

A dramatic painting depicting a group of men on a wooden raft or small boat, struggling against a stormy sea. The scene is illuminated by a bright, golden light from the left, suggesting a sunset or sunrise. The men are in various states of distress and exhaustion; some are lying down, while others are actively engaged in tasks like pulling ropes or holding up a flag. The overall mood is one of intense struggle and survival.

# Learning to Signal in a Dynamic World

Dr J McKenzie Alexander

Department of Philosophy, Logic and Scientific Method  
London School of Economics and Political Science

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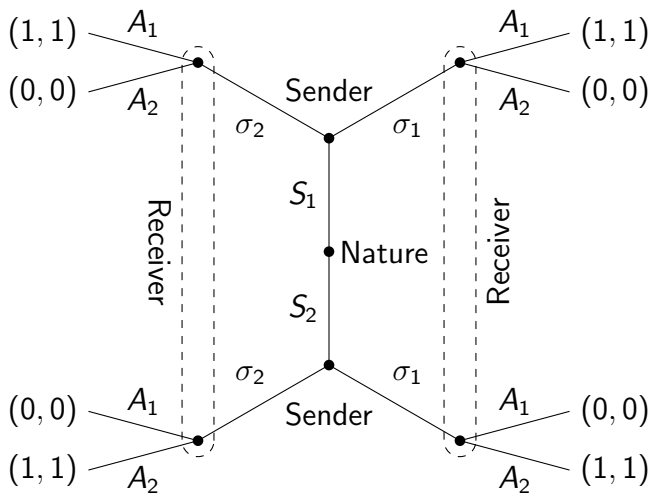
# Outline

- 1 Introduction: Lewis signaling games and the move to reinforcement learning
- 2 Inventing new signals with forgetting
- 3 Coping with a dynamic environment
- 4 Inventing new signals with discounting
- 5 Conclusion

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# Lewis Sender-Receiver games



# The emergence of meaning via reinforcement

Regarding the two-state, two-signal and two-action game (states equiprobable), Skyrms writes:

“Spontaneous emergence of signaling [. . .] requires no strategic reasoning, just chance and reinforcement. This is, in fact, just what happens. Individuals *a/ways* learn to signal in the long run. This is not only confirmed by extensive simulations, it is also a theorem.”

(Skyrms, 2010, pg. 94)

# Learning to signal

Regarding more complicated problems, Skyrms says:

“How hard is it to learn to signal? This depends on our criterion of success for the learning rule. If success means spontaneous generation of signaling in many situations, then all the kinds of learning that we have surveyed pass the test [...] If it means learning to signal with probability one in all Lewis signaling games, a simple payoff-based learning rule will do the trick. It is easy to learn to signal.”

(Skyrms, 2010, pg. 105)

# Two key assumptions, and two questions

Skyrms assumes that the structure of the Lewis signaling game is *fixed*. The number of state-action pairs is taken as given, as is the number of possible signals (except for chapter 10).

Reinforcement learning then operates inside this setting.

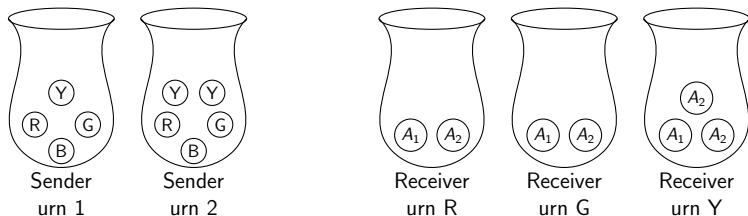
- 1 Can efficient, minimal signaling systems emerge *ex nihilo* in a fixed sender-receiver game?
- 2 If so, what then happens if the structure of the game is made *dynamic*, varying the number of state-action pairs, or what counts as a “correct response”?

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# Inventing new signals: The Hoppe-Pólya Urn

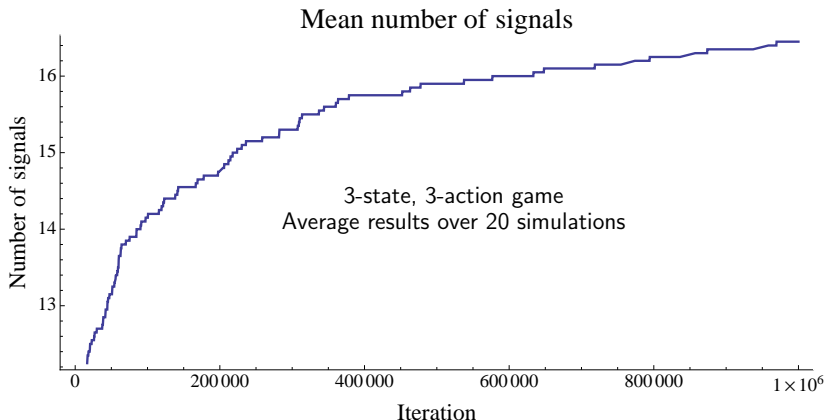


After successful invention

- State of the world: 2.
- The Sender draws the black ball from urn 2 and hence tries out a new signal Y.
- The Receiver creates a new urn for the signal. Suppose she draws, by chance,  $A_2$ . This is the correct act.
- Reinforcement occurs.

