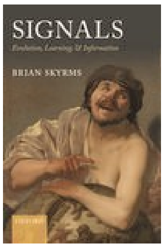

Signals: Evolution, Learning, and Information
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CHAPTER

10 10 Inventing New Signals

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Abstract

This chapter presents a simple, tractable model for the invention of new signals. It can be easily studied by simulation, and connections with well-studied processes from population genetics suggest that analytic results are not completely out of reach.

Keywords: signalling, new signals, communication

Subject: Philosophy of Science, Epistemology, Philosophy of Language

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New signals?

Agents may not have enough signals to convey the information that they need to communicate. Why can't the agents simply invent new signals to remedy the situation? We would like to have a simple, easily studied model of this process. That is to say, we want to move beyond the closed models that we have studied so far, where the theorist fixes the signals, to an open model in which the space of signals itself can evolve. I can find no such account in the literature. I would like to suggest one here.

Invention in nature: genetic evolution

The fixed number of signals in a Lewis signaling game is, after all, an artificial limitation. In nature those signals had to be invented. If they were invented, new signals could be invented as well. The range of potential new signals is highly dependent on the nature of the signalers. The availability of new signals for bacteria, for instance, is constrained by molecular biology. Even so, over evolutionary time, different species of gram-
p. 119 negative bacteria[2] have managed to ↳ invent different quorum-sensing signaling systems by evolving ways to make small side-chain modifications to a basic signaling molecule.[3]

Quorum-sensing was discovered in bacterium, *Vibrio fisheri* that inhabits the light organ of the Hawaiian squid, *Euprymna scolopes*. *Euprymna* is a nocturnal hunter. If there is a full moon, it can be highly visible against the illuminated surface of the water and become prey itself. It uses its light organ to counter this and render itself less conspicuous to its predators. The light, itself, is made by the bacteria living in the light organ. The squid supplies the bacteria with nutrients and the bacteria provide the squid with camouflage.

The bacteria regulate light production by quorum-sensing. They produce a small, diffusible (AHL) signaling molecule. It is auto-inducing—when its concentration in the ambient environment increases, the bacteria produce more of it. This happens inside the light organ. High enough concentrations, a *quorum*, trigger gene expression that turns on the light. (The squid turns the lights off by simply expelling bacteria from the organ and replacing them with seawater.)

Subsequently, quorum-sensing signaling based on slight modification of the AHL molecule has been found in other gram negative bacteria. *Psuedomonas aeruginosa* uses quorum-sensing to turn on virulence and biofilm formation in the lungs of cystic fibrosis patients. A bacterium (*Erwinia carotovora*)[4] that rots plants uses AHL-based quorum-sensing to turn on both virulence against the plant and production of antibiotics against competitor bacteria that could also exploit the damaged host. An ancestral signaling system has been modified for a variety of different uses.

Gram positive bacteria[5]—including such sometimes nasty customers as *Staphylococcus aureus*—have parallel signaling systems based on different signaling molecules. In a review of quorum-sensing, Melissa Miller and
p. 120 Bonnie Bassler conclude: ↳

> Bacteria occupying diverse niches have broadly adapted quorum sensing systems to optimize them for regulating a variety of activities. In every case quorum sensing confers on bacteria the ability to communicate and to alter behavior in response to the presence of other bacteria. Quorum sensing allows a population of individuals to coordinate global behavior and thus act as a multi-cellular unit. Although the study of quorum sensing is only at its beginning, we are now in a position to gain fundamental insight into how bacteria build community networks.[6]

Evolution creates and modifies signals in even the most primitive organisms.

Invention in nature: cultural evolution

Invention in genetic evolution may be highly constrained and take a long time. In cultural evolution and in individual learning there is more latitude for new signals, and evolution of the signaling space is ongoing.

