

# The Evolution of Language Groups among Cooperating Digital Predators

PATRICK B. HALEY

Supervisor: Risto Miikkulainen

Second Reader: David Hillis

Departmental Reader: Etienne Vouga

Collaborator: Aditya Rawal

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Computer Science Dept., The University of Texas at Austin, Austin, TX 78712

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# Abstract

**Author:** Patrick Haley

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**Supervising Professor:** Risto Miikkulainen

Many species of animals have evolved complex means for communicating with one another. Oftentimes, communication is essential for the execution of tasks that require cooperation between individuals, such as group hunting and mate selection. As a result, communication itself becomes essential for survival. While these facts are readily observed, the evolutionary processes underlying them are less understood, in large part because observational - much less controlled - studies of these processes are impossible. Both the timescales and population sizes required for such studies are simply too great.

To address these problems, this thesis uses simulated predators to study the evolution of language in animals. These digital predators evolve to perform two cooperative tasks: hunting and mate selection. After the populations of predators have evolved to perform both tasks successfully, the population is decomposed into both language groups and cooperative groups. Spectral clustering identifies predators that speak similar languages, while merge clustering is used to find those groups of predators that are the most successful when working together.

Analysis of the groups generated by these two different methods shows that the most successful pairings are not necessarily those in which the two individuals are speaking the same language. Rather, organisms can evolve to speak a different language than the one to which they respond. Moreover, even though one task - mate selection - evolves earlier in evolutionary history, the language diversity it produces counteracts any head-start provided for the evolution of the second task. Thus, not only is language important for the evolution of cooperative task success, but the appearance of language groups can also play a determinant role in the evolution of cooperation.

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# 1 Introduction

For animals that live in groups, communication is essential for survival. Predatory sea trout use visual cues to coordinate their attacks on their prey [1]. Birds use song to advertise their fecundity and physical displays to exaggerate their fitness [2–6]. Meerkats send warning signals communicating the threat of predation [7,8]. Such cooperative behavior is not always perfect, as tragedies of the commons can emerge, among vigilant prey, for example [9,10]. But whether it is through sound, smell, or sight, many animals have evolved to work together to increase their collective fitness through cooperative, communicative behaviors.

Yet even while the importance of communication for the survival of many animals is readily observed, the evolutionary origin of animal communication remains an open question in biology [11,12]. The fossil record is often unhelpful for the study of how animals cooperated – much less communicated – with one another [13]. Animal communication is also likely the product of many instances of convergent evolution, such that cross-species studies may or may not be useful for determining the evolutionary history of communication [14,15]. More practically, as is true for many areas of evolutionary biology, observational studies are too short relative to the timescale of evolution [16], with only a few exceptions [17].

Animals that do communicate with one another often have evolved to use that ability to perform not just one task, but a wide range of tasks [18–20]. For example, mate selection and predator-prey interactions are two behavioral arenas that are often governed by communication. As such, it is difficult to know, first, whether these forms of communication evolved simultaneously or sequentially and, second, to what extent the evolution of communication to achieve one task affects the success of another type of communication [21–23]. It seems that the development of vocalizations for mate selection could allow animals to speak to one another during prey capture; but it is also possible that one task could monopolize a wide range of vocal patterns, such that relatively few options remain to be associated with other tasks.

A final question in relation to the evolution of communication is the unlikely probability

that a single language for communication sweeps a species' population. Rather, it would appear much more likely that different subpopulations of the same species might evolve to use forms of communication that are anywhere from mildly to drastically different from one another; and, indeed, this phenomenon can be observed in nature [24, 25]. Again, though, the evolutionary ramifications of a large diversity in language groups is unclear. While it is certainly advantageous for an individual to be able to cooperate successfully with as many conspecifics as possible, the division of a larger population into language groups might allow it to more quickly explore phenotypic space. The evolutionary effects of such structured populations have been observed in other contexts [26–28], so the same might be true of communication.

Answering these questions requires detailed knowledge of each individual's language across an immense span of time – hundreds or thousands of generations. For these reasons, physical experiments or observational studies cannot accomplish very much, which is why computer simulation have been used to study these questions. With artificial predators, every individual's neural network (its brain) can be tracked across the entire evolutionary run, providing the necessary breadth and depth of information about how predators are communicating with one another. The usefulness of computer simulations for evolutionary biology is well-known [29, 30], particularly the approach of evolving neural networks [31–33].

Past studies have already shown that populations of neural networks are capable of evolving a common language to perform certain tasks [34–36]. Many of these studies, however, used clonal populations, populations wherein every individual has the same neural network, such that the question is not whether the predator can speak to *other predators*, but rather whether it can speak to *itself*. By contrast, only the physical features of the predators are regulated in this thesis (such that it is communication that must evolve, rather than physical traits), while allowing a diversity of languages and decision-making strategies to emerge within the population.