# Inventing new signals

This model of invention generates signaling systems, but many unnecessary signals are also generated.



# Inventing with Forgetting

Skyrms et al. (2011) augment this model of inventing signals with forgetting to see if minimal, as well as efficient, signaling systems can be generated.

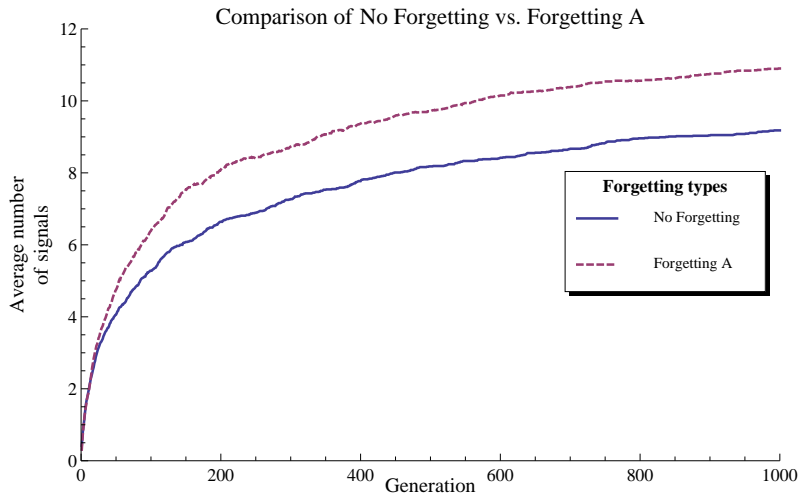
**Forgetting A.** Periodically select an urn at random, then select a ball from the urn and throw it away.

**Forgetting B.** Periodically select an urn at random, then select a *colour* found in *that* urn, and throw away one ball of that colour.

In both cases, the mutator ball is excluded.

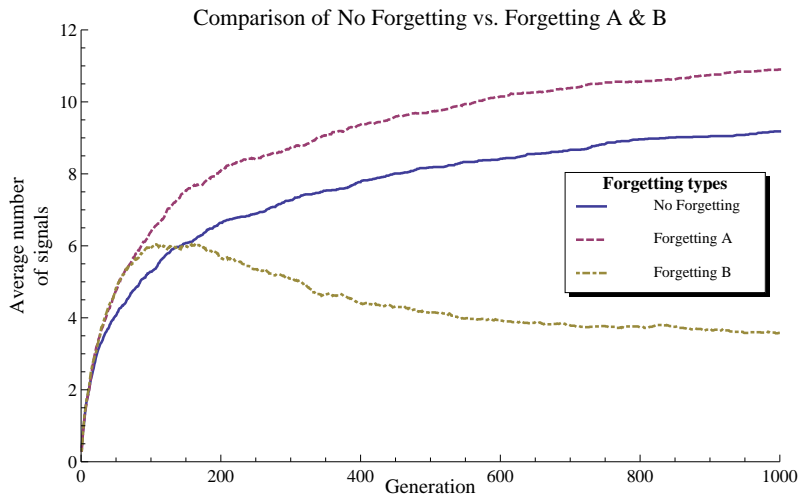
# “Forgetting A” is worse than “No Forgetting”

3 states, 3 actions, all states equally likely.



# Comparison of both forgetting methods

3 states, 3 actions, all states equally likely.



# Average number of signals remaining

Simulation results: equiprobable states, each entry the average of 1,000 simulations run for 1,000,000 iterations each, forgetting rate of  $\frac{1}{3}$ .

|           | No Forgetting | Forgetting A | Forgetting B |
|-----------|---------------|--------------|--------------|
| 3 states  | 16.276        | 19.879       | 3.016        |
| 4 states  | 17.491        | 21.079       | 4.005        |
| 5 states  | 18.752        | 22.686       | 4.982        |
| 6 states  | 20.097        | 24.069       | 5.975        |
| 7 states  | 21.336        | 25.82        | 6.96         |
| 8 states  | 22.661        | 27.14        | 7.941        |
| 9 states  | 23.815        | 28.684       | 8.929        |
| 10 states | 24.925        | 30.663       | 9.928        |



## Summary, so far

The model of inventing signals, with Forgetting B, is *extremely effective* at arriving at efficient, minimal signaling systems.

So is it really true, then, that “it is easy to learn to signal”?



# Forgetting with unequal state probabilities

Consider a 3-state, 3-action game with Forgetting B rate  $p$ .

Each iteration, there's a  $\frac{p}{3}$  chance of a ball being thrown out of the Sender's urn used in state  $i$ .

If the probability of state  $i$  is *less* than  $\frac{p}{3}$ , reinforcement learning won't occur fast enough to overcome the rate at which balls are removed!

# Forgetting with unequal state probabilities

## Illustration

3-state, 3-action game with Forgetting B rate  $\frac{1}{3}$ .

