

Evolution of Neural Complexity in Division of Labor Tasks

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Abstract

We evolve artificial agents to perform a simple tracking task in three conditions: one individual (Isolated Condition) and two joint action conditions with division of labor. The joint conditions differ by whether two agents switch complementary roles during the task (Generalist Condition) or always play the same role (Specialist Condition). At the end of evolutionary runs we calculate the agents' neural complexity using Tononi-Sporns-Edelman (TSE) complexity measure which relates to Integrated Information Theory (IIT). We show that (1) division of labor with specialization leads to a level of neural complexity comparable to the complexity of performing the same task alone, and that (2) both are lower than neural complexity when performing the task jointly with role switching. We further consider viewing collaborating agents as a single extended system and calculate its joint neural complexity. We demonstrate that contrary to our predictions, the same pattern of results, i.e., Generalists' complexity being higher than Specialists', holds also in this conceptualization.

Introduction

Social brain hypothesis (Dunbar, 2009; Shultz and Dunbar, 2010) proposes that the well-noted increase in human brain size over our evolutionary history, especially since the genus *Homo* (Tobias, 1971; Ruff et al., 1997) is related to increased demands on our cognitive processing of social information, such as the need to keep track of specific individuals and their relationships within an ever-growing group. This hypothesis, despite its popularity and an intuitive appeal, has faced criticism from several directions.

First, both before and after the formulation of the social brain hypothesis, a variety of different factors have been proposed for the observed pattern of encephalization, such as hunting (Krantz, 1968), language (Parker and Gibson, 1979), greater reliance on vision (Barton, 2004) or cooking (Carmody et al., 2011). Second, it has been pointed out that over the more recent history (Holocene), human brain has actually been shrinking (Brown, 1987; Henneberg, 1988). Since the complexity of our social interactions has arguably only increased during the same period, it seems inconsistent to claim that now it has led to an opposite pattern of

brain changes than in the earlier stages of evolution (Bednarik, 2014). However, social factors cannot be completely discounted either since an increase in the number and type of our interactions was accompanied by an increase in their ordered patterning through culture and social institutions. This could have, in fact, reduced demands on social cognitive processing¹ or rather, our brain could remain equally effective with a smaller size by learning to offload part of the work onto external sociocultural resources (Bednarik, 2014; Heinrich, 2015; Sterelny, 2017).

Interestingly, a similar discussion has been playing out with respect to the brain size in eusocial insects. On the one hand, it has been found, for instance, that long-term gregarious locusts have larger brains than solitary ones (Ott and Rogers, 2010) and that group size in ants is positively correlated with brain size (Kamhi et al., 2016). Contrary to that, O'Donnell et al. (2015) found that investment in the brain central processing areas in wasps is lower in social compared to solitary species and Riveros et al. (2012) showed that social complexity in ants is associated with reduced brain size. While also here non-social factors might be complicating observed correlations, the hypothesis of collective intelligence has been frequently raised, whereby globally coordinated performance is proposed to be a result of cognitively simple mechanisms of individual ants operating in conjunction with social structuring of their behaviors (Anderson and McShea, 2001; Couzin, 2009; Sasaki and Pratt, 2012).

Thus, the hypothesis common to both taxa is that increased social organization, such as, for instance, division of labor, can lower the cognitive effort required of the individuals and allow for a smaller brain tissue investment. This association can be studied by looking at archaeological evidence or large-scale correlations between insect society structures and their brains. However, another method we can bring to bear on the discussion is through simulation

¹Another possibility that has been raised, and that goes under the name of self-domestication hypothesis (Hare, 2017), is that smaller brains have been actively selected for, as a by-product of selection for prosociality.

of artificial agents engaged in different types of coordination tasks and direct measurement of their brain complexity. This is precisely the aim of the current study. We now describe our choice of a coordination problem and a measure of brain complexity.

