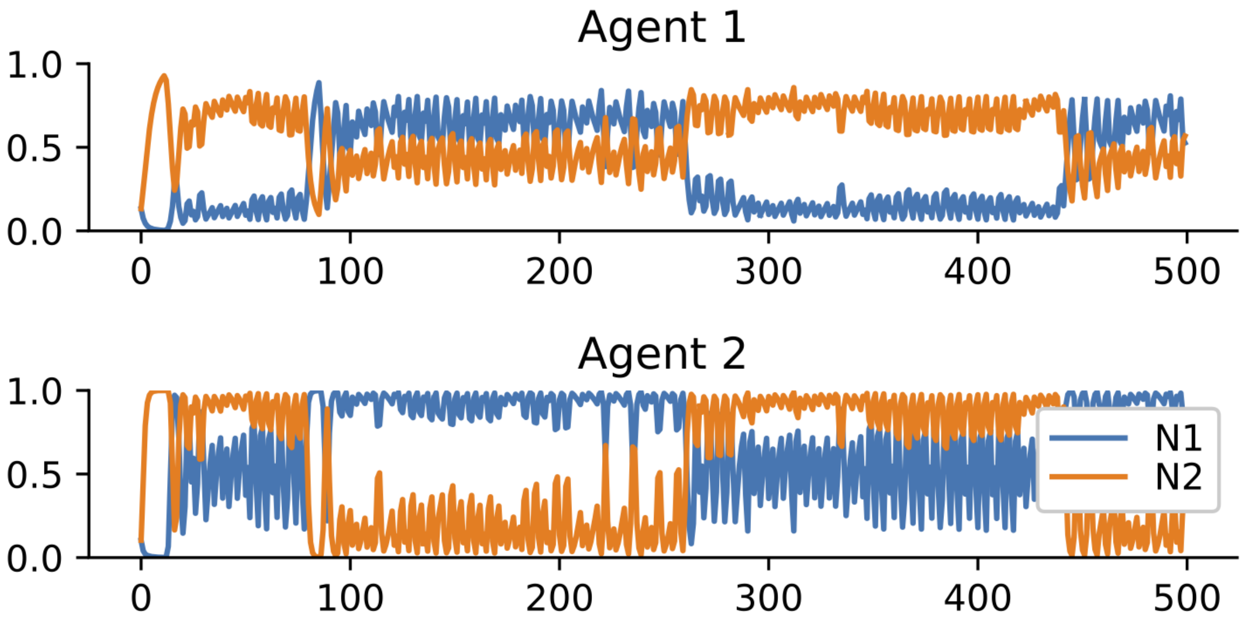


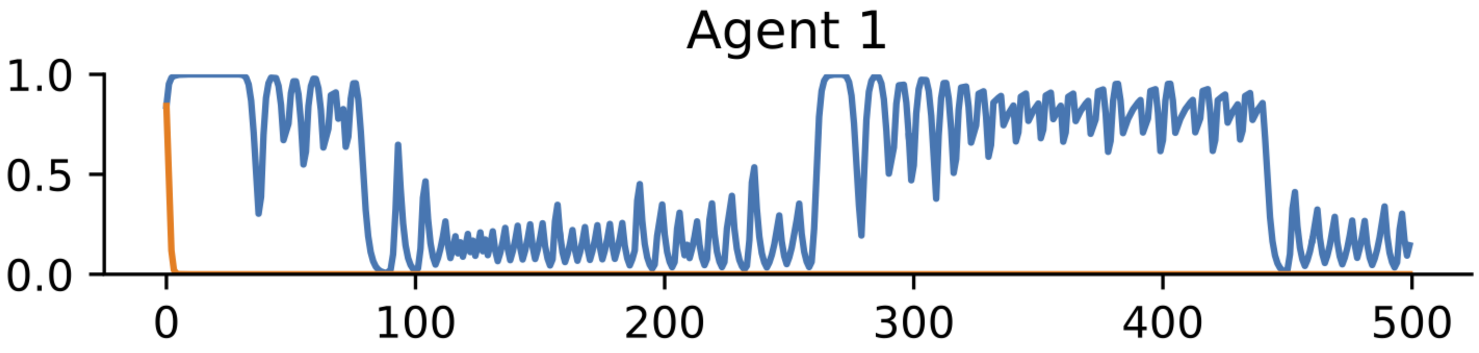
Positions



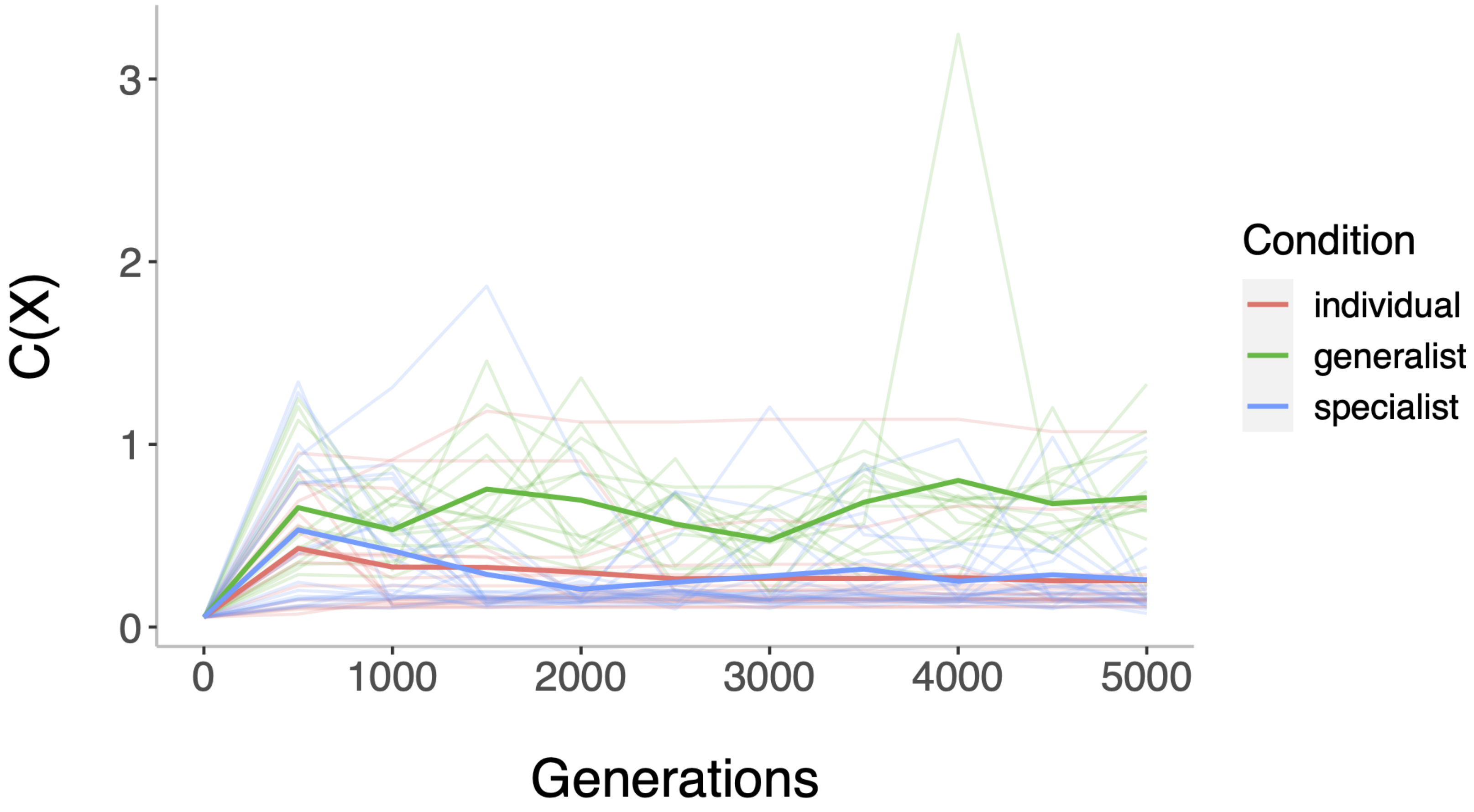
Evolved behavior

Neural output



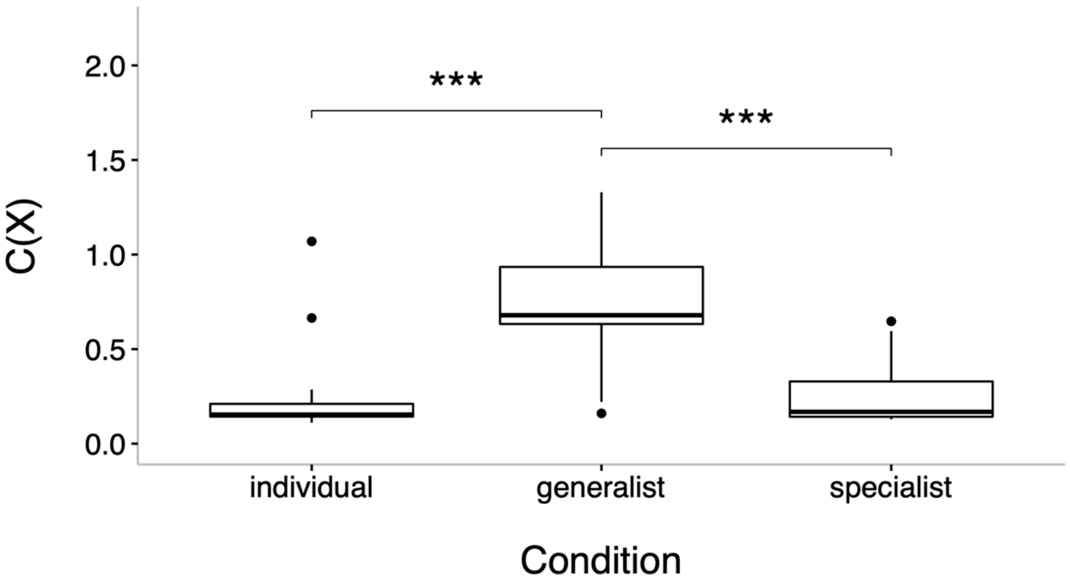


Evolution of neural complexity

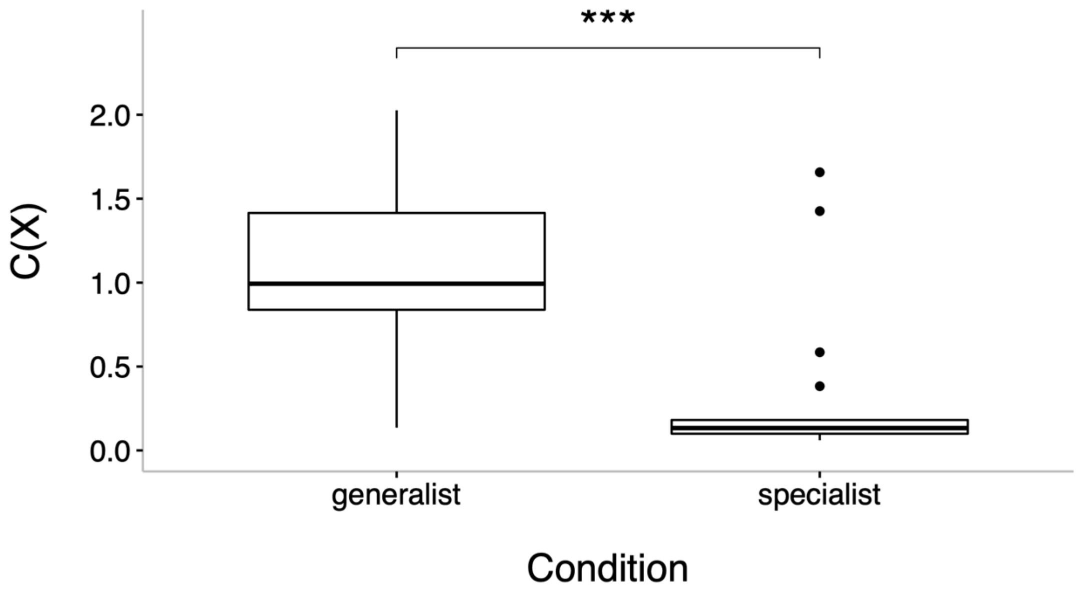


Neural complexity per condition

Individual-level complexity



Dyad-level complexity



Conclusions

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Hypotheses:

- individual level
  - $C_{generalists} > C_{individuals}$ & $C_{specialists} > C_{individuals}$
  - $C_{generalists} > C_{specialists}$
- dyadic level: $C_{generalists} \approx C_{specialists}$

Results individual level

- $C_{generalists} > C_{individuals}$
- $C_{generalists} > C_{specialists}$