This thesis is an extension of past work on the sequential evolution of different tasks [37].

In this experiment, predators evolve to perform two simple cooperative tasks: mate selection and prey capture. In the past, the goal was to learn how the evolution of one task promoted or inhibited the evolution of another task.

This thesis, though, is concerned with how diverse language groups emerge within a population. As noted before, since language homogeneity is not an enforced constraint, it is probable that multiple languages exist in the population at any moment in time, though the impact of such language groups on the evolutionary history of a population is initially unclear. Moreover, it is unknown how well these language groups correlate with subgroups within the population that work well with one another. One hypothesis is that several distinct subpopulations will emerge, wherein predators speak the same language and cooperate effectively with one another, while performing less well when paired with individuals outside their language group.

The results of this thesis show that language and success groups are surprisingly uncorrelated. In many instances, individuals speaking the same language are less likely to cooperate effectively with one another than they are to work well with individuals speaking a different language. In essence, certain individuals evolve to speak one language and hear/understand a different language. The data also show that, while a population might evolve to perform a certain task (namely, mate selection) early on, the diversity of languages created in the process make it that much more difficult to evolve a subsequent task.

## 2 Methods

This thesis builds on the experimental methodology of an earlier paper [37] by introducing new ways of analyzing the language and success groups that form within the population of predators. In addition, new trials of each experimental setup (i.e., the various sequences of cooperative tasks that underlie the fitness evaluation) are performed to gain a better understanding of how language changes in these different conditions.

## 2.1 Experimental Setup

To study how language groups emerge, the population of predators is modeled as a collection of neural networks that must evolve to successfully perform one or more tasks. Neural networks are a well-studied means of representing animal behavior and decision-making [31, 38]. Making cooperation integral to the success of each task ensures that the neural networks must evolve some shared language or languages. The construction of the neural networks and the two tasks is the same as in an earlier study [37].

### Neural Networks

Each neural network consists of four input neurons, ten hidden neurons, and four output neurons. Two input neurons are used by the predator to sense the message sent by the other predator, with one neuron each for sensing the distance to the prey (while performing the hunting task) and one for knowing which task (hunting or mating) is currently being evaluated. Similarly, two output neurons represent the message sent by the predator to the other predator. The remaining two output neurons are used by the different tasks: the third neuron represents the decision whether or not to mate during mate selection, while the fourth neuron decides whether the predator will move toward the prey during prey capture.

The hidden neurons represent the decision-making processes that vary between individuals. Weighted edges connect each input neuron to the hidden neurons, which in turn are connected to the output neurons. The values of these weights evolve between generations, to represent changing communication strategies. The value stored in each neuron is a real number between zero and one, but output neurons are rounded to whole numbers (i.e., predators cannot advance 0.7 steps during prey capture or send 0.2 as a message to the other predator).

### Mate-Selection Task

At the beginning of the simulation, each predator is assigned a two-bit physical feature that determines its compatibility with potential mates, such that 16 out of the 64 total number



of individuals have each of the four possible features. The fitness function describing this compatibility is designed such that a given feature will be compatible with two of the four possible features. Therefore, the problem for a predator is not whether it is physically compatible with other predators (because it will always be compatible with half of the population), but rather whether it can effectively communicate to discover when it should or should not mate.

Mate selection occurs in two phases. First, in the messaging phase, each predator sends a message to the other. Second, in the decision phase, this message is heard by the other predator, which determines whether to mate or not. A successful decision is one in which each predator chooses to mate if they are compatible or chooses not to mate if they are incompatible. A successful decision increments the fitness of the two predators.

However, the decision to mate affects the next generation only insofar as this generation undergoes fitness-proportionate selection (i.e., there is no crossover between specific pairings that choose to mate). This selection occurs within each of the four feature subpopulations, according to a binary tournament style selection [39], such that there are always 16 members of the population with each of the four features. Otherwise, if one physical feature swept the population, the need to communicate compatibility would disappear.

### **Prey-Capture Task**

The prey-capture task represents a situation wherein predators must coordinate their movements, such that they attack the prey simultaneously. Therefore, unlike in the mate-selection task, the two predators being evaluated are placed in geometric space, namely a one-dimensional line. One predator is placed on each side of the prey a random distance away. The challenge for the predators is that they know their distance from the prey, but not from each other, meaning that they must communicate to plan their attack. The distance from a predator to its prey is provided as input to the predator's neural network.

At each moment in time, each predator receives the message sent by its partner. Then,

the predator must make two decisions: What message to send for the next time step and whether to move forward or stay in place. If both predators move forward and land on the prey at the same time, they are successful. Otherwise, if one arrives first, they are unsuccessful. Moreover, there is a time limit within which the prey must be captured.

