Habitat, Communication and Cooperative Strategies

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Abstract

Using communication is not the only cooperative strategy that can evolve when organisms need to solve a problem together. This paper describes a model that extends MacLennan and Burghardt's (1993) model to show that using a spatial world in a simulation allows a wider range of strategies to evolve in response to environmental demands. The model specifically explores the interaction between population density and resource abundance and their effect on the kinds of cooperative strategies that evolve. Signaling strategies evolve except when population density is high or resource abundance is low.

1 INTRODUCTION

MacLennan and Burghardt (1993) used a simulation to demonstrate that signaling could evolve as a cooperative strategy. Each individual (a *simorg*) in the population was fixed in one location while playing an abstract game. One simorg perceived something that no other simorgs could, and if any other simorgs acted appropriately to that simorg's situation, they were awarded points for cooperating. Since the simorgs in their world weren't located in the same point in space as any other simorg (by design), they needed another way to coordinate their actions. MacLennan and Burghardt designed their simulation so that each simorg could also send one of several signals that others could detect. After many generations of evolution, the population converged to consistently use a unique signal for each situation, thus enabling cooperation in any of those situations. One could reasonably conclude that the need for cooperation was a strong ecological pressure on the evolution of signaling. Thus, we might expect signaling to evolve in any population in which cooperation was helpful (for example, see Steels 1997). Why isn't this actually the case?

For example, cooperation might help the snow leopard hunt its prey, but it hunts alone, as opposed to the lion, which sometimes hunts in groups (Nowak 1991). Harris' hawks (Attenborough 1991) sometimes engage in cooperative hunting of a rabbit, but they do not appear to use signaling to coordinate their actions. Each hawk closes in on the prey based on the locations of the other hawks and the prey itself. Of course, coordinated activity is much more common in many ant, bee, wasp and termite species.

MacLennan and Burghardt's simulation points out a very important feature in a system of signalers: the need for cooperation can be a pressure for the evolution of signaling. However, their model only allows for one *cooperative strategy* to evolve: the use of signaling to coordinate an action. What if the simorgs could have moved about and affected their world? In this richer world, natural selection would have more raw material to work with. As a result, simorgs might be able to evolve a multitude of cooperative strategies in addition to signaling. A rich world means a more complicated simulation, possibly with results that are highly variable and more difficult to interpret; therefore, MacLennan and Burghardt's simulation is an important first step towards asking how signaling can evolve in a population. I will describe a simulation that extends MacLennan and Burghardt's by adding a spatial world (two dimensions) and allowing the inhabitants to move around in that world and interact—albeit quite simply—with the objects they encounter.

In addition to showing how spatiality can contribute to the kinds of cooperative strategies that a species can evolve for coping with its environment, this project also attempts to show how evolution can be used as a *guide* to understanding the mechanisms behind a particular behavior. Knowing the function of a behavior can help elucidate the mechanism behind that behavior (Cosmides and Tooby 1994). Furthermore,an evolutionary simulation can also show what kinds of modifications are *likely* to occur to a behavioral mechanism. A model-builder can then construct a simple model for an historically earlier version of the behavior in question and analyze the complex mechanism for the modern behavior as a series of modifications to the simple (early) one.[1]

1.1 OTHER WORK ON THE EVOLUTION OF COMMUNICATION/LANGUAGE

The idea of using a spatial world in a simulation of the evolution of communication is not new. Werner and Dyer (1991) created a simulation that demonstrated that sexual selection could produce cooperative communicators. Their simulation used a spatial world filled only with blind males and immobile females. Females evolved to send a sequence of signals that the males evolved to follow. My simulation differs from theirs in that all of my individuals were of the same type (no gender distinction) and they were assigned fitness values based on acquiring resources which required cooperation to use.