Regarding coordination scenario, it is first important to note that there is a large body of simulation studies on division of labor, especially in the field of swarm robotics. However, many of them focus on the problem of how coordinated task performance (e.g., optimal foraging, Montanier et al. 2016, or specialization strategy, Goldsby et al. 2012) can emerge in a population of agents that have no access to the global state of the environment and population needs. Compared to this type of work, our approach is different in three ways. First, in more common swarm robotics scenarios it is often the case that certain factors are manipulated (the agents' internal perception or decision-making mechanisms, the type of the environment etc.) and the type of coordination that emerges is a dependent variable. In our case, since we are interested in brain complexity *given* a particular coordination scenario, the type of coordination is instead the manipulated factor, i.e., we design our agents to coordinate in a certain way. Second, in typical simulations the focus is on the *population* of coordinating agents. We instead start with a more minimal case of just two agents performing a task together in any given experimental trial, although they have a chance to do it with a number of partners. We believe this is sufficient for understanding the fundamental properties of cognitive requirements posed by coordination to individual brains.² Third, many tasks employed in division of labor simulations and studied in eusocial insect research are of the “distributive” kind.³ That is, they can be performed concurrently by agents that do not need to “mind each other”. For instance, one could think of one ant defending the colony from an attacker and another ant bringing food back to the nest. While we plan to address this case in the future, in the present study we focus on a more cognitively challenging case of performing a task which requires two agents to perform different parts of it concurrently in such a way that they interlock in appropriate ways in producing an overall outcome. We believe this type of task better reflects a level of coordination difficulty implied by the social brain hypothesis.

With respect to both insect and human sociality it has been pointed out that the type of social coordination adopted in a population might have implications for brain size and cognitive complexity. Thus, greater task specialization might lead to lower complexity while greater reliance on behaviorally flexible individuals would instead require higher complexity (Gronenberg and Riveros, 2009; Riveros et al., 2012; Slors,

²This is not to say that extending our study to a full group interaction is not a promising future research area.

³See Abramova and Slors (2015) for a distinction between *distributive* and *contributive* action coordination.

2019; O'Donnell et al., 2015). For this reason, we focus specifically on comparing two coordination scenarios: that of generalist and specialist agents. In particular, we set up a simple, yet cognitively motivated (Knoblich and Jordan, 2003), task of a 1D environment that contains a target that moves back and forth at different speeds. The agents control a tracker and are assessed on how closely they can follow the target. We implement three conditions for this experiment:

1. In the Isolated Condition (**IC**) each agent controls the movement of the tracker alone, which mimics a case of solitary individuals and serves as a cognitive complexity baseline.
2. In the joint Generalist Condition (**GC**), the tracker is controlled by two agents, one of which moves it to the left and the other to the right. The agents switch roles in different trials such that in order to be successful each agent has to be able to control the tracker in both directions.
3. In the Specialist Condition (**SC**), the tracker is still controlled by two agents as in GC but two populations of agents are evolved separately such that half of the agents ever experience only left direction control and the other half only right direction control.

We evolve artificial agents controlled by a small neural network in these three conditions and compare their brain complexity. Now, the question of how to operationalize this dependent variable is by no means straightforward. The simplest measure such as the number of neurons (used, for instance in a related study by Nagar et al., 2019) does not seem appropriate because a smaller brain can in principle be more cognitively efficient than a bigger brain, depending on its organization and its embedding in a particular task environment. In the field of biological complexity, a great variety of more general measures have been proposed, many of which focus on whether some time series produced by the organism shows signs of an underlying chaotic process (Adami, 2002). However, such measures often require additional tests that differentiate between chaos and randomness (Gan and Learmonth, 2015) and furthermore, a measure specifically appropriate for cognition should also correlate with adaptive behavior, possibly increase over evolution in parallel with improvement in performance and capture some properties of a cognitive *system*, rather than isolated time series.