## **Task Sequences**

In past work [37], the goal was to understand how evolving a language to perform task affected the later evolution of a second task. Therefore, prey were evaluated first based only on either the mate-selection task or the prey-capture task, and the remaining task was introduced to the fitness function after a percentage of the population could successfully perform the first task. Additionally, there is the experiment wherein both tasks are coevolving from the beginning, which are called the interleaved tasks. This experimental structure is retained for this thesis, to see how these differences might affect the evolution of language groups in the population.

When the first task is introduced, fitness is evaluated using only that task until 25% of the population is 90% successful in performing that task. At that point, the second task is introduced. Again, when both tasks are coevolving, evolution continues until 25% of the population is 90% successful both tasks. This threshold was chosen based on an earlier finding that this threshold produced less variant language strategies [37]. If a successful strategy is not found within 500 generations, the run is ended. For each of the three task sequences, 10 evolutionary runs are evaluated.

## **Genetic Algorithm**

The population consists of 64 predators. During each generation, 3000 random pairings of these predators are selected. The fitness of each pairing is assessed using the current task (i.e., mate selection, prey capture, or both). Then a binary tournament selection is used to decide which parents will be used to create the next generation. The two-bit physical

features are inherited directly, and selection only occurs between members with the same physical features, such that there are always 16 members of the population with the same physical feature.

When the offspring are created, for each weight in the neural network, there is a 40% chance that the weight will mutate. This mutation takes the form of adding or subtracting a randomly generated value to or from the weight. This mutation is what causes changes in decision-making and communication strategies over time.

## **2.2 Describing the Population**

Past studies have focused on several broad characteristics of the population: What percentage of the population is successfully performing a given task and how long does it take for them to reach this point [37]. This paper goes further by investigating how the predators are communicating with one another, whether they are using the same language of symbols, and how successful individual pairings are when attempting to cooperate. For this reason, it is necessary to find additional means of describing the population.

### **Description of Predator Languages**

A language is defined as the series of messages generated by a predator under all environmental conditions. Because the neural network architecture does not contain hidden memory neurons, neurons that record past events for consideration at a later time step, the neural network conforms to the Markov property. Therefore, it is unnecessary to consider all possible histories leading to a predator's decision to output a message. Instead, when analyzing the population, all possible sets of inputs are provided at one moment in time, the message each predator sends is recorded, and this message is stored in a matrix called the response matrix, which is a 64-by-216 matrix of binary values.

## **Finding Successful Predator Pairings**

During each generation in the evolutionary simulation, it is highly probable that every predator will have encountered every other predator at least once. But during the analysis phase, these pairings individually must be recorded individually. Therefore, after the simulation is complete, all possible pairings of predators in the population are considered. The pairing is then tested using the task for that given generation and store their fitness in an adjacency matrix called the success matrix. When the two tasks are interleaved, equal weight is assigned to the two tasks when computing the success matrix. The success matrix is therefore a 64-by-64 matrix with values in  $[0, 1]$  indicating how successful each pairing is, with 1 indicating 100% success in the pairing.

## **2.3 Data Analysis**

Once it is possible to describe the language spoken by individual predators and evaluate the fitness of predator pairings, the goal is to understand if and when subgroups with similar languages and/or success rates emerge in the population. For this purpose two different clustering techniques are used, agglomerative hierarchical clustering and spectral clustering, in addition to principal components analysis (PCA). While PCA provides a useful tool for visualizing differences in the population, the two clustering algorithms allow for comparisons regarding how often shared language correlates with the success of predator pairs.

### **Principal Components Analysis**

Principal components analysis (PCA) is used to compare the languages spoken by different individuals. PCA produces a series of uncorrelated variables that describe the language data. By performing PCA on the response matrix and considering the first and second components – those that account for the most variance in the data – a two-dimensional representation of the languages being spoken by different predators is created. This representation allows for the visual study of the languages’ and language groups’ evolution over time.

## Agglomerative Hierarchical Clustering

Agglomerative hierarchical clustering (AHC) is a bottom-up approach to generating clusters of data points that is used to study the response matrix [40]. AHC begins with each data point – in this case, the language spoken by a predator – in its own group. Then, a pair of groups is greedily chosen based on minimum distance between groups. Because the response matrix is composed of binary messages, the Hamming distance between groups for a distance metric [41]. The two selected groups are then merged into a single group.

This process is repeated until some target number of groups is achieved. Based on observations from the PCA diagrams of language groups, populations consistently evolved at most three language groups. Therefore, AHC is repeated until only three language groups remained. But while the PCA diagrams considered only the first two components of the data, AHC considers every part of a predator’s language when selecting which groups to merge, such that it provides a richer description of predator language.