State probabilities:  $\langle \frac{4}{9} - \frac{\varepsilon}{2}, \frac{4}{9} - \frac{\varepsilon}{2}, \frac{1}{9} + \varepsilon \rangle$  with  $\varepsilon = \frac{1}{10,000}$ .

|         | Sender<br>Signals |         |         |        |               | Receiver<br>Actions |         |         |
|---------|-------------------|---------|---------|--------|---------------|---------------------|---------|---------|
|         | 0                 | 14      | 18      | 223714 |               | Act 1               | Act 2   | Act 3   |
| State 1 | 1                 | 6744670 | 0       | 0      | Signal 14     | 8892328             | 1       | 1       |
| State 2 | 1                 | 0       | 6737099 | 0      | Signal 18     | 2                   | 8884925 | 1       |
| State 3 | 1                 | 0       | 0       | 831    | Signal 223714 | 1                   | 1       | 1031869 |

After 20,000,000 iterations

But there's a greater problem concerning learning to signal...

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# Learning to signal in a dynamic world

All of the cases discussed in *Signals* use a fixed number of state/action pairs.

What happens if the environment is dynamic? That is,

- 1 What if new state-action pairs are added over time?
- 2 What if the correct response to a given state of the world is swapped with another state?

# Adding new states

Let  $q$  be the probability that a new state-action pair is added to the model at the start of a given iteration.

Suppose we have an  $N$ -state,  $N$ -action signaling game with state probabilities of  $\langle p_1, \dots, p_N \rangle$ .

If a state-action pair is added, the new state probabilities are:

$$\left\langle \frac{N}{N+1}p_1, \dots, \frac{N}{N+1}p_N, \frac{1}{N+1} \right\rangle$$

# Adding new states II

The choice of  $\frac{N}{N+1}$  as the renormalization factor ensures that if we begin with equiprobable states, we continue to have equiprobable states.

$$\begin{aligned} \left\langle \frac{1}{3}, \frac{1}{3}, \frac{1}{3} \right\rangle &\xrightarrow{\text{New state}} \left\langle \frac{3}{4} \cdot \frac{1}{3}, \frac{3}{4} \cdot \frac{1}{3}, \frac{3}{4} \cdot \frac{1}{3}, \frac{1}{4} \right\rangle \\ &= \left\langle \frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4} \right\rangle \end{aligned}$$

# A simulation result

Beginning with a 1-state, 1-action model with an addition probability of 0.001:

After 5,000 iterations

|         | Sender<br>Signals |      |     |     |     |     |     |     |     |     |
|---------|-------------------|------|-----|-----|-----|-----|-----|-----|-----|-----|
|         | 0                 | 2    | 9   | 22  | 69  | 85  | 86  | 102 | 187 | 225 |
| State 1 | 1                 | 1227 | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 1   |
| State 2 | 1                 | 0    | 708 | 0   | 0   | 0   | 0   | 0   | 0   | 1   |
| State 3 | 1                 | 0    | 0   | 466 | 0   | 0   | 0   | 0   | 0   | 0   |
| State 4 | 1                 | 0    | 0   | 0   | 0   | 169 | 0   | 0   | 0   | 1   |
| State 5 | 1                 | 0    | 0   | 0   | 158 | 0   | 0   | 0   | 0   | 1   |
| State 6 | 1                 | 0    | 0   | 0   | 0   | 0   | 175 | 0   | 0   | 0   |
| State 7 | 1                 | 0    | 0   | 0   | 0   | 0   | 0   | 117 | 0   | 1   |
| State 8 | 1                 | 0    | 0   | 0   | 0   | 0   | 0   | 0   | 11  | 0   |
| State 9 | 1                 | 0    | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 2   |

|            | Receiver<br>Actions |       |       |       |       |       |       |       |       |
|------------|---------------------|-------|-------|-------|-------|-------|-------|-------|-------|
|            | Act 1               | Act 2 | Act 3 | Act 4 | Act 5 | Act 6 | Act 7 | Act 8 | Act 9 |
| Signal 2   | 1794                | 1     | 1     | 1     | 1     | 1     | 1     | 1     | 1     |
| Signal 9   | 1                   | 972   | 1     | 1     | 1     | 1     | 1     | 1     | 1     |
| Signal 22  | 1                   | 1     | 684   | 1     | 1     | 1     | 1     | 1     | 1     |
| Signal 69  | 1                   | 1     | 1     | 1     | 264   | 1     | 1     | 1     | 1     |
| Signal 85  | 1                   | 1     | 1     | 248   | 1     | 2     | 1     | 1     | 1     |
| Signal 86  | 1                   | 1     | 1     | 1     | 1     | 245   | 1     | 1     | 1     |
| Signal 102 | 1                   | 1     | 1     | 1     | 1     | 1     | 186   | 1     | 1     |
| Signal 187 | 1                   | 1     | 1     | 1     | 1     | 1     | 1     | 34    | 2     |
| Signal 225 | 1                   | 1     | 1     | 1     | 1     | 1     | 1     | 1     | 2     |

# Measuring how effectively signals are invented

Let  $\vec{s} = \langle s_i \rangle_{i=1}^{\infty}$  denote the sequence of outcomes, where

$$s_i = \begin{cases} 1 & \text{if the signaling attempt was successful,} \\ 0 & \text{otherwise.} \end{cases}$$

Then

$$\frac{\sum_{i=1}^k s_i}{k}$$

measures the cumulative frequency of signaling success up to iteration  $k$ , and

$$\frac{\sum_{i=k-100}^k s_i}{k}$$

measures the “moving frequency” of signaling success over the past 100 iterations at  $k$ .