An example of a measure that fits these criteria and that enjoys good theoretical and empirical support is Tononi-Sporns-Edelmans (TSE) complexity (Tononi et al., 1994). As a precursor to Integrated Information Theory (IIT) (Tononi, 2004; Tononi et al., 2016) which is hypothesized to capture the essence of consciousness (Tononi, 2008), TSE also quantifies the “information that is generated by the whole mechanism above and beyond the information generated by its parts” (Oizumi et al., 2014, p.8). However, the

applicability of this measure is broader and extends to any mechanism that cannot be reduced to its parts and is therefore suitably complex.

TSE complexity has a number of characteristics that make it a suitable choice for operationalization of brain complexity. It is low for both completely regular and completely random processes. It allows us to look at the complexity of a network as a whole, while taking into account the contribution of various neuronal subsets (including individual units), thereby quantifying its complexity in terms of interplay between integration and differentiation of its neuronal units' activity. Finally, it has been found to correlate with the system fitness, in that it increases over evolution with agents required to perform various tasks (Yaeger, 2009) and in that it is also higher for more difficult tasks that involve rich sensory information and pose high motor demands (Seth and Edelman, 2004).⁴

In sum, the main aim of our study is to compare how TSE complexity, calculated from the time series of neural activation of evolved agents, differs between the three conditions outlined above. We make the following predictions. If social brain hypothesis is correct, TSE complexity in joint conditions (GC and SC) should be higher than in IC because coordinating with another agent is inherently more complex than performing a task alone.⁵ Moreover, if collective intelligence hypothesis is correct and task specialization is less cognitively demanding, TSE complexity should be lower in SC than in GC.

Starting from a collective intelligence view, we can make an additional prediction. Coordinated joint action can be said to involve an emergence of a higher-level functional entity that spans the interactants, not reducible to the individuals involved (De Jaegher and Di Paolo, 2007; Marsh et al., 2009). More generally, on the level of the whole social system characterized by division of labor, components might be specialized but global behavior integrated (Lawrence and Lorsch, 1967). That is, the concepts of differentiation and integration also apply to social units, not just individuals and therefore also TSE complexity can be calculated based on statistical dependencies of neural activity pooled from both agents' brains (cf. an application of this strategy to human behavioral data, Engel and Malone 2018).

In our study this means that we can calculate the com-

⁴Another possible measure is predictive information (Bialek et al., 2001) which focuses on the correlation between inputs and outputs. However, some concerns have been raised to what extent this focus on the input-output layers of the organism can capture the complexity of the internal nodes (Edlund et al., 2011). We leave it to future work to explore the applicability of this measure to our use case.

⁵Note that this is just a first small step in directly testing the predictions of the social brain hypothesis. A further test, that we leave for future work, could, for instance, examine how neural complexity varies depending on the number and types of coordination partners in the joint conditions.

plexed brain complexity of agents in joint conditions. We predict that whenever the pairs of agents manage to establish a successful way to solve the task, it should not matter how exactly the division of labor is performed and how it is realized in the individual brains. Therefore, no difference in TSE complexity should obtain between GC and SC.

Methods

Tracking task

The implemented simulation⁶ is similar to the one described in Sangati and Hofmann (2020) and based on the psychological experiment paradigm of Knoblich and Jordan (2003). The environment is a 1D unbounded continuous line that contains a tracker and a target (Figure 1). The target moves horizontally following an oscillatory motion with constant velocity and reverses at fixed points of the environment. More precisely, it always starts at the central position 0 and inverts its velocity at coordinates 200 and -200 .

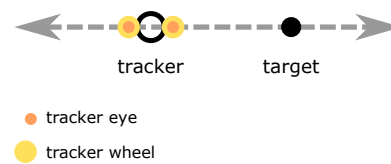


Figure 1: Experimental setup.