My simulation is most similar to Ackley and Littman's (1994) simulation which showed the evolution of altruistic behavior using signaling. Interestingly, the individuals in Ackley and Littman's world evolved to send signals to their nearby fellows even if they themselves might not benefit from such actions. This was due to the specialized spatial selection method used in their program—where you are constrains whom you mate with. My project, on the other hand, used a two-dimensional world with resources that varied in location and frequency and required cooperation to use, and selection was a non-spatial fitness-proportionate method.

Common to most artificial life (AL) programs (including Belew and Menczer's LEE (1996), Holland's ECHO (1995) and many others) is the idea of a *population* of individuals that interact in their world. This is extremely important when studying a behavior such as communication. Communication does not happen in a vacuum; it is a population-level phenomenon (Parisi 1997). AL simulations of a population of communicators demonstrate how important the *environment* and *other communicators* are to the study of communication.

[1] See Hendriks-Jansen (1998) for a deeper discussion of these issues.

Other models of the evolution of communication and language focus on form (including Oliphant and Batali (1997) and Steels(1996)), while my model is concerned with the relationship of signals to contexts and actions in a simulated world.

1.2 PROJECT GOALS

When organisms must cooperate to utilize resources, such as food, in their environment, they will evolve strategies to maximize the amount of resources utilized. Several factors that might affect the types of strategies that evolve are the abundance of resources and the density of the population. Since there is a cost to sending signals (primarily metabolism and predator attention), some populations may not use signaling to aid cooperation because the signaling costs outweigh their benefits. The *CoopEvol* model described herein explores the interaction of population density and resource abundance in determining when communication will evolve as a cooperative strategy. Under some experimental conditions, org populations evolved a cooperative strategy that used signaling and under other conditions they didn't.

2 THE *COOPEVOL* MODEL AND SIMULATION

2.1 OVERVIEW

Briefly, the *CoopEvol* simulation consists of a grid-world comprised of sectors. Each sector can contain a resource and up to three simulated organisms (*orgs*). Orgs and resources are the only objects in the world. Each org may act once per time step based on its current input (what the org can "see" and "hear"). Occasionally, a few orgs will utilize a resource. When this happens, each org is awarded some fitness points. A generation of orgs acts for 50 time steps, after which a genetic algorithm produces a new generation of orgs, and the simulation repeats the above process. The simulation runs for 1000 generations.

2.2 THE TASK

The orgs have basically one task ahead of them: gather resources. The resources require at least two orgs to be present to collect a fitness reward. The orgs need to use different strategies depending on the parameters—various values of resource abundance and population density—of the particular experimental run.

2.3 THE SIMULATION

The simulation begins by creating an initial *population* of 100 orgs (each possessing a randomly created *chromosome*) and placing them at random locations in the world. This is the first generation. These orgs act for 50 time steps, receiving input from the world and producing an output per time step. Some of their actions may result in changes in fitness. After 50 time steps, a standard genetic algorithm is employed (Mitchell 1996). Mates are selected proportionately from the population based on their fitness.[2] Each selected pair of mates creates 2 children using single-point crossover and mutation (mutation rate is 0.001). After enough children have been created to fully replace the original population, the old population is discarded and the children become the population for the next generation. A run of the simulation ends after 1000 generations.[3]

2.4 THE WORLD

All world events and org actions happen at some *time step.* If multiple events and actions occur at the same time step, then they are performed simultaneously.

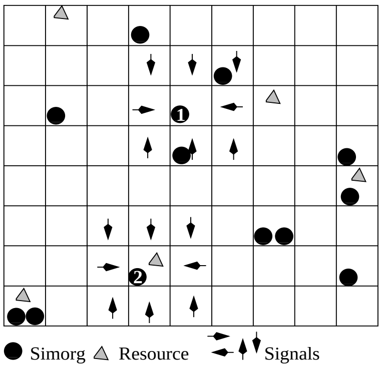


Figure 1: The World with Orgs and Resources

Notice in the world shown in figure 1 that "org #1" is signaling (its signals point back to it) and several nearby orgs can hear it. However, since org #1 doesn't see any resources, it may be a waste of time for the hearers to move towards the signal's source. Org #2, on the other hand, sees a resource and needs help in order to utilize it. Unfortunately, no orgs are close enough to hear its signal.[4]