## Spectral Clustering

Spectral clustering is a technique for converting an adjacency matrix for the entire population into multiple, highly-connected subpopulations [42, 43]. As described in the Shi-Malik algorithm [42], the normalized Laplacian matrix is calculated from the adjacency matrix according to the formula  $L^{\text{norm}} = I - D^{-\frac{1}{2}}AD^{-\frac{1}{2}}$ , where  $I$  is the identity matrix and  $D$  is the diagonal matrix for  $A$ , such that:

$$d_{i,j} = \begin{cases} a_{i,j} & i = j \\ 0 & i \neq j \end{cases}$$

The first  $k$  eigenvectors of the transformed matrix are calculated, where  $k$  is the target number of groups. To be consistent with AHC, this target is again  $k = 3$ . The k-means clustering algorithm is used on these eigenvectors to sort them into  $k$  groups. These clusters are those subpopulations that experience the most success when paired with one another.

## Coherence of Clustering Algorithms

Using the clusters generated by AHC and spectral clustering, the aim is to study how often the former technique – which analyzes language groups – agrees with the latter – which defines groups with high cooperative success. For this reason the *coherence* metric is defined. All possible predator pairings in the population are considered. For each pairing, the question is asked whether the two predators are in the same language group and success group *or* if both clustering techniques place the two predators in different groups. The number of times the two clustering algorithms agree is counted, divided by the total number of pairings, and this value is called the coherence for the population.

## 3 Results

Figure 1 shows six representative populations, with each dot representing a different predator neural network in the population. The position of the predator on the map is based on the first two principal components, after PCA is used to analyze the language spoken by each predator. Therefore, PCA allows for a geometric representation of the groups defined by agglomerative hierarchical clustering, which also is based on predator language. (Figure 2 confirms the correlation between PCA and AHC.) On the other hand, the mutually-successful subpopulations given by spectral clustering are represented by the different colors in figure 1. The size of each predator on the map is scaled according to its success within its subpopulation, and predators that are less than 15% successful within their groups are removed from the map.

Figure 1 shows that, within each of the three experiments, some populations evolved higher coherence values, while others evolved low coherence values. Similar results were found across all 10 runs of each experiment: certain populations evolved high coherence, while others did not, with no clear differentiation between the three experiments. Figure 3 demonstrates that there was no significant difference in coherence between experiments,