For instance, the vocal capabilities of monkeys allow for a range of potential signals that, when required, can be tapped by learning. Vervet monkeys who have encountered a new predator have learned both a new signal and a new evasive action:

> Vervets on the Cameroon savanna are sometimes attacked by feral dogs. When they see a dog, they respond much as Amboseli vervets respond to a leopard; they give loud alarm calls and run into trees. Elsewhere in the Cameroon, however, vervets live in forests where they are hunted by armed humans who track them down with the aid of dogs. In these circumstances, where loud alarm calls and conspicuous flight into trees would only increase the monkeys′ likelihood of being shot, the vervets′ alarm calls to dogs are short, quiet and cause others to flee silently into dense bushes where humans cannot follow.[7]

p. 121 The dynamics of learning, when the need arises, is able to modify the signaling system in a highly efficient way.

General principles

There is nothing really mysterious about the modification of the vervets′ signaling system described above. First, nature presents the monkeys with a new state—one different from “all clear” or from the presence of any of the familiar predators. The salience of this new state, “dogs and hunters,” is established when the first monkey is shot. An appropriate new escape action is discovered. In principle it might be discovered just by group trial and error, although we do not want to sell the vervets short on cognitive ability.

Once we have the new state and the appropriate new action we are in the kind of information bottleneck that we described in Chapter 1. We have seen that such bottlenecks can sometimes spontaneously arise from dynamics of evolution and learning. What is required is the invention of a new signal. Senders have lots of potential signals available to them. These are just actions—in this case, vocalizations—that receivers are liable to notice. Senders try potential signals, receivers try actions, and happy coincidences are rewarded.

General principles of invention emerge. We can suppose that there are acts that the sender can take which the receiver will notice. These could be tried out as signals—either on a short time scale or a very long one. The potential signals may be sounds, or movements, or secretions of some chemical. They may bear some resemblance to other signals, or to other features of the environment that receivers already tend to monitor. With some probability a new signal can be actualized—a sender will send it and a receiver will pay attention to it.

Verbal statement of general principles is not hard, but we still lack a simple model that can serve as a focal
p. 122 point for analysis. How should we incorporate the invention of new signals in the Lewis ↳ model of signaling games? We would like to retain as much as possible the simplicity and analytical tractability of the original model, while having an open rather than a closed set of signals.

The Chinese restaurant process

We begin with an example that may appear overly fanciful, but which will nevertheless turn out to be relevant. Imagine a Chinese restaurant, with an infinite number of tables, each of which can hold an infinite number of guests. People enter one at a time and sit down according to the following rule. If N guests are already seated, the next guest sits to the left of each of the N guests already seated with probability 1/(N+1), and goes to an unoccupied table with probability 1/(N + 1). [One could imagine a ghost sitting at the first unoccupied table, and then the rule would be to sit to the left of someone—including the phantom guest—with equal probability.][8]

The first person to enter sits at the first unoccupied table, since no one but the phantom guest is there. The phantom guest moves to the first unoccupied table. The second person to enter now has equal probability of sitting with the first, or at an unoccupied table. Should the second join the first, the third has a 2/3 chance of sitting at their table and a 1/3 chance of starting a new one. Should the second start a new table, the phantom guest moves on, and the third will join one or the other or start a third table with equal probability. This is the *Chinese restaurant process*, which has a surprising number of applications, and which has been well studied as a problem in abstract probability theory.[9]

Since there is only one phantom, the probability of a new table being selected goes down as the number of
p. 123 guests goes up. But if there is an infinite stream of guests, at any point in the process the ↳ probability that no

new table will ever be selected is always zero. In the limit an infinite number of tables will be occupied. Nevertheless, for long finite stretches of time the number of occupied tables may be small.

To get a feel for the process, suppose that four guests have entered. We could have four tables occupied (1+1+1+1), or three (2+1+1) or two {(2+2) or (3+1)} or one (4). The last possibility, that all guests sit at the first table is six times as probable as the first alternative in which each guest chooses a different table.[10] The possibility of three guests at one table and one at the other can be realized in four different ways. Numbering the guests in order of appearance, they are: {1,2,3}{4}, {2,3,4}{1}, {1,3,4}{2}, and {1,2,4}{3}. Each has equal probability—which guests are at which tables does not matter.