2.5 THE CONTENTS OF THE WORLD

2.5.1 Orgs

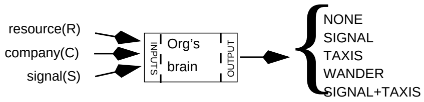


Figure 2: An Org, A Stimulus-response Agent

An org must respond to its current input at each time step. This response is based on the org's "brain," a *deterministic* lookup table(see figure 2). This brain maps each possible environmental situation to an output. Orgs have 3 simple detectors (as labeled in figure 2): "resource" (R) detects if a resource is present in the current sector, "company" (C) detects if any other orgs are present in the sector, and "signal" (S) detects if a signal came from a nearby org on the last time step.

Orgs have 5 kinds of outputs: SIGNAL (send a signal without moving), TAXIS (move toward the source of a signal), WANDER (move to an adjacent sector in a random direction), SIGNAL+TAXIS (send a signal and then move toward the source of a signal), and NONE (do nothing).

The signal range is 2 sectors away in all directions. A signal points back to the sender so that receivers can locate the sender. If an org detects more than one signal, it follows the one sent earliest by the org with the highest current fitness.

If there is no signal in a sector, a TAXIS output means that the org moves north. When an org attempts to TAXIS and it hasn't received a signal, TAXIS is treated as a "WANDER north" output. The sample org brain below (table 1) shows an org that will TAXIS when it is alone in a sector and hears no signal (denoted by the input "(no input)"). In this case, the TAXIS output will result in this org moving north (since it is not receiving a signal). However, if this org is alone in a sector with a resource and it receives a signal, it will first send its own signal and then move towards the signal it currently hears ("SIGNAL+TAXIS").

Each org also has a *chromosome,* which completely determines the structure of the org's brain. The GA uses the chromosome to simulate reproduction, and a new org's brain is decoded directly from its chromosome. The brain has 8 entries (one for each possible input type), and the chromosome has a gene that codes for

[2]Stochastic universal sampling with sigma scaling, $\sigma = 2$ (Mitchell 1996).

[3]The simulation was written in Java. A version is available on my website, http://www.cs.indiana.edu/~elyk

[4]In the actual simulation, signal range is 2 sectors instead of the single-sector range shown.

Table 1: Sample Org Brain

Input	Output
(no input)	TAXIS
—S	NONE
–C–	TAXIS
–CS	WANDER
R—	SIGNAL
R–S	SIGNAL+TAXIS
RC–	NONE
RCS	NONE

each entry. Each gene can have one of 5 values between 0 and 4. Decoding a genome is a simple matter of decoding the first gene as the first entry in the org's brain, and so on. The brain shown in table 1 is coded by the following genome: `20231400`, where 0=NONE, 1=SIGNAL, 2=TAXIS, 3=WANDER, and 4=SIGNAL+TAXIS.

Figure 3 shows several possible situations in which orgs may find themselves. Org 1 has only a resource in its sector and does not detect any signals. Thus, its input (context) is "R—". On the other hand, orgs 2 and 3 are in a sector together, so their "company" input is on ("C") and they also detect a signal that came from the east. Thus, the input for each is "–CS" during this time step (the dash at the beginning indicates that the resource detector did not detect anything in this sector). Orgs 4 and 5 detect each other, a resource, and a signal in their sector. Their input is thus "RCS".