The tracker is placed on the same line and is free to move horizontally without colliding with the target or any boundary. Both target and tracker are points in space with no dimension. The tracker perceives the target by means of two eyes located at the opposite sides of its body and aligned with the environmental line. The eyes are sensitive to how far the target is to the right or left of the tracker. The signal to both eyes is maximum when the target and tracker overlap and 0 when the target is on the opposite side of the tracker's body for a given eye. When the target is on the same side, the signal decreases linearly reaching 0 when the target is more than 200 units away. The tracker moves by means of two wheels controlling its right (positive) and left (negative) velocity respectively. The overall velocity is given by the difference of the right and left velocities.

The goal of the tracker is to try to stay on top of the target as much as possible.

Agent architecture

We investigate 3 conditions in which the tracker is controlled by one or two artificial agents. In all cases each agent is implemented as a Continuous Time Recursive Neural Network (CTRNN) (Beer, 1995) with 2 sensors, 2 brain neurons, and 2 motors (see Figure 2).

⁶The source code and details to reproduce the results are available at <https://github.com/oist/ecs-u-dol-simulation>

and scaled during simulation to the parameter ranges specified above. The genomes are composed of 16 parameters (time constants, bias terms, gains, weights of inter-neurons, sensors, motors). The population of agents is initialized with all parameters set to 0.⁷

In the IC, the population size is 48, whereas for the GC and SC it is 96 since agents are undergoing the simulation in pairs. However, while generalists are evolved in a single population, the specialists are evolved in two distinct populations (one learning to control the left tracker wheel, and the other the right) that are evaluated and reproduced separately.

In each generation, in the IC all agents in the population perform the task alone. In the GC the population is first split randomly into 2 equally sized groups A and B and each agent in A is paired with 3 random B agents to perform the task. In the SC, the populations are evolved separately but each agent in A is still paired with 3 random agents in B for the simulation. This way we ensure that the agents acquire a more general capacity to perform the task with different partners rather than co-evolving together with a specific partner.

Each task run consists in 4 trials where the target moves with velocities $[1, -1, 2, -2]$ respectively. Each trial last for $L = 500$ units of time, and after each trial t the average distance between the position of the tracker (x_{tr}) and the target (x_{tg}) is computed as the trial error E_t :

$$E_t = \frac{1}{L} \sum_{i=0}^L |x_{tr} - x_{tg}| \quad (4)$$

The overall experiment error is the average of the 4 trial errors. In the joint conditions this experiment error is further averaged across performance with 3 partners to obtain task error value for each agent.

After sorting the population based on increasing overall error (best performance first), the population fitness is obtained with Fitness Proportionate Selection method with maximum expected offspring parameter set to 1.1. During the reproduction phase, a mating pool is obtained by selecting 95% of the agents of the previous generation based on the Roulette Wheel Selection algorithm. The new generation is created by copying the best 5% of the agents of the previous generation without modification (elite population), and the remaining population is obtained by crossover and mutation on the mating pool: for consecutive pair of agents in the shuffled mating pool (the parents), two new individuals are generated i) via crossover with probability of 0.1, uniformly across all genotype sites, otherwise ii) by duplicating the parent and applying a zero-mean Gaussian mutation noise with variance of 0.05. Each experimental setup is run on 20 random seeds for 5,000 generations.

⁷This is to ensure that neural complexity (see following sections) is 0 at the beginning of the evolution.

Neural complexity

We follow the approach by Seth and Edelman (2004) which calculates TSE complexity for a general case of a system X comprising \mathcal{N} nodes (e.g., neural units). In our case, X is analogous to a single agent.