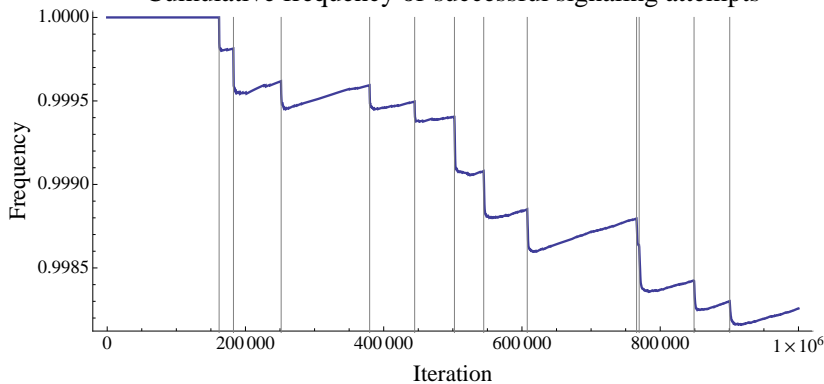


# Simulation results

Initial model: 1-state, 1-action signaling game, forgetting rate 0.333

New state probability 0.00001.

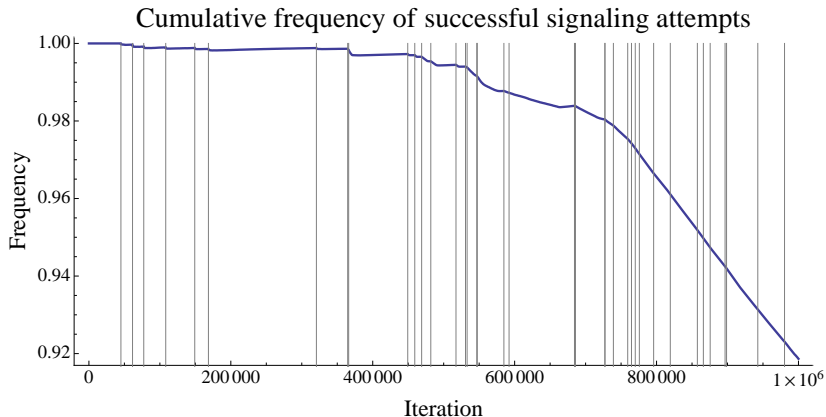
Cumulative frequency of successful signaling attempts



# A simulation result

Initial model: 1-state, 1-action signaling game, forgetting rate 0.333

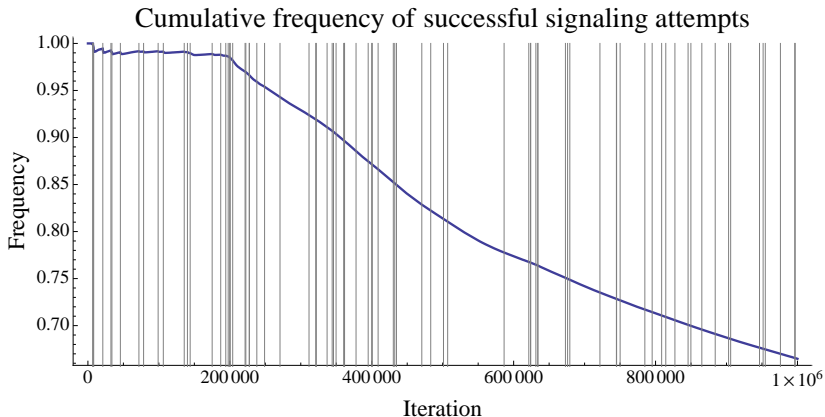
New state probability 0.0000333.



# A simulation result

Initial model: 1-state, 1-action signaling game, forgetting rate 0.333

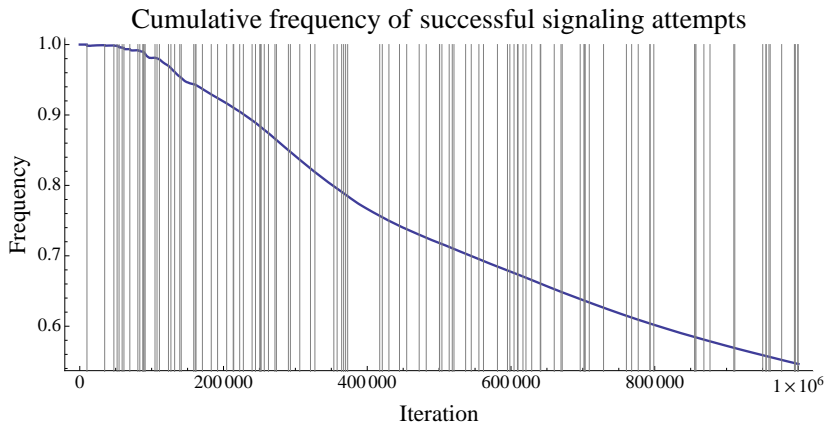
New state probability 0.0000666.