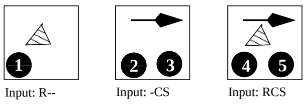


Figure 3: Various Org Situations and Corresponding Inputs

2.5.2 Resources

There is only one kind of resource: "food". This resource is hard to use; it requires that at least two orgs be present in the sector containing the resource in order for the resource to be utilized. A resource is worth 100 points, split evenly among the orgs utilizing it (thus it is really worth 50 or 33 points since no more than 3 orgs can occupy one sector). Orgs do not have an action to utilize a resource—they automatically utilize a resource if at least 2 orgs are present. Thus, orgs will often accidentally cooperate in utilizing resources during experimental runs. However, they can increase their effectiveness by employing various strategies. Orgs might call to others when there is a resource in their sector or they might simply "pair up" and wait in a sector until a resource appears.

Resources are renewable and appear at frequencies governed by the independent variable, resource abundance. A resource that appears in a sector remains there for 6 time steps before it disappears again, unless it is utilized first.

2.6 THE POINT

The *CoopEvol* simulation is intended to show that orgs evolve various strategies in a spatial world. Some strategies involve signaling, *but some do not* because signaling incurs a fitness cost. Non-signaling strategies are possible because orgs can alter their environment with their actions (unlike MacLennan and Burghardt's simulations), and orgs can use their non-signal ("visual") inputs to guide their actions. Resource abundance, population density and signal cost all determine whether or not signal use evolves.

3 EXPERIMENTS

3.1 DESIGN

The *CoopEvol* project explored the interaction between two variables: population density and resource abundance. These two variables were manipulated to get nine separate conditions, with three values for each variable: low, medium and high. These values do not match any specific values found in nature; they are simply low, medium or high relative to each other.

For each of these conditions, signal cost was 10 points (1/5 or 1/3 the value of utilizing a resource). Population size was constant throughout the simulations; there were always 100 orgs in each generation. Each simulation was run for 1000 generations, with each generation lasting 50 time steps.

Resource abundance (RA) affected the frequency with which a resource would appear in a sector in the world. When RA was "low," a resource would appear in a sector on a 1 in 40 chance per time step (about once per sector per generation); "medium" was a 1 in 15 chance (about 3 times in each sector per generation) and "high" was a certainty (constant food supply).

Population density (PD) was manipulated through the world dimensions. "Low" population density was a 50 x 60 world (a 1:30 ratio of orgs to sectors), "medium" was a 30 x 30 world (a 1:9 ratio) and "high" was a 10 x 10 world (a 1:1 ratio).

3.1.1 Controls

The *nosig* controls were the same as the above conditions except that the orgs' signals were blocked from ever being sent. However, senders still lost fitness points for signaling. Since signaling had no benefit and only lowered fitness, all populations in these conditions should have evolved to never signal. The only exception was those conditions where signaling cost was outweighed by massive resource availability. The population's fitness and the strategy it evolved were compared to non-control runs that evolved signaling under the same RA and PD values. If the average fitness were similar for both types of runs, then signaling must have been an arbitrary outcome for that condition.

3.2 HYPOTHESIS/PREDICTIONS

Evolved strategies should fall into two categories: signaling and non-signaling. Orgs should evolve signal-based, resource-gathering strategies when the benefits (extra resources gained) outweigh the costs (signal cost). Signaling benefits should occur when orgs need to find each other: resource abundance (RA) is high and population density (PD) is not high. Signaling should also be beneficial when resources need to be found: RA is low and PD is not low. When orgs and resources are abundant, no single strategy may predominate as very little action is needed to succeed; even signaling cost may be negligible. When orgs and resources are rare, signaling should be too expensive. These predictions are shown in figure 4.

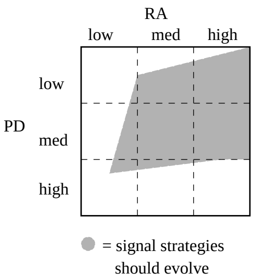


Figure 4: Predictions for Variable Interactions

3.3 RESULTS

The main experiment had nine separate conditions. Each condition was run 10 times. Data were taken at the 1000th generation for each run. I shall describe the data from two experimental runs and summarize the data from the rest. Some runs showed extreme oscillations in the use/absence of signaling. This was to be expected because some of the conditions had little pressure for or against signaling. In most runs, after 1000 generations, all members of the population were clones or minor variants of a single prototypical genotype (although this prototype varied from run to run).