Given any subset X^k of k nodes and the complementary subset $X \setminus X^k$, we can compute the mutual information between these two subsets (i.e., bipartition of X) as:

$$MI(X^k; X \setminus X^k) = H(X^k) + H(X \setminus X^k) - H(X) \quad (5)$$

where $H(X)$ denotes the entropy function and is calculated as (Cover and Thomas, 1991):

$$H(X) = \frac{1}{2} \ln((2\pi e)^{\mathcal{N}} |\text{cov}(X)|) \quad (6)$$

where cov is the $\mathcal{N} \times \mathcal{N}$ covariance matrix of X , and $|\cdot|$ denotes its determinant.⁸

TSE complexity $C(X)$ is then computed by first enumerating all possible subsets X_j^k with j being the j th bipartition with k nodes (for $k = 1, \dots, \mathcal{N}/2$), and then computing the average MI over all $\mathcal{S}_k = \binom{\mathcal{N}}{k}$ bipartitions ($X_j^k, X \setminus X_j^k$), and finally summing over k :

$$C(X) = \sum_{k=1}^{\mathcal{N}/2} \frac{1}{\mathcal{S}_k} \sum_{j=1}^{\mathcal{S}_k} MI(X_j^k; X \setminus X_j^k) \quad (7)$$

It is apparent that in our case TSE complexity in equation 7 can be calculated via incorporating various subsets of agents' nodes. Given the differences in motor nodes' function across different conditions, we discard these nodes and consider sensor and inner nodes only. In other words, we compute $C(X)$ for our system X comprising 4 nodes (2 sensors and 2 inner neurons) for individual agents, or alternatively of 8 nodes for two agents combined (in joint conditions only). Moreover, of all the nodes that form these agents' neural architecture, the two inner nodes N_1 and N_2 (Figure 1) are the only units that are actively involved in information processing. Therefore, we explicitly focus on these inner nodes and follow Seth and Edelman (2004) by examining only partitions that divide X into pairs comprising a single neuron N_i (the i -th neuron of the agent) and the set of all remaining nodes, thereby reducing equation 7 to the following:

$$C(X) = \frac{1}{2} \sum_{i=1}^2 MI(X_{N_i}; X \setminus X_{N_i}) \quad (8)$$

The formula above is applicable in all three scenarios when analyzing the neural complexity of a single agent. In

⁸In the case where X is a single node N we have that $|\text{cov}(X)| = \text{var}(N)$.

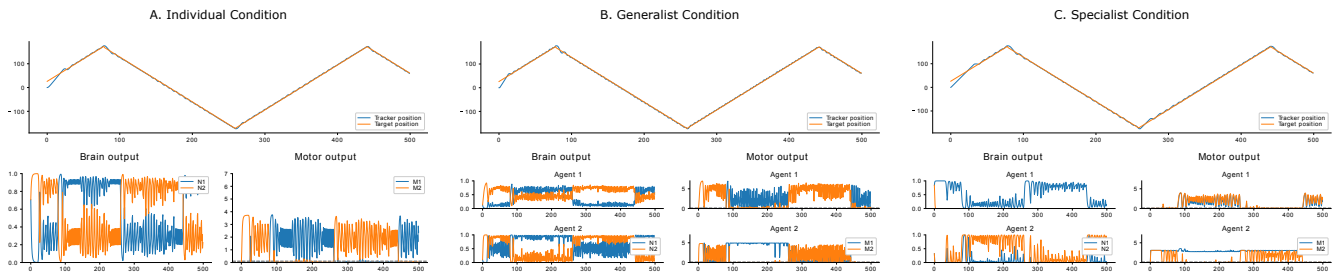


Figure 3: Behavior and activity.

order to compute the *joint* complexity of two agents performing the task together (i.e., in GC and SC) we treat the two agents A and B as a system Y composed of two independent processes X_A and X_B . In this regard, the independence of X_A and X_B can be verified through the observation that A and B do not share and/or communicate information with one another and therefore they act independently. This, in turn, indicates that the cov of Y relates to the joint covariance of two independent processes X_A and X_B (Cormen et al., 2006):

$$\text{cov}(Y_j) = \text{cov}(X_{j_A}) + \text{cov}(X_{j_B}) \quad (9)$$

where each subset of nodes Y_j corresponds to the aligned nodes of the two processes (X_{j_A}, X_{j_B}). The complexity of Y is then straightforwardly computed by using equation 9 (i.e., the joint covariance matrix of independent processes X_A and X_B) in equation 6 while computing MI in equation 8.