# A simulation result

Initial model: 1-state, 1-action signaling game, forgetting rate 0.333

New state probability 0.0001.



# Swapping states

Let  $p$  be the probability that, at the start of each iteration, the correct response to a given state of the world *permanently* switches.

Think of this as a change in the fitness landscape due to elements beyond the control of the Sender and Receiver.

## Example

|         |                    |        |                    |
|---------|--------------------|--------|--------------------|
| Before: | State 1 → Action 1 | After: | State 1 → Action 3 |
|         | State 2 → Action 2 |        | State 2 → Action 2 |
|         | State 3 → Action 3 |        | State 3 → Action 1 |

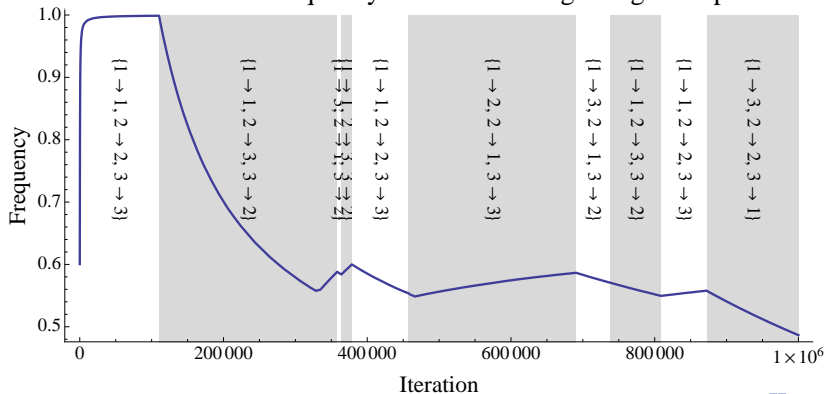
How well does inventing with Forgetting B cope?

# A simulation result

3-state, 3-action signaling game, forgetting rate 0.333, swap rate 0.00001

In a dynamic environment, the model of Skyrms et al. (2011) takes too long to “unlearn” a signaling system.

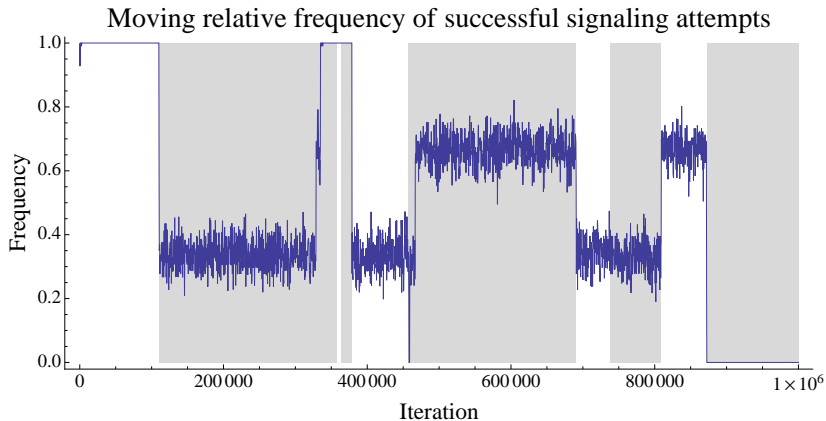
Cumulative frequency of successful signaling attempts



# A simulation result

3-state, 3-action signaling game, forgetting rate 0.333, swap rate 0.00001

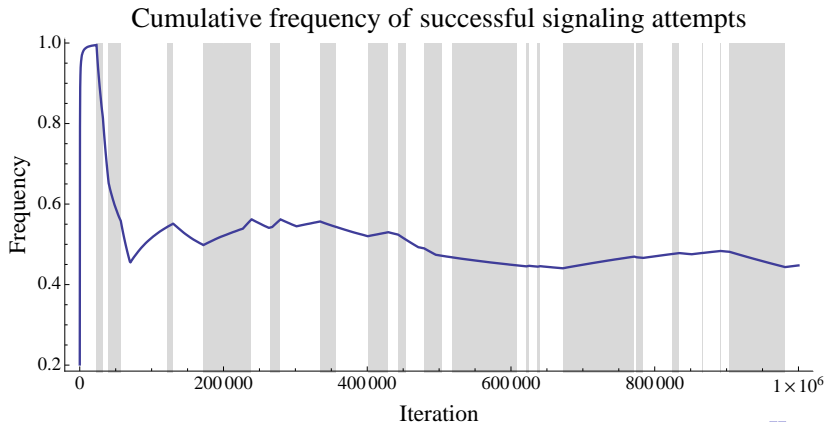
Once the initial signaling system is learnt, the overall performance is effectively determined by chance:



# A simulation result

3-state, 3-action signaling game, forgetting rate 0.333, swap rate 0.0000333

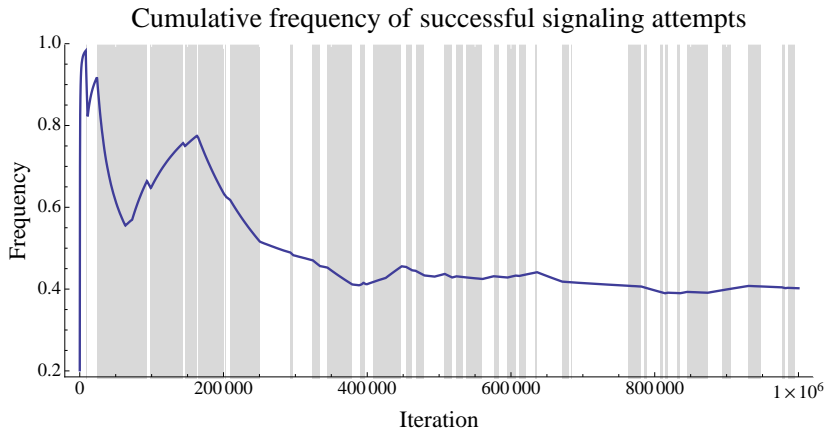
Increasing the dynamic element of the signaling problem drives the model's performance to effectively that of chance:





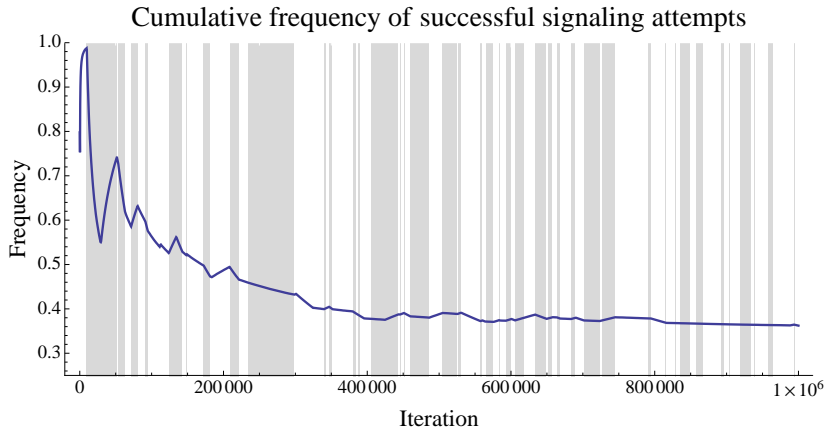
# A simulation result

3-state, 3-action signaling game, forgetting rate 0.333, swap rate 0.0000666



# A simulation result

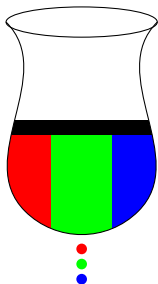
3-state, 3-action signaling game, forgetting rate 0.333, swap rate 0.0001



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# The leaky Hoppe-Pólya urn



Consider a Hoppe-Pólya urn, but filled with liquids rather than discrete balls.

A black liquid, which floats on the others, corresponds to the “mutator” ball.

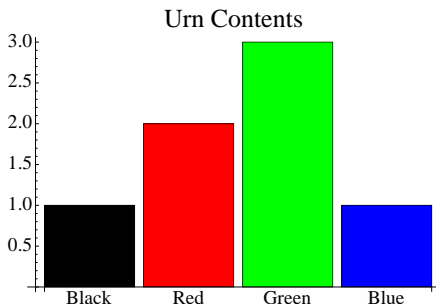
Reinforcement occurs by pouring a cup of coloured liquid into the urn.

But the urn is leaky, so over time the non-black coloured liquids drain away.

# The leaky Hoppe-Pólya urn

This is a model of reinforcement with *discounting*. (Except for the black liquid.)

The discount rate is how quickly the urn drains.



Discount rate of 0.75

# The leaky Hoppe-Pólya urn

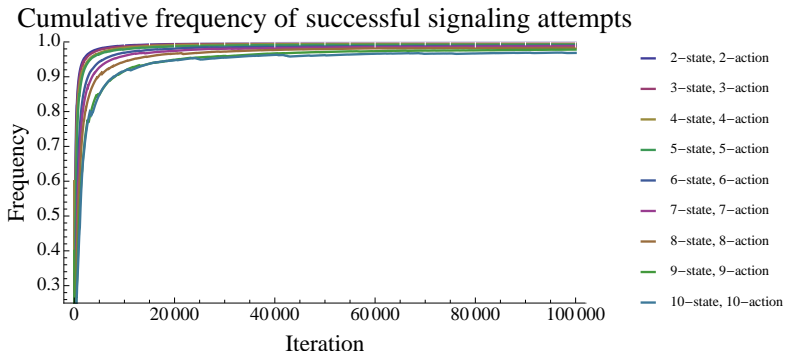
Because discounting only assigns probability 0 to a signal in the limit, a *cutoff threshold*  $\tau$  is introduced.

If the probability of a signal dips below  $\tau$ , that signal is eliminated.

Discounting also applies to the *Receiver's* urns — except that the cutoff threshold doesn't apply. (Why? Signals are purely conventional, but actions are not.)