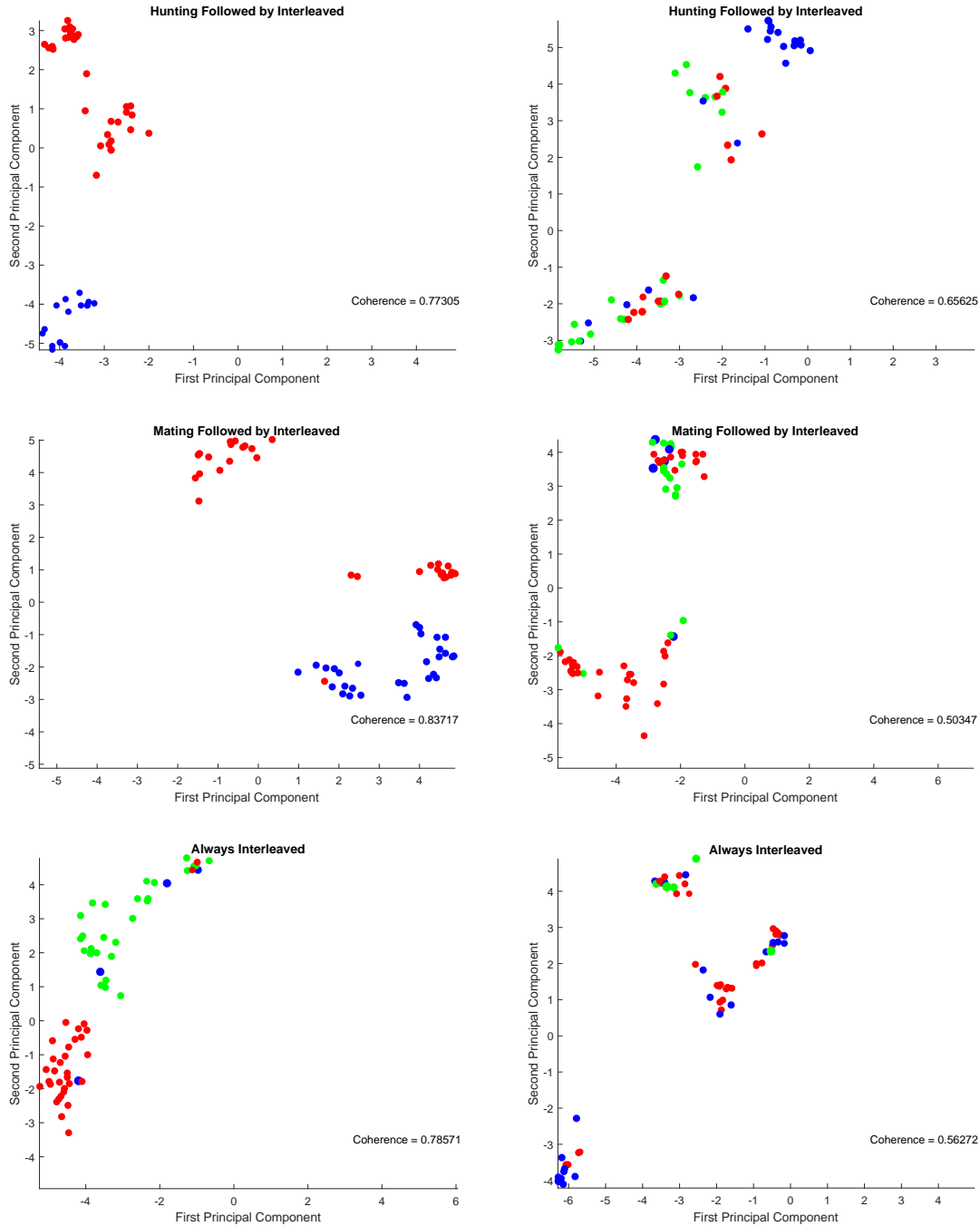


Figure 1: Maps of populations at the end of each experiment. Each dot is a predator. Predator position is based on the first two principal components of the predator’s language. Colors indicate groups of predator that can successfully cooperate. Size of the predator is scaled according to predator success within the group. The left column shows certain populations in each of the three experiments that evolved high group coherence, while the right column contains populations within the same experiments that evolved little correlation between shared language and task success. That each experiment produced both low and high coherence populations indicates that task sequence is not predictive of coherence.

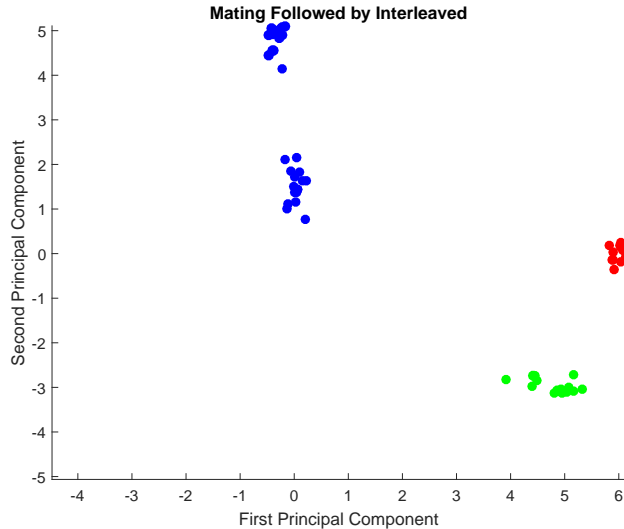


Figure 2: Demonstration of the correlation between agglomerative hierarchical clustering (AHC) and principal component analysis (PCA), when both are used to analyze language. Position on the x- and y-axes is determined by PCA of language, while color is determined by AHC. If PCA gives an accurate geometric depiction of the AHC groups, close predators are expected to be the same color, as is seen here.

either at the midpoint or at the end of the experiment (Wilcoxon rank-sum  $p > 0.05$ ). However, it can be seen that all coherences tended to be higher than 50%.

It is also interesting to study how long it takes cooperative tasks to evolve under different conditions. Figure 4 shows how long it takes in each experiment to reach the 25% population, 90% successful threshold. This time is measured both at the point at which the second task is added (when the first task has been achieved) and at the end of the simulation. For the always interleaved trial, the midpoint of the evolutionary run is used as a stand-in for this transition point.

As can be seen in 4, the first task to evolve by itself is mating, while the cooperative prey-capture task takes about twice as long to evolve. This difference is significant (Wilcoxon rank-sum  $p < 0.05$ ). Nevertheless, when the second task is added, approximately the same amount of time is required to evolve this second task. If anything, introducing hunting after first evolving mating takes longer, even though mating evolved first, though the difference is not significant (Wilcoxon rank-sum  $p > 0.05$ ). Meanwhile, coevolving the two tasks – shown in the two rightmost columns of figure 4 – takes the most time.