Considering equation 9, there are two points that deserve further clarification. First, one might argue that the presence of common task violates the assumption of independence. However, such a common drive on its own is insufficient to reject this assumption (e.g., daily commuters who share a same bus schedule act independently, despite having a common drive i.e., catching the same bus). More importantly, our GA setting does not impose any constraints on joint action-space of agents in GC and SC settings.

Second, it may also appear plausible to argue that $H(Y) = H(X_A) + H(X_B)$ is more adequate an expression for combining the two agents' neural activity. However, this is a mistake due to two observations. (1) $H(X_A) + H(X_B) = MI(X_A; X_B) - H(X_A; X_B)$ where $H(X_A; X_B)$ is joint entropy of X_A and X_B . (2) even the use of its correct expression i.e., $MI(X_A; X_B) = H(X_A) + H(X_B) - H(X_A; X_B)$ would result in capturing the higher-level shared information (e.g., perception of environment shared by A and B) than information integration by their neural units, as reflected at their individual level.

Results

Evolved behavior

Agents evolved in all conditions were able to find a way to effectively control the tracker to stay on top of the target. However, the number of seeds that converged to a solution varied in different conditions: 16 out of 20 in the IC, 13 in the GC and 19 in the SC, suggesting that perhaps the Generalist case was more difficult to evolve.

Figure 3 shows examples of behavior and neural and motor activation for all conditions from the best agent of the population of selected seeds. The plotted data was obtained for a trial in which the target moves in a slightly different way than during evolution, i.e., with random velocity in the range $\pm[1, 2]$, random starting position within 50 units of the center and random reversal point within 50 units of the original reversal points. That way we test whether the agents are able to generalize to a situation they were not trained on. We can see that in all conditions the agents quickly catch up to the target and are able to follow it.

With respect to neural output we can observe that it seems to reflect the symmetric nature of the task and a resulting symmetric nature of sensory input (the tracker receiving visual information about the target from either left or right eye) and of motor output (the necessity to activate left or right tracker wheel). While this mapping between input/output and neural activity is not in principle a necessary outcome, it is not unexpected and resembles well-established evidence for topologies present in actual brains.

Another important note about neural activity is that while Figure 3A shows an example of an individual agent which is activating both of its inner nodes, the best agent of the majority of seeds (14 out of 16) in this condition “uses” only one of its neurons in a sense of neuron output varying over the trial time and correlating with input and output. The other neuron in such cases is either at maximum or minimum level of activation and remains constant, not contributing in a time-varying manner to behavior. The same is true for the majority of the agents in the SC (26 out of 38) even if they are performing the task together with an agent that effectively uses both neurons (example shown in Figure 3C). By contrast, only 2 best performing agents in the GC use

only one neuron, presumably because of the higher task demands. As discussed below, this might have implications for our results concerning neural complexity.

With respect to motor activation, all examples shown involve clear alteration of left and right motor output, whether realized within a single agent or across collaborating agents. There are a few seeds in which a “braking strategy” emerged, in which both motors are active at a given time making the tracker stop temporarily (due to our exclusive motor implementation). There does not seem to be any correlation of this strategy with either conditions or performance level so we do not discuss it further.

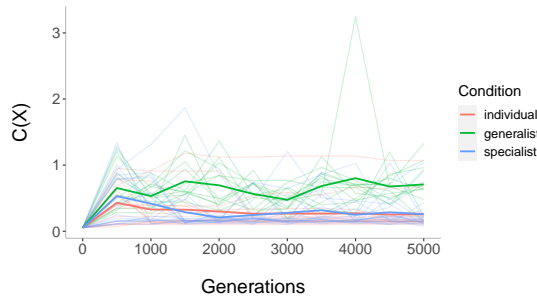


Figure 4: Changes in neural complexity over generations.