# Inventing new signals with discounting

Inventing with discounting does nearly as well as inventing with forgetting (here, the discount rate is 0.95):



# Inventing new signals with discounting

Efficiency considerations, discount rate: 0.95

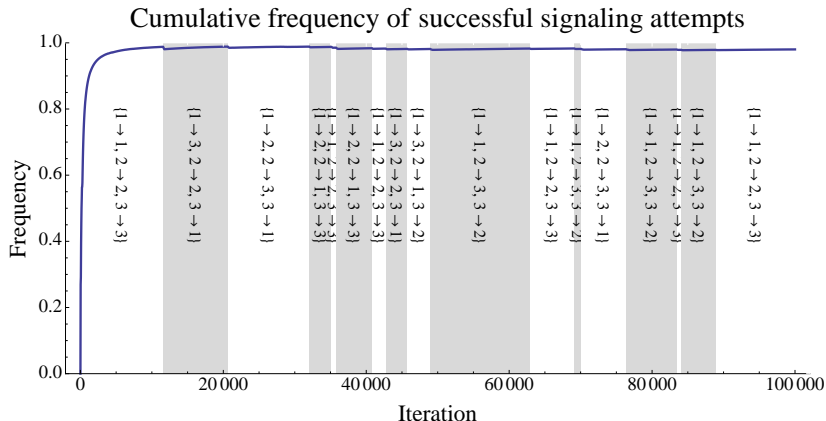
| Game type             | Mean number<br>of signals |
|-----------------------|---------------------------|
| 2-states, 2-actions   | 3.47958                   |
| 3-states, 3-actions   | 4.29091                   |
| 4-states, 4-actions   | 5.21725                   |
| 5-states, 5-actions   | 6.21697                   |
| 6-states, 6-actions   | 7.211                     |
| 7-states, 7-actions   | 8.19678                   |
| 8-states, 8-actions   | 9.04261                   |
| 9-states, 9-actions   | 9.13345                   |
| 10-states, 10-actions | 8.03297                   |



# Inventing with discounting: swapping states

3-state, 3-action game, discount rate 0.95, swap probability 0.0001.

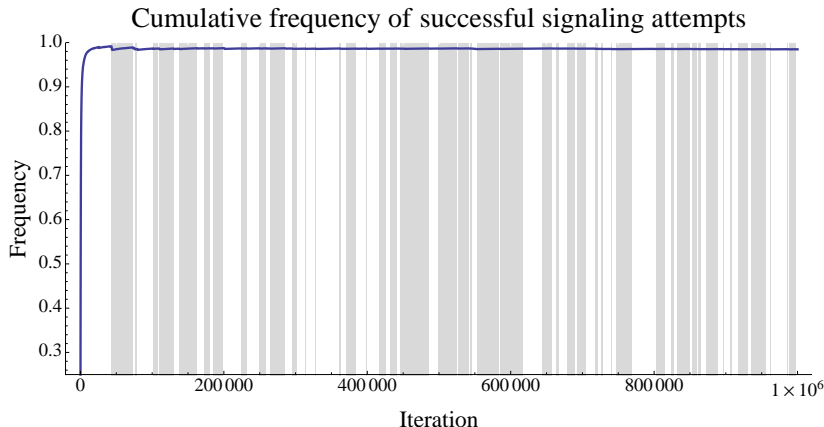
Unlike the standard urn model, discounting responds rapidly to swapped states:



# Inventing with discounting: swapping states

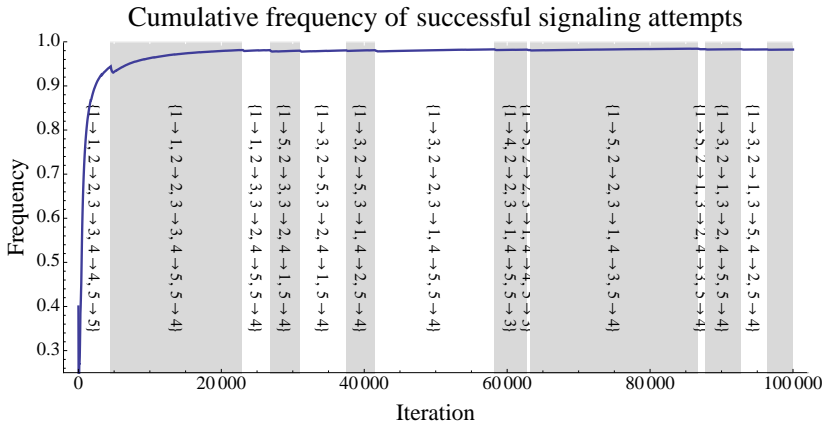
3-state, 3-action game, discount rate 0.95, swap probability 0.0001.