Adding up the probabilities of the ways of getting the (3+1) pattern we get (8/24). Likewise, we find the probability of the (2+2) pattern as (3/24). The probability that two tables are occupied is the sum of these, or (11/24). We may notice in passing that the probability of unequal occupation of two tables (3+1) is much more likely than that of equal occupation (2+2). The probabilities of different numbers of tables being occupied are:

One Table:	(6/24)
Two Tables:	(11/24)
Three Tables:	(6/24)
Four Tables:	(1/24)

As more and more guests come in, the expected number of occupied tables grows as the logarithm of the number of guests.

p. 124

Hoppe's urn

If we neglect the seating order of guests at a table, and just keep track of the number of guests at each table, the process is equivalent to a simple urn model. In 1984 Hoppe introduced what he called “Pólya-like urns” in connection with “neutral” evolution—evolution in the absence of selection pressure. In a classical Pólya urn process, we start with an urn containing various colored balls. Then we proceed as follows: A ball is drawn at random. It is returned to the urn with another ball of the same color. All colors are treated in exactly the same way. We can recognize the Pólya urn process as a special case of reinforcement learning in which there is no distinction worth learning—all choices (colors) are reinforced equally. The probabilities in a Pólya urn process converge to a random limit. They are guaranteed to converge to something, but that something can be anything.

To the Pólya urn, Hoppe adds a black ball—the *mutator*.[11] The mutator does not mutate in the sense explored in earlier chapters, where colors in the urn mutate to one another. Rather, it brings new colors into the game. If the black ball is drawn, it is returned to the urn and a ball of an entirely new color is added to the urn. (There are, of course, lots of variations possible. There might be more than one black ball initially, and Hoppe considered this possibility. The number of black balls might not be fixed, but might itself evolve in various ways. Here, however, we will stick to the simplest case.) The Hoppe-Pólya urn model was meant as a model for neutral selection, where there are a vast number of potential mutations which convey no selective advantage.

(It also has an alternative life in the Bayesian theory of induction, having essentially been invented in 1838 by the logician Augustus de Morgan to deal with the prediction of the emergence of novel categories.)[12]

p. 125 It is evident that the Hoppe-Pólya urn process and the Chinese restaurant process are the same thing. Hoppe's colors correspond to the tables in the Chinese restaurant; the mutator ball corresponds to the phantom guest. After a finite number, N, of iterations the N guests in the restaurant, or the N balls in Hoppe's urn, are partitioned into some number of categories. The categories are colors for the urn, tables for the restaurant. But the partitions we end up with can be different each time; they depend on the luck of the draw. We have *random partitions*, which may have a different number of categories, different numbers of individuals in each category, and different individuals filling out the numbers—all of which we have seen in our little example with four guests.

We also saw in our example that all ways of realizing the pattern of one table with three guests and one table with one were equally likely. This is generally true of the process. All that affects the probability is a specification of the number of tables that have a given number of guests. This specification is called the partition vector. In our example is it 1 table with one guest, 0 tables with 2 guests, 1 table with 3 guests, 0 tales with four guests: <1,0,1,0>? The fact that any arrangement of guests with the same partition vector has the same probability is called *partition exchangeability*, and it is the key to m:mathematical analysis of the process.

There are explicit formulas to calculate probabilities and expectations of classes of outcomes after a finite number of trials. The expected number of categories—of colors of ball in Hoppe's urn or the expected number of tables in the Chinese restaurant—will be of particular interest to us, because the number of colors in a sender's urn will correspond to the number of signals in use. This is given by a very simple formula.[13] Results are plotted in figure 10.1:

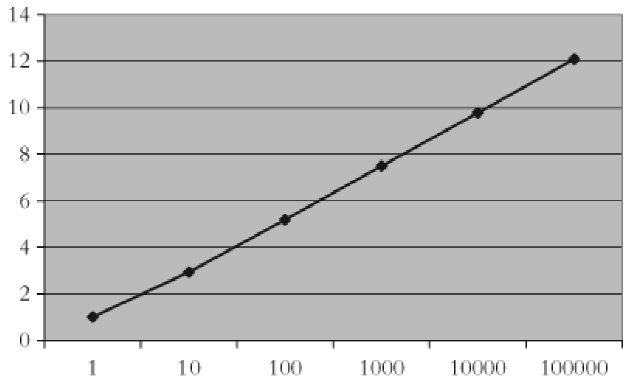

Figure 10.1: Expected number of categories.

p. 126 For even quite large numbers of trials, the expected number of categories is quite modest. There is something else that I would like to emphasize. For a given number of categories, the distribution of trials among those categories is not uniform. We can illustrate this with an example that is simple enough to graph. Suppose we have ten trials and the number of categories turns out to be two (two colors of ball, two tables in the restaurant) which will happen about 28% of the time. This can be realized in five different ways of partitioning 10: 5 + 5, 4 + 6, 3 + 7, 2 + 8, 1 + 9. There is a simple way of calculating the probability of each—the Ewens sampling formula. The results are graphed in figure 10.2.

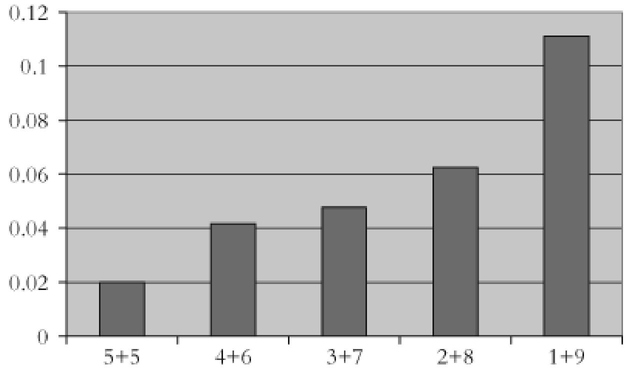

Figure 10.2: Probability of partitions of 10 into two categories.

The more unequal a division is between the categories, the more likely it is to occur. Some colors are numerous, some are rare. Some tables are much fuller than others. Finally, let us notice that the Hoppe urn can be redescribed in a suggestive way. You can think of it as a way of moving between Pólya urns. The mutator process is kept track of on the side, say with an urn of one black and many white balls. Pick a white ball from the auxiliary urn and you add another white ball, and sample from your current Pólya urn. Pick the black ball from the auxiliary urn and you move to a different Pólya urn with all the old balls and with one more ball of one
p. 127 more ↳ color. This is a little like moving between games, and we will make it the basis of doing just that.

Reinforcement with invention

We remarked that Pólya urn process can be thought of as reinforcement learning when there is no distinction worth learning—all choices (colors) are reinforced equally. The Hoppe-Pólya urn, then, is a model that adds useless invention to useless learning. That was its original motivation, where different alleles confer no selective advantage.

If we modify the Pólya urn by adding differential reinforcement—where choices are reinforced according to different payoffs—we get the Herrnstein–Roth–Erev model of reinforcement learning of the foregoing chapters. If we modify the Hoppe-Pólya model by adding differential reinforcement, we can get reinforcement
p. 128 learning that is capable of invention.[14] ↳

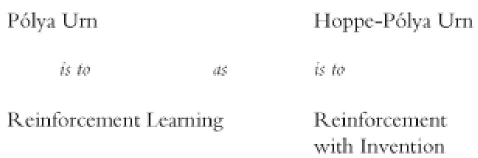

Figure 10.3: Urn models.

Inventing new signals[15]

We use the Hoppe-Pólya urn as a basis for a model of inventing new signals in signaling games. For each state of the world, the sender has an additional choice: *send a new signal*. A new signal is always available. The sender can either send one of the existing signals or send a new one. Receivers always pay attention to a new signal. (A new signal means new signal that is noticed, failures being taken account of by making the probability of a successful new signal smaller.) Receivers, when confronted with a new signal, just act at random. We equip them with equal initial propensities for the acts.