3.3.1 Run #1: No Signaling ("Quiet")

The following data were from a single run when resource abundance (RA) was low and population density (PD) was high (RA=low/PD=high). At generation 1000, the population's average fitness was 110 (quite low compared to runs from other conditions). No signals were ever sent, and thus no TAXIS responses were output. These orgs had brains that generally looked like the first brain in table 2, which I will call an "aggregate brain" (this is the "average brain" of the population in the 1000th generation). This particular run evolved orgs that did nothing if a resource was present and wandered randomly otherwise.

Table 2: Aggregate Org Brains from Two Runs

Input	Output	
	Run #1	Run #2
(no input)	WANDER	WANDER
—S	WANDER	TAXIS
–C–	WANDER	TAXIS
–CS	WANDER	TAXIS
R—	NONE	SIGNAL
R–S	NONE	TAXIS
RC–	NONE	NONE
RCS	NONE	NONE

3.3.2 Run #2: Signaling

Another run showed very different results: signaling evolved. When RA=med/PD=low, orgs in this run signaled a total of 750 times, responded to signals with TAXIS 361 times, and had an average fitness of 245 (during generation 1000). Table 2 shows the aggregate brain of this population. These orgs evolved to do nothing when they were with other orgs and a resource, TAXIS towards all other signal inputs, wander when the sector did not contain a resource, and signal only when they found a resource and were alone.

I used a variant of MacLennan and Burghardt's (1993) *denotation matrix* to show which contexts evoked both signaling and responses to signals. Each row in table 3 shows the eight input types and the percentage of SIGNAL responses to each input (out of all responses including NONE, WANDER, TAXIS) over the entire duration of the 1000th generation. Run #1 showed no signaling at all (as evidenced by the brain in table 2). On the contrary, Run #2 showed a large proportion of signaling occurring almost exclusively when a resource was detected.

Table 3: Signal Responses for 2 Runs: RA=low/PD=high, and RA=med & PD=low

Input	**% SIGNAL responses**	
	Run #1	Run #2
(no input)	0	0
—S	0	0
–C–	0	0
–CS	0	0
R—	0	94
R–S	0	0
RC–	0	0
RCS	0	10

Signaling involves not only the context in which the signal was sent, but the response to that signal. A similar type of denotation matrix for TAXIS (table 4) shows that, during generation 1000, orgs in run #1 never responded with TAXIS to signals (because none were ever sent) while orgs in run #2 would TAXIS in all cases *except* when they were currently with another org and a resource.

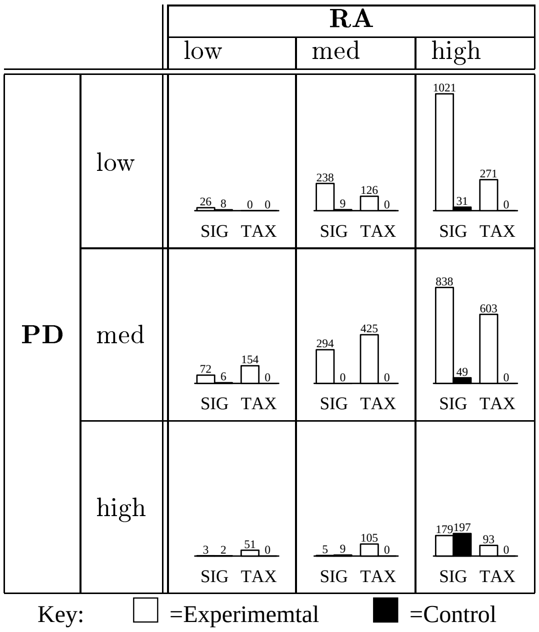
Table 4: TAXIS Responses for each *Signal* Context, RA=low/PD=high, and RA=med/PD=low