Evolved neural complexity

As argued in the Introduction, if higher neural complexity is to be indicative of better agent fitness in facing environmental demands, we would expect it to increase over evolution. We therefore looked at how our measure $C(X)$ changes over generations. The results are plotted in Figure 4. The faint lines represent complexity values for all the converged seeds and the thick lines the mean for each condition. While there is a lot of variability among the different seeds, it seems that overall complexity increases in the first 500 generations from the imposed starting point of 0 and then remains stably high for the GC but actually drops for the other two conditions. When examining individual seed plots and specifically how $C(X)$ changes in line with changes in performance (not shown here), it can be noted that complexity increases during the time in which the evolutionary algorithm is searching for a task solution. Then, one of two things happen. If the agents settle on a “use both inner neurons” solution, complexity remains high. However, if they find that using only one inner neuron is sufficient, complexity drops. We address this further in the Discussion.

To understand how neural complexity differs between conditions, we compared its values from the best agents of the last generation of the seeds that converged on a task solution.⁹ We find that for the regular individual-level

⁹While it might be worthwhile to examine complexity in the failed seeds to understand how this measure reflects fitness, here we

$C(X)$, i.e., neural complexity calculated from each individual agent, there is a statistically significant difference between conditions, $F(2, 45) = 15.7, p < .001$, specifically with agents in the GC having higher neural complexity than those in the IC (effect size $d = -1.59$) and SC ($d = -1.83$), both at $p < .001$, as shown by Bonferroni-corrected pairwise t-tests but no difference between IC and SC (Figure 5).

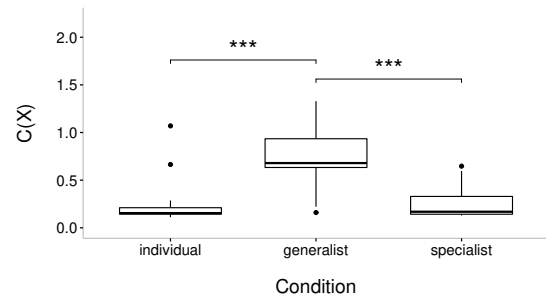


Figure 5: Individual-level neural complexity.

Similarly, joint neural complexity calculated from two agents performing the task together is significantly higher in the GC than in the SC, $t(23.16) = 4.0169, p < .001, r = .64$, contrary to our predictions. Results of this comparison are shown in Figure 6.

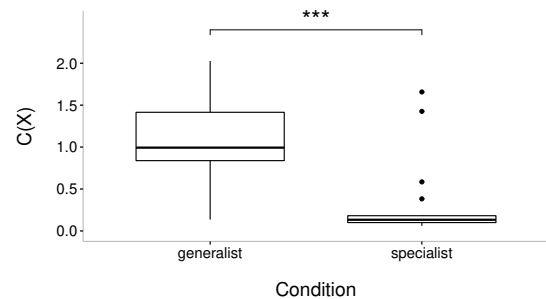


Figure 6: Dyad-level neural complexity.

Discussion

In this work we tried to address the relationship between neural complexity as a proxy for cognitive complexity and varying levels of social complexity in a simple tracking task. We compared both a non-social condition to social conditions and two social conditions that differ in the level of division of labor employed by the agents. We hypothesized that neural complexity will be higher in social conditions than in the isolated condition, and higher in a more generalist type of division of labor (GC) than in a more specialized type (SC). We further attempted to quantify neural complexity of

are specifically interested in comparing its levels between different behavioral settings *assuming* the solution was found.

a joint system of two interactive partners taken as a whole hypothesizing that it will not differ between the two social conditions. Our predictions were partially confirmed.