One million iterations of the discount model:



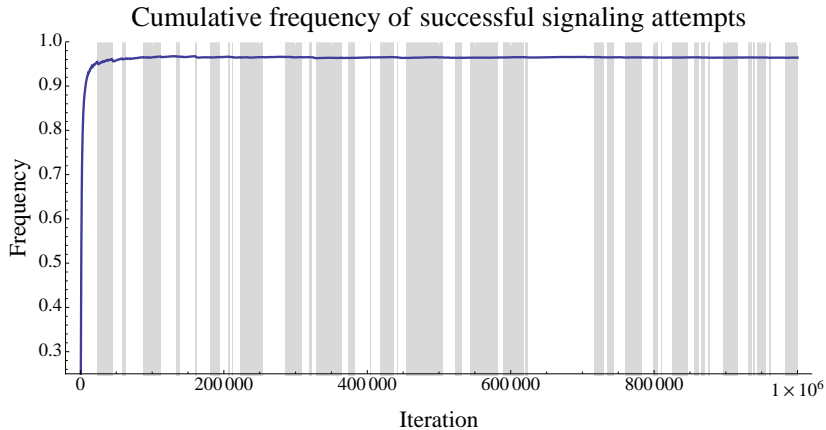
# Inventing with discounting: swapping states

5-state, 5-action game, discount rate 0.95, swap probability 0.0001.



# Inventing with discounting: swapping states

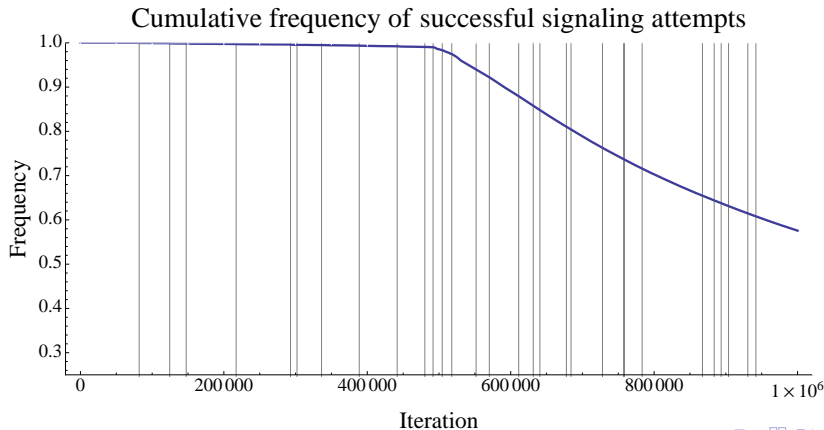
10-state, 10-action game, discount rate 0.95, swap probability 0.0001.



# Inventing with discounting: adding new states

Initial game: 1-state, 1-action, new state probability 0.000333, discount rate 0.95

Unfortunately, the discounting model is little better at handling the addition of new states than the original model.



# Efficient drift in signaling systems

In real languages, drift occurs, even though effective communication occurs at each point in time.

*Whan that Aprille with his shoures soote  
The droghte of Marche hath perced to the roote,  
And bathed every veyne in swich licour,  
Of which vertu engendred is the flour;*

(Chaucer)

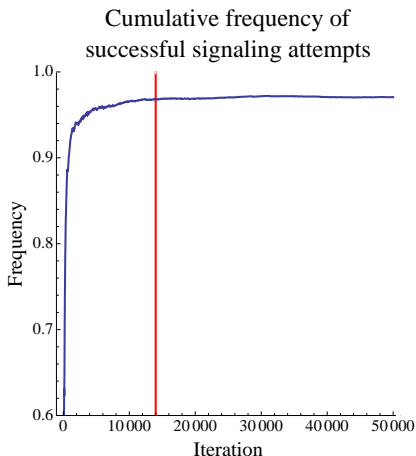
*Is it thy will, thy image should keep open  
My heavy eyelids to the weary night?  
Dost thou desire my slumbers should be broken,  
While shadows like to thee do mock my sight?*

(Shakespeare)

*Fa' shizzle dizzle  
It's Big Snoopy D-O double Gizzle  
Wit my nephew Swizzle, you know it's off the hizzle*

(Snoop Dogg)

# Signaling drift while maintaining efficiency



|         | Sender<br>Signals |         |        |         |
|---------|-------------------|---------|--------|---------|
|         | 0                 | 97      | 223    | 229     |
| State 1 | 0.1               | 0       | 8.2927 | 0       |
| State 2 | 0.1               | 3.22687 | 0      | 0       |
| State 3 | 0.1               | 0       | 0      | 6.40263 |

|            | Receiver<br>Actions |         |         |
|------------|---------------------|---------|---------|
|            | Act 1               | Act 2   | Act 3   |
| Signal 97  | 0                   | 3.22687 | 0       |
| Signal 223 | 8.2927              | 0       | 0       |
| Signal 229 | 0                   | 0       | 6.40263 |

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# Conclusion

- The model of inventing signals with forgetting in *Signals* (and Skyrms et al., 2011) effectively generates efficient, minimal signaling systems in many cases.
- Yet this model performs poorly in dynamic environments.
- Inventing with discounting has improved performance in one kind of dynamic environment (swapping).
- Inventing with discounting also allows efficient drift between signaling systems over time.
- How to cope with the problem of adding new state/action pairs remains an open question.

# References and miscellaneous readings I

Brian Skyrms. *Signals: Evolution, Learning, & Information*.  
Oxford University Press, 2010.

Brian Skyrms, Sandy Zabell, and J. McKenzie Alexander.  
Inventing signals with forgetting. *Dynamic Games and Applications*, 2011.

# Outline

## 6 Simulation results