Now we need to specify exactly how learning proceeds. Nature chooses a state and the sender either chooses a new signal, or one of the old signals. If there is no new signal the model works just as before. If a new signal is introduced, it either leads to a successful action or not. When there is no success, the system returns to the state it was in before the experiment with a new signal was tried.

p. 129 But if the new signal leads to a successful action, both sender and receiver are reinforced. The reinforcement now constitutes the sender's new initial propensity to send the signal in the state in which it was just sent. The receiver now begins keeping track of the success of acts taken upon receiving the new signal. In terms of the urn model, the receiver activates an urn for the signal, with one ball for each possible act, and adds to that urn the reinforcement for the successful act just taken. The sender now considers the new signal not only in the states in which it was tried out, but also considers it a possibility in other states. So, in terms of the urn model, a ball for the new signal is added to each sender's urn, in addition to the reinforcement ball added to the urn for
p. 130 the state that has just occurred.[16] The new signal has now established itself. We have ↳ moved from a Lewis signaling game with N signals to one with N+1 signals.

Before Successful Invention

Sender Urn 1: R, G, B	Receiver Urn R: A1, A2
Sender Urn 2: R, G, B	Receiver Urn G: A1, A2

After Successful Invention
(in State 2 with Act 2)

Sender Urn 1: R, G, B, Y	Receiver Urn R: A1, A2
Sender Urn 2: R, G, B, Y, Y	Receiver Urn G: A1, A2
	Receiver Urn Y: A1, A2, A2

Figure 10.4: In state 2 a black ball is drawn, act 2 is tried and is successful. A yellow ball is added to both senders' urns and a reinforcement yellow ball is added to the urn for state 2.The receiver adds an urn for the signal yellow, and adds an extra ball to that urn for act 2.

In summary, one of three things can happen:

1. No new signal tried, and the game is unchanged. Reinforcement proceeds as in a game with a fixed number of signals.
2. A new signal is tried but without success, and the game is unchanged.
3. A new signal is tried with success, and the game changes from one with n states, m signals and o acts to one with n states, m+1 signals, o acts.

Starting with nothing

If we can invent new signals, we can start with no signals at all, and see how the process evolves. Consider the three-state, three-act Lewis signaling game with states equiprobable. As before, exactly one act is right for each state. We can gain some insight into this p. 131 ↳ complicated process from our understanding of the Hoppe urn. In fact, once senders learn to signal successfully in a given state, the sender's urn for that state is a Hoppe urn.

If we ran the process forever, we would end up with an infinite number of signals. But if we run a large finite number of iterations, we would expect a not-so-large number of signals. In simulations of our model of invention, starting with no signals at all, the number of signals after 100,000 iterations ranged from 5 to 25. (A histogram of the final number of signals in 1,000 trials is shown in figure 10.5.)

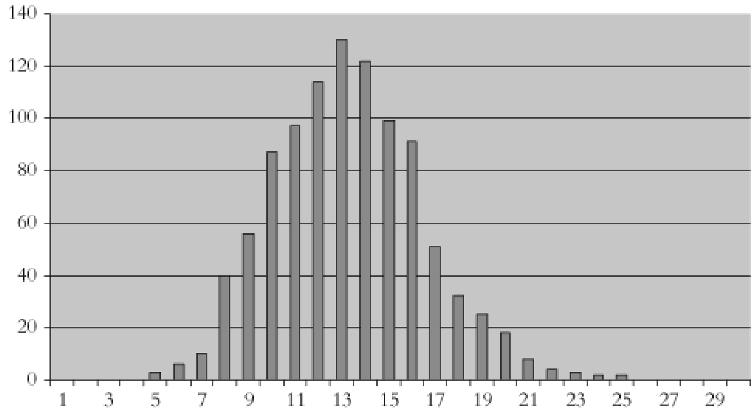

Figure 10.5: Number of signals after 100,000 iterations of reinforcement with invention. Frequency in 1,000 trials.