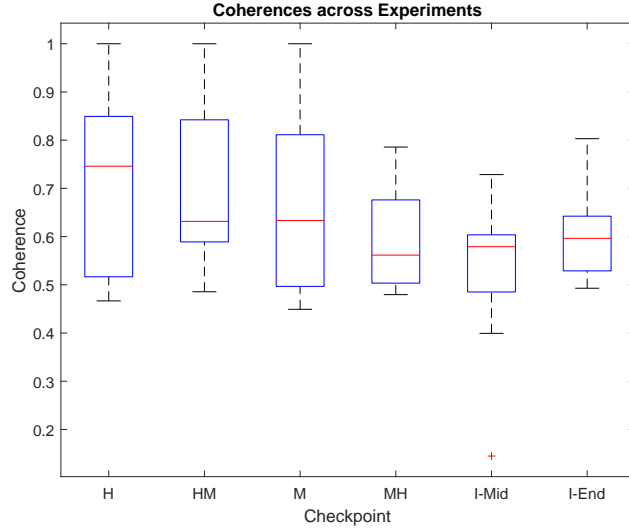


Figure 3: Boxplots showing the coherences at different points in the three experiments. From left to right, H is the population after only evolving hunting, HM after evolving hunting and then both, M after mating only, and MH after mating then both. I indicates that the two tasks were interleaved, and the population in this experiment is analyzed at both the mid- and end-point of the evolutionary run. There are no significant differences in coherence between experiments (Wilcoxon rank-sum  $p > 0.05$ ).

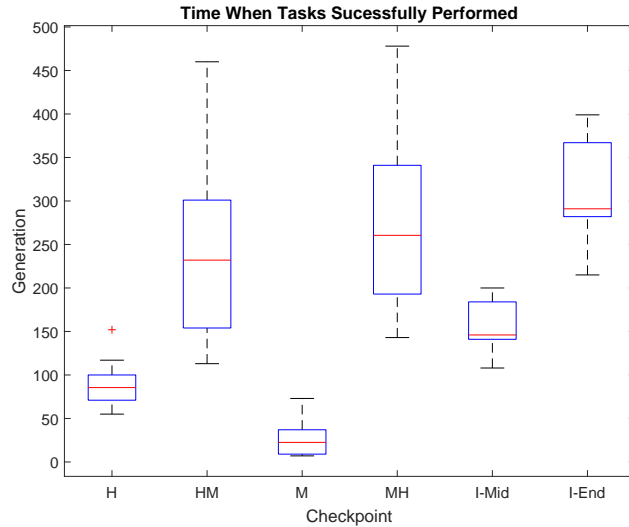
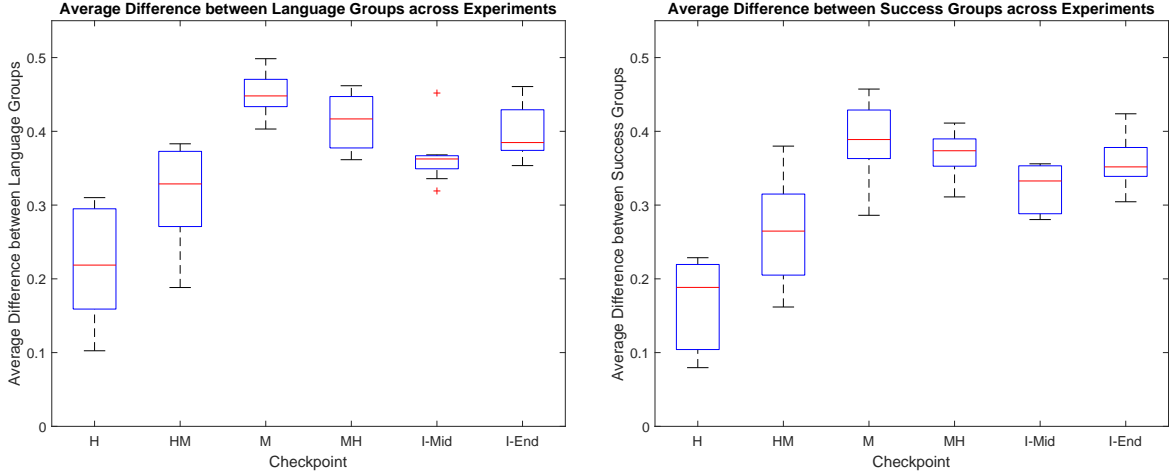


Figure 4: Boxplots showing how long it takes to achieve task success in the three experiments. From left to right, H is the population after only evolving hunting, HM after evolving hunting and then both, M after mating only, and MH after mating then both. I indicates that the two tasks were interleaved, and the population in this experiment is analyzed at both the mid- and end-point of the evolutionary run. Evaluated alone, the mating task evolved before the hunting task, while both took less time than the interleaved tasks. But the difference between mating and hunting disappears after the second task is introduced.