Input	**% TAXIS responses**	
	Run #1	Run #2
—S	0	100
–CS	0	100
R–S	0	100
RCS	0	0

3.3.3 Data Summary for All Conditions

Summaries of the data from all conditions appear in the tables below. Both experimental and control results are shown for each condition. Table 5 shows averages of the number of signals (SIG) sent during generation 1000 in each condition as well as the average number of TAXIS responses to those signals (TAX). TAXIS counts are 0 in each case for the *nosig* controls because the orgs could never receive signals. Average fitnesses from each condition are shown in table 6.

Table 5: SIGNAL and TAXIS Totals for Experimental and Control Conditions



4 CONCLUSIONS

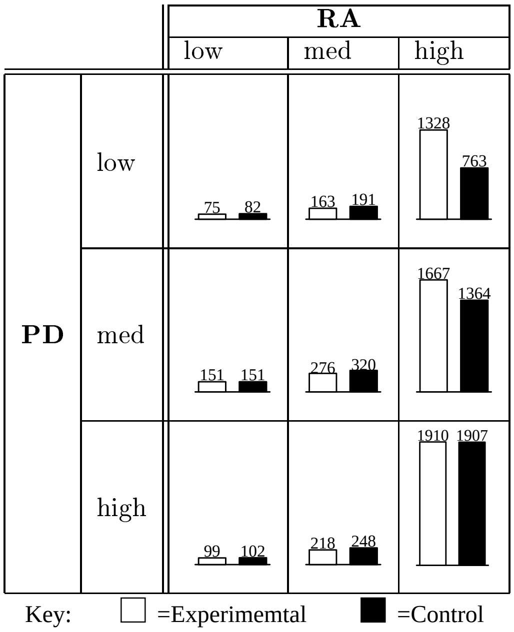
4.1 INTERPRETATION OF RESULTS

4.1.1 Two Strategies: *Signaling* and *Quiet*

The population for each run was labeled as either "Signaling" (S) or "Quiet" (Q) based on the number of signals they sent (N_{sig}) and the number of TAXIS responses to those signals (N_{tax}). The overall classification of each condition is shown in table 7. A 2D scatterplot of N_{sig} vs. N_{tax} responses over all experimental runs showed a reasonable cluster when $N_{sig} \geq 96$ and $N_{tax} \geq 42$. These values were used as cutoff values: any run where N_{sig} and N_{tax} did not both exceed these values was categorized as "Quiet", otherwise, it was "Signaling". In five conditions, all runs gave the same results. However, four conditions (RA=high/PD=high, RA=med/PD=med, RA=med/PD=low, and RA=low/PD=med) resulted in the runs being split into signaling and quiet subgroups.

A two-tailed t-test was used to determine the statistical significance of the difference between the control and experimental S_{avg} for each condition. A similar test was run for T_{avg}. These t-tests used N_{sig} and N_{tax} as data points for all runs under each condition. Finally, the average fitnesses for all runs under each condition were compared with the cor-

Table 6: Average Population Fitnesses for Experimental and Control Conditions



responding control run fitnesses to determine if the experimentally-evolved strategy was more effective at resource-gathering than the control-evolved strategy.

4.1.2 Quiet Conditions

"Quiet" orgs clearly evolved in 3 conditions. For RA=low/PD=low, all 10 runs were quiet. N_{sig} and N_{tax} in each run never got above the signaling thresholds. S_{avg} did not differ significantly from the controls ($p_s = .471$) and neither did fitness ($p_f = .694$). Similar results were obtained when RA=low/PD=high and RA=med/PD=high.