Avoiding pooling traps

Recall that in a version of this game with the number of signals fixed at 3, classical reinforcement learning sometimes falls into a partial pooling equilibrium. In basic Roth–Erev reinforcement learning with initial propensities of 1, about 9% of the trials led to imperfect information transmission. Using reinforcement with invention, starting with no signals, 1,000 trials *all* ended up with efficient signaling. Signalers went beyond inventing the three requisite signals. Lots of synonyms were created. By inventing more signals, they avoided the traps of partial pooling equilibria.

And recall that in the game with two states, two acts, and the number of signals fixed at 2, if the states had unequal probabilities agents sometimes fell into a total pooling equilibrium—in which no information at all is transmitted. In such an equilibrium the receiver would simply do the act suited for the most probable state and ignore the signal and the sender would send signals with probabilities that were not sensitive to the state. The probability of falling into total pooling increased as the disparity in probabilities became greater. When one state has probability .6, failure of information transfer hardly ever happens. At probability .7 it happens 5% of the time. This number rises to 22% for probability .8, and 44% p. 132 ↳ for probability .9. Highly unequal state probabilities appear to be a major obstacle to the evolution of efficient signaling.

If we take the extreme case in which one state has probability .9, start with no signals at all, and let the players invent signals as above they reliably learn to signal. In 1,000 trials they never fell into a pooling trap; they always learned a signaling system. They invented their way out of the trap. The invention of new signals makes efficient signaling a much more robust phenomenon.

Synonyms

Let us look at our results a little more closely. Typically we get efficient signaling with lots of synonyms. How much work are the synonyms doing? Consider the following trial of three-state, three-act signaling game, starting with no signals and proceeding with 100,000 iterations of learning with invention.

Trial 2:	
signal 1 probabilities in states 0,1,2	0.00006, **0.71670**, 0.00006
signal 2 probabilities in states 0,1,2	0.00006, **0.28192**, 0.00006
signal 3 probabilities in states 0,1,2	0.09661, 0.00006, 0.00080
signal 4 probabilities in states 0,1,2	0.00946, 0.00042, 0.00012
signal 5 probabilities in states 0,1,2	**0.86867**, 0.00012, 0.00006
signal 6 probabilities in states 0,1,2	0.00006, 0.00006, **0.81005**
signal 7 probabilities in states 0,1,2	0.02393, 0.00006, 0.00012
signal 8 probabilities in states 0,1,2	0.00006, 0.00006, **0.14338**
signal 9 probabilities in states 0,1,2	0.00006, 0.00018, 0.04449
signal 10 probabilities in states 0,1,2	0.00012, 0.00006, 0.00043
signal 11 probabilities in states 0,1,2	0.00012, 0.00012, 0.00006
signal 12 probabilities in states 0,1,2	0.00054, 0.00012, 0.00018
signal 13 probabilities in states 0,1,2	0.00018, 0.00006, 0.00012

p. 133 Notice that a few of the signals (shown in boldface) are doing most of the work. In state 1, signal 5 is sent 87% of the time. Signals 1 and 2 function as significant synonyms for state 2, being sent more than 99.5% of the time. Signals 6 and 8 are the major synonyms for state 3. The pattern is fairly typical. Very often, many of the signals that have been invented end up little used. This is just what we should expect from what we know about the Hoppe urn. Even without any selective advantage, the distribution of reinforcements among categories tends to be highly unequal, as was shown in figure 10.2. Might not infrequently used signals simply fall out of use entirely?

Noisy forgetting

Nature forgets things by having individuals die. Some strategies (phenotypes) simply go extinct. This cannot really happen in the replicator dynamics—an idealization where unsuccessful types get rarer and rarer but never actually vanish. And it cannot happen in Roth–Erev reinforcement where unsuccessful acts are dealt with in much the same way.