- $C_{specialists} \approx C_{individuals}$

Results dyadic level

$C_{generalists} > C_{specialists}$

Limitations and future work

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Complexity results seem to depend on the number of inner neurons effectively used.

Both the task and agent architecture are extremely simplified.

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Both the task and agent architecture are extremely simplified.

Joint complexity measure is preliminary:

- assumption of Gaussianity
- assumption of agent independence

Behavioral, social, cognitive and neural complexity are tricky concepts!

??????????

$Var(aX + bY) = a^2 Var(X) + b^2 Var(Y) + 2ab COV(X,Y)$

When X and Y are independent: $COV(X,Y) = 0$ (in our case $a = b = 1$)

$COV(X,X) = Var(X)$

NOTE: In actuality, what is needed is:

$COV(X + Y, Z) = COV(X, Z) + COV(Y, Z)$, where X, Y, and Z are the two agents and the target, respectively. Specifically, the present case corresponds to $Z = 0$ i.e., $COV(X + Y, 0) = COV(X, 0) + COV(Y, 0) = COV(X) + COV(Y)$.

$$COV(aX + bY, cW + dV) = acCOV(X,W) + adCOV(X,V) + bcCOV(Y,W) + bdCOV(Y,V)$$

Setting W = X and V = Y, we have

$$\begin{aligned} COV(aX + bY, cX + dY) &= acCOV(X,X) + adCOV(X,Y) + bcCOV(Y,X) + bdCOV(Y,Y) \\ &= acCOV(X,X) + bdCOV(Y,Y) + (ad + bc)COV(X,Y) \end{aligned}$$

Given the assumption of X and Y independence in our article, we get:

$$COV(X,Y) = COV(Y,X) = 0$$

And therefore,

$$COV(aX + bY, cX + dY) = acCOV(X,X) + bdCOV(Y,Y)$$

COV(X,X) = Var(X) if X is univariate & COV(X) if multivariate.