4.1.3 Signaling Conditions

"Signaling" orgs clearly evolved in 3 conditions. For RA=high/PD=low, all 10 runs evolved signaling. Signaling is evidenced here by N_{sig} and N_{tax} for each run being above the thresholds determined in the scatterplot of N_{sig} vs. N_{tax}. Also, S_{avg} and T_Pavg in the experimental condition differed significantly from S_{avg} ($p_s < .001$) and T_{avg} ($p_t < .001$) of the control condition. Furthermore, signaling benefitted the population, as evidenced by the difference between the mean fitnesses of the control and experimental conditions ($p_f < .001$). Similar results with the same significance values were obtained when RA=high/PD=med.

A special case of signaling and quiet both evolving happened when RA=med/PD=low: 4 runs evolved signaling while 6 were quiet. Here, the signaling group differed significantly from the control group ($p_s < .026$, $p_t < .025$). In addition, the signaling group exceeded the control group in fitness ($p_f = .014$), indicating that signaling was a superior strategy to being quiet. The quiet group did not differ significantly from the control group based on S_{avg} or T_{avg}, but it achieved a *lower* mean fitness than the control group ($p = .019$). Perhaps the control group, being forced into a quiet strategy, was able to explore the solution space well, while the quiet experimental group developed signaling early, but later abandoned this strategy and was forced into a local minimum due to already being located in a signaling region of the solution space.

4.1.4 Ambiguous Conditions

There were 3 ambiguous cases where signaling and quiet populations both evolved and achieved the same fitness results. For RA=low/PD=med, 4 runs evolved signaling while 6 were quiet. The signaling runs differed significantly from the controls on bothS_{avg} and T_{avg} ($p_s = .012$, $p_t = .005$), however fitness did not differ ($p_f = .904$). Thus, signaling and control (deaf) populations achieved the same fitness values. The quiet group also achieved the same fitness results as the control population ($p = .992$). A similar result was obtained with RA=med/PD=med ($p_s < .001$, $p_t < .001$, $p_f = .448$), where 9 runs evolved signaling and 1 was quiet.

When RA=high/PD=high, 6 runs evolved signaling while 4 were quiet. In this condition, neither the signaling nor the quiet groups differed from the control group based on S_{avg} ($p_s = .745$ and $p_s = .471$, respectively). The signaling populations also did not show any increase in fitness due to their signaling strategy ($p_s = .896$). Interestingly, signaling evolved (if using only N_{sig} as a criterion) in several control runs without adverse effects to fitness, even though signaling could not help at all. This is probably due to the high availability of both resources and other orgs, so fitness costs of signaling were outweighed by massive resource availability.

Table 7: Variable Interactions

		Resource Abundance		
		low	medium	high
Population Density	low	Q	S/Q	S
	medium	$*$	$*$	S
	high	Q	Q	$*$

4.1.5 Summary of Results

Signaling orgs evolved to send and respond to signals to help locate each other and/or resources. Quiet orgs evolved non-signaling strategies, using their "visual" inputs (detection of resources or other orgs in their current sector) to maximize resource intake. Overall, orgs evolved *signaling* cooperative strategies when population density was not high and resource abundance was not low. These results are shown in table 7 (where "S" indicates signaling evolved, "Q" indicates non-signaling, "*" indicates that signaling could evolve but had no effect on fitness).

4.2 IMPLICATIONS AND FUTURE DIRECTIONS

The extensions to MacLennan and Burghardt's model have shown a more complex picture of the forces at work in shaping communicative behavior. The evolution of communication depends not only on the cooperative pressure from the environment but also on the interaction between population density and resource abundance. Can the results of the *CoopEvol* model predict the cooperative and communicative behaviors of real species (e.g., bees, wolves, dolphins, humans)? Undoubtedly, many other factors besides those explored here affect the likelihood of a particular species evolving signaling behavior for cooperation. One of the most important of these is sociality. I plan to extend the *CoopEvol* model by including some elements of sociality (such as learning from elders) and by adding more complex tasks that orgs must solve. By slowly adding new layers of complexity to the model and understanding their implications, this series of models may lead to a better understanding of the origins and structure of communication.

Acknowledgments

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