Evolution in a finite population is different. In the models of Sebastian Shreiber,[17] a finite population of different phenotypes is modeled as an urn of balls of different colors. Successful reproduction of a phenotype corresponds to the addition of balls of the same color. So far this is identical to the basic model of reinforcement learning. But individuals also die. We transpose the idea to learning dynamics to get a model of reinforcement learning with noisy forgetting.

For individual learning, this model may be more realistic than the usual model of geometrical discounting. That model, which discounts the past by keeping some fixed fraction of each ball at each update, may be best p. 134 suited for aggregate learning—where individual fluctuations are averaged out. But individual learning is ↳ noisy, and it may be worth looking at an urn model of individual reinforcement with noisy forgetting.

Inventing and forgetting signals

We put together these ideas to get learning with invention and with noisy forgetting, and apply it to signaling. It is just like the model of inventing new signals except for the random dying-out of old reinforcement, implemented by random removal of balls from the sender′s urns.

The idea may be implemented in various ways. Nature might, with some probability, pick an urn at random, pick a ball from it at random and throw it away. (The probability is the forgetting rate.) Or alternatively, Jason McKenzie Alexander suggests that nature pick an urn at random, pick a color in that urn at random, and throw a ball of that color away. Either way, there is one less ball in that urn and the trial is over.

Now, it is possible that the number of balls of one color, or even balls of all colors could hit zero in a sender′s urn. Should we allow this to happen, as long as the color (the signal) is represented in other urns for other states? There is another choice to be made here. If the number of balls of a certain color is zero in all sender′s urns, then the corresponding signal is extinct and the receiver′s urn corresponding to that signal dies out.

There is a lot of territory to explore in these forgetting models. Preliminary simulations suggest the following. The first kind of forgetting that we took from finite population evolution (balls removed with equal probability) doesn′t change the distribution of signals much at all. Usage of synonyms continues to follow a kind of power law distribution, with little-used signals persisting. This makes sense, because mostly it is the frequently used signals that are dying. But Alexander′s kind of forgetting can be remarkably effective in pruning little-used signals without disrupting the evolution of efficient signaling. Often, in long simulation p. 135 runs, we get close to ↳ the minimum number of signals needed for an efficient signaling system.

Inventing new signals

We now have a simple, tractable model for the invention of new signals. It can be easily studied by simulation, and connections with well-studied processes from population genetics suggest that analytic results are not completely out of reach. It invites all sorts of interesting variations. Even the most basic model has interesting properties, both by itself and in combination with forgetting.

Notes

1 For more analysis of this model of inventing new signals, see Skyrms and Zabell forthcoming.
2 So called, because they do not take up the violet stain in Gram's test. Gram negative bacteria tend to be pathogens.
3 Taga and Bassler 2003; Miller and Bassler 2001.
4 See Miller and Bassler 2001.
5 So called, because they do take up the dye in Gram's stain test.
6 Miller and Bassler 2001.

7 Cheney and Seyfarth 1990, 169 who refer to Kavanaugh 1980.

8 Variations place some number of phantom guests at the first unoccupied table.

9 Aldous 1985; Pitman 1995.

10 (1)(1/2)(2/3)(3/4) = (6/24) vs. (1)(1/2)(1/3)(1/4) = (1/24).

11 Hoppe 1984.

12 I owe my knowledge of this to Sandy Zabell. For both history and analytical discussion see Zabell 1992, 2005.

13 SUM (from i=0 to i=N-1) 1/(1+i).

14 Alternatively, we can interpret this as a model of evolution in a finite, growing population.

15 We note that the same kind of urn model could be used for inventing new actions on the part of the receiver. But if this were done, we would need to specify the payoffs of potential new actions in each state. There is no general principled way to do this, although in specific applications there might be some plausible approach.

16 We could add a fractional ball, and make fraction a parameter to adjust the strength of the sender's generalization of the new signal from one situation to another. Here we just stick to the simplest formulation where strength of generalization is one.

17 Shreiber 2001.