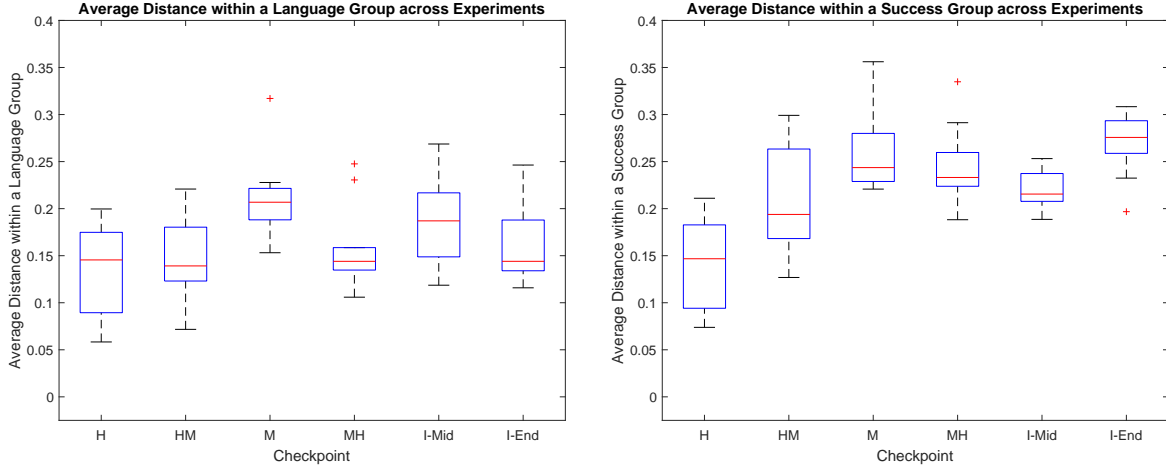
(a) Language difference between predators that speak different languages.

(b) Language difference between predators belonging to different success groups.

Figure 5: Boxplots comparing the average difference in language between predators in different groups. Graphs are shown for language difference between both language groups (figure a) and success groups (figure b). From left to right, H is the population after only evolving hunting, HM after evolving hunting and then both, M after mating only, and MH after mating then both. I indicates that the two tasks were interleaved, and the population in this experiment is analyzed at both the mid- and end-point of the evolutionary run. Predators that evolve to capture prey first have less language differentiation than those that begin by learning how to successfully mate with one another.

To see why these differences between evolutionary runs occur, despite there being no difference in measured coherence, difference in language is considered. Figure 5a shows how different language groups (found using AHC) are from one another on average, while figure 5b shows the average difference in language between members of different successful subpopulations (found using spectral clustering).

Populations evaluated using only the prey-capture task evolve relatively similar languages, while the amount of language differentiation among mating-only predators was significantly greater (Wilcoxon rank-sum  $p < 0.05$ ). Even after the second task was introduced, populations that began by evolving to mate maintained higher degrees of language differentiation (Wilcoxon rank-sum  $p < 0.05$ ). Meanwhile, language differentiation increased between the mid- and end-points of the experiment with interleaved tasks, though the difference was not significant (Wilcoxon rank-sum  $p > 0.05$ ).



(a) Language difference between predators that speak a common language.

(b) Language difference between predators belonging to the same success group.

Figure 6: Boxplots comparing the average difference in language between predators within the same group. Graphs are shown for language difference within both language groups (figure a) and success groups (figure b). From left to right, H is the population after only evolving hunting, HM after evolving hunting and then both, M after mating only, and MH after mating then both. I indicates that the two tasks were interleaved, and the population in this experiment is analyzed at both the mid- and end-point of the evolutionary run. As with inter-group language differentiation, predators that evolve to hunt first have less intra-group language differentiation than those that begin by learning to mate.

Figure 6 demonstrates that these groups that emerge are similar within each group. This effect is most pronounced in the populations that begin with the hunting task. Therefore, together with the inter-group similarity demonstrated in figure 5, this intra-group similarity means that the prey-capture task tends to produce homogeneous populations consisting of tight-knit language groups. Nevertheless, in all cases, the distance between groups is greater than the distance within a group, indicating that some coherent language groups emerged in all cases.

## 4 Discussion and Future Work

The first surprising result is that shared language is not necessarily an accurate predictor of cooperative success. Though many populations evolved a high measure of coherence, of which several are shown in figure 1, others did not. This finding contradicts the intuitive human

expectation that individuals using one form of communication (e.g., a particular birdsong) are most likely to respond to a similar signaling strategy. For example, native English speakers not only use English most readily to communicate with others, but they are also most likely to respond to English words best. The findings here suggest that even simple neural networks prefer to partition language production from language comprehension, such that this relationship found in humans no longer holds. Moreover, considering the wide array of asymmetric communication relationships in nature (e.g., predators and prey, male and female conspecifics, etc.), this partitioning may not be unrealistic.

Still, consistent differences in language-success coherence across the different experiments might be hoped for, but no such pattern emerges. No two experiments evolve coherences that are significantly different from one another at either checkpoint in evolution. Though figure 3 might suggest that coherence is highest in populations that begin with hunting and lowest in those that are always evaluated using both tasks, more experimental trials are necessary before statements of significant difference can be made.