First, with respect to the individual-level comparison, we found that as expected, GC agents had the highest level of neural complexity. However, it did not seem to differ between SC and IC agents. This is surprising given that in the SC the agents had to coordinate with each other in controlling the tracker and we would expect this task to pose a higher cognitive demand than having to control the tracker individually. It might be, however, that this difficulty was offset by the fact that in this setting each of the agents had to learn to control only one tracker wheel (left or right). Therefore, the individual sensory-motor coordination demand was lower.¹⁰ This result highlights the fact that an overall task complexity might stem from different sources, related to general sensory processing and motor control, as well as social coordination, and their effects on a particular task (or, more generally, within a particular ecological niche) might not always be easily distinguished.

Second, our observations on how neural complexity changes over evolution as well as comparisons between conditions at the end of evolution suggest that it is highly dependent on the number of inner nodes that the agents effectively make use of in solving the task. This means that higher complexity values in the GC might reflect the fact that more agents in that condition use both neurons. On the one hand, this might make neural complexity measure seem redundant as we could simply consider the number of neurons used (which would effectively reduce to a simple measure of brain size). On the other hand, it confirms that the measure is picking up something important about the neural resources required in the task: that GC needs the contribution of both inner nodes. It remains to be seen whether in a task that is difficult enough to require the use of *all* available nodes in *all* conditions, the measure would be sensitive enough to differentiate between them if such a difference exists.

Third, the fact that even joint neural complexity is higher in the GC than in the SC might mean two things. It could be that the way we operationalized the joint version of $C(X)$ is too conservative to truly capture the distributed nature of the system of two agents collaborating in a task. In particular, the formulation of TSE in our study relied on two important assumptions: (1) Gaussianity of agents' neural activity (as in Seth and Edelman (2004); Tononi et al. (1994)) (2) independence of agencies in GC and SC settings. Whereas the first assumption simplified TSE computation for agents' multivariate neural representation, the second assumption allowed for reduction of joint (i.e., two agents in GC and SC) to an ordinary (i.e., single agent) TSE computation. Al-

¹⁰Note also that if the ability to use one or both motors was a deciding factor affecting individual complexity, we would expect no difference between IC and GC conditions which was not the case.

though these simplifications enabled us to analyze the effect of social settings on evolution of individuals' brain dynamics, they might have prevented us from detecting any potential non-linear effects of an emergent higher-level system (Candadai et al., 2019; Froese et al., 2013) that could have delivered a joint complexity pattern of results different from their individual version. However, how to formalize a collective intelligence idea in a way that is both mathematically and biologically plausible remains an outstanding challenge and our contribution should be taken as a preliminary step in this direction.

Another possibility with respect to our joint TSE results is that the joint GC system is truly more complex than the joint SC system. This could be due to a higher flexibility, redundancy and tolerance of component loss of the former, as has been argued for colony fitness of social insects (Jongepier and Foitzik, 2016). In a small post-hoc test of this possibility on our evolved agents we run the best agent pair from GC and SC (from the same seeds as depicted in Figure 3) in an isolated simulation, i.e., asking them to control the tracker without the partner contribution. In this test the GC agents were still able to perform the task while the SC agents performance completely disintegrated. Thus, the joint result might reflect a real advantage of the GC division of labor.

As a concluding thought, on conceptual grounds, the relationship between social, neural and cognitive complexity is by no means straightforward. The notion of *social complexity* can encompass anything from the number of individuals in the group and their genetic relatedness, through patterns of parental care to the organization of various social activities (Kappeler, 2019; Fischer et al., 2017; Bergman and Beehner, 2015; Anderson and McShea, 2001). Brain complexity can mean the total brain volume, the number and type of neuronal connections or dynamic properties of generated neural activity. It can apply to the whole brain or particular brain regions, for instance those believed to be specifically associated with processing social input. Finally, cognitive complexity will depend on our understanding of cognition in general and how we choose to rank different tasks. As a result, sweeping statements about relationships between different levels of complexity are unlikely to be productive. However, minimal agents-based simulations of the type presented in this work can help disentangle the various factors that contribute to different types of complexity.

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