Despite the lack of clear differences in coherence values, dramatic differences in the timing of evolution across the three experiments are observed (figure 4). The mating task consistently evolves the earliest by itself, while the prey-capture task takes twice as long to evolve. And similar to what was found in previous work [37], the most challenging task sequence is when predators attempt to evolve hunting and mating strategies simultaneously from the beginning of the simulation, which requires the population to navigate a much more complicated fitness landscape.

Closer analysis of the languages spoken in the population suggest why this might be the case. Populations that learn to mate first have much greater language differentiation than those that learned to hunt first. Consequently, when the second task is introduced, already-mating predators are a more fragmented population, because of the diversity of languages present in the population. The results here suggest that whatever head-start is granted by evolving mating earlier is negated by the difficulty of trying to evolve a successful hunting

strategy, given this fragmentation of language. On the other hand, after a larger number of generations, the predator populations finally succeed in learning to hunt, but the languages they use to do so are much more homogeneous, which seemingly provides a better foundation for future language evolution.

It is possible, however, that this homogeneity or heterogeneity is not an inherent characteristic of hunting or mating communication, but rather an artifact of the fact that populations take longer to arrive at a successful hunting strategy. Further experiments are needed to determine whether this is the case: for example, populations can be forced to evolve only mating (even after reaching the success threshold) for as long as the hunting task took to evolve. Then it could be seen whether the mating-only population similarly converges to a single common or several similar languages, given so much evolutionary time. Nevertheless, these results still give insight into the importance of homogeneity in pre-existing language for the successful evolution of a second, unrelated task.

Another possible explanation for the language diversity among mating predators is that these populations are inherently structured. As described above, to isolate the evolution of communication, the number of each of the four phenotypes in the population is fixed at 16 of 64. To accomplish this fixed state, selection for the mate-selection task occurs only among predators with a common phenotype. Therefore, these phenotypic groups provide a structure to the population that is not present in populations evolving to perform the prey-capture task. The multiple languages used by mating prey might reflect the multiple subpopulations present. Further work could be done to investigate this relationship either by structuring the prey capture population as well or by finding a non-structured means of maintaining phenotypic diversity in the population.

There also remains an open question about the value of coherence as a measure of the agreement between language and cooperative success. At present, coherence uses the simplest possible metric: when the two clustering methods (AHC and spectral clustering) agree, coherence increases. But there is no way to account for variations in the nature of this

agreement. For example, disagreement about outlier pairs could be either punished severely or mostly ignored. More study is required to find a metric that better captures the clear difference in language development between experiments observed in figures 5 and 6.

Finally, the goal is to know not only how different the languages in the population are, but also how it is that the predators are effectively communicating (i.e., what they are actually saying). To do so requires moving beyond metrics like the Hamming distance as general descriptors of language difference and actually investigating case studies of when predators are able to successfully – or unsuccessfully – communicate with one another. But before such an analysis can be performed, an understanding of which populations consistently evolve such successful pairings is required. For that reason, further work is needed to understand how not only language, but also language subgroups, evolve within the population and determine the population’s ability to successfully perform cooperative tasks.

## 5 Conclusion

This thesis has extended past work to move beyond the observation that digital predators can evolve to communicate with one another and to begin to ask how such communication might be described. As a result, new ways of characterizing language groups and success groups in the population have been introduced. Although some metrics like coherence remain imperfect measures of a possible relationship between shared language and task success, the results of this thesis suggest that the appearance of language groups within a population can have important ramifications for the evolution of communication. Future work can build on this thesis to study whether the appearance of diverse language groups is a consequence of the tasks themselves or some other factor like population structure or convergence to a single language over longer timescales. Once the languages present in a population can be adequately described, it might then be possible to characterize how these languages emerge within a populations and interact with one another to affect the evolution of cooperation.

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## Biography

Patrick B. Haley was born in Huntsville, Alabama, on March 9, 1994. He has lived in Austin since 2000. He majored in Plan II, Computer Science, and Philosophy at the University of Texas at Austin, where he studied from 2012 through 2016. While an undergraduate, he performed research at UT Austin, Michigan State University, and the Deutsches Zentrum für Luft- und Raumfahrt. His work in computational biology has been published in *Royal Society Open Science*, and he has spoken at multiple conferences on artificial life (ALIFE 2014 and ECAL 2015). In addition, he served as Chair of the Dean's Scholars Council, Editor-in-Chief of the Texas Undergraduate Research Journal, and Co-Chair of the Research Student Advisory Council. He was elected to Phi Beta Kappa as a junior, inducted into the Friar Society at UT Austin, and named a Dean's Honored Graduate by the College of Natural Sciences. Patrick will go to Princeton Theological Seminary in the fall, where he plans to complete an MDiv in preparation for a PhD in Philosophy and Theology.