Smart Agents Don't Need Kin – Evolving Specialisation and Cooperation with Tags

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Abstract

In a previous paper (Hales 2002) we presented simulation results that demonstrated the evolution of "tag based" groups composed of cooperative (in-group altruistic) individual agents performing specialised functions. We hypothesised that a key to the efficiency of the specialisation process was the "searching strategy" employed by agents to locate other members of their group with the required skills for given task contexts. Specifically, we hypothesised that "smart" searching strategies would improve efficiency over the "dumb" strategies implemented so far. In this paper we test this hypothesis. Even when the costs for smart searching are much higher, *very substantial* increases in donation between *non-kin* are produced.

Introduction

A previous model (Hales 2002) demonstrated tag[1] processes that were sufficient to evolve sustained altruistic behaviour between agents who are *not kin related*. Additionally we showed that this non-kin based altruism is a basis for the evolution of groups of heterogeneous (specialised) individuals who, although not kin related, cooperate and work to benefit the *group as a whole*.

We concluded from the previous model that although group directed non-kin altruism was sustained, agents with *smarter* partner selection strategies could *outperform* agents with the dumb strategies tested so far. In this paper we test this hypothesis by implementing smart strategies. We show that, even when the costs of the smart strategies are significantly higher than dumb strategies, smarter strategies do sustain more efficient forms of specialised, altruistic agent groups.

Finally we conclude by proposing that in harsher and more realistic environments, than the one modelled, a *smarter* and more equitable form of "resource sharing" strategy would outperform the limited (dyadic) kinds of sharing so far explored. We hypothesis that *smart sharing* strategies could sustain more efficient and internally specialised groups particularly when combined with *smart searching*. We would expect such *smart groups* to outperform *dumb groups*.

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[1] Tags are identifiable markers (physical markings, gestures or social cues) that can be compared by other agents to their own tags.

The Model

The model consists of a population of 100 evolving agents. The tag matching mechanism follows that of Riolo et al (2001). The specialisation process follows Hales (2002). Here we briefly summarise the model. Each agent has three traits, a tag $\tau \in [0,1]$, a tolerance threshold $1 \leq T \geq 0$, and a skill type $S \in \{1,2\}$. Initially, tags, thresholds and skills are allocated uniformly randomly. In each generation, each agent is awarded some number P of resources. Each resource is assigned a required skill type. Resources can only be "harvested" by agents possessing the required skill type. The skill type assigned to a resource is randomly assigned from those skills that do not match the receiving agents skill[2]. An agent therefore is never awarded a resource that matches its skill type. Since the agent cannot harvest the resource, it searches for another agent in the population with required skill and tag values.

Donation only occurs if a recipient is found with the required skill type and with a sufficiently similar tag value. A recipient tag is considered to be sufficiently similar if it is within the tolerance of the donating agent. Specifically, given a potential donor agent D and a potential recipient R a donation will only be made when $| \tau_D - \tau_R | \leq T_D$. This means that an agent with a high T value may donate to agents over a large range of tag values. A low value for T restricts donation to agents with very similar tag values to the donor. In all cases donation can only occur when the skill type of the receiving agent matches the skill type associated with the resource. If a donation is made the donating agent incurs a cost, c, and the recipient gains a benefit, b (since it can harvest the resource). In all experiments given in this paper, the benefit b = 1 but the cost c is varied as is the size of the skill set S (see results).

In contrast to a previous model (Hales 2002) we assume an agent searches for a potential recipient using a *smart* searching strategy. Here, we do not model the *actual mechanism employed* but just the *outcome* assuming a smart strategy were used. We assume that some efficient mechanism exists which allows agents to *find a potential recipient in the population if one exists*[3]. As discussed previously (Hales 2002) a number of plausible mechanisms can be hypothesised – based on spatial and/or cognitive relationships (e.g. "small world" social networks, meeting places, central stores – see the later discussion for more on this).

After all agents have been awarded P resources and made any possible donations the entire population is reproduced. Reproduction is accomplished in the following manner – each agent is selected from the population in turn, its score is compared to another randomly chosen agent, and the one with the highest score is reproduced. Mutation is applied to each trait of each offspring. With probability 0.1 the offspring receives a new tag (uniformly randomly selected). With the same probability, gaussian noise is added to

[2] Results obtained from a model in which agents may be awarded resources matching their own skill types produced similar results to those presented in this paper.

[3] If several suitable recipients exist in the population we assume here that one of them is selected to receive the donation at random.

the tolerance value (mean 0, standard deviation 0.01). When T < 0 or T > 1, it is reset to 0 and 1 respectively. Also with probability 0.1 the offspring is given a new skill type (uniformly randomly selected).

Results

The first set of results, in Table 1 below, show the donation rates achieved as a percentage of total awards made and the average tolerance values in a 2-skill scenario. The results are over 30,000 generations with 30 replications. Each replication represents an individual run started with a different pseudo-random number seed. The standard deviations are over the 30 runs executed for each unique P value setting[4]. The column labelled "dumb" show the results from previous experiments using a *dumb* random recipient search strategy (Hales 2002). They are given here for comparison purposes. In order to make a "fair" comparison we also consider the results of the smart strategy when the cost, c, is increased from c = 0.1 to c = 0.5 (in all cases the benefit, b, is held at 1).

Awards (P)	Donation Rate – Ave % (st.dev. in brackets)			Tolerance – Ave (st.dev. in brackets)		
	Dumb c = 0.1	Smart C = 0.1	Smart c = 0.5	Dumb c = 0.1	Smart c = 0.1	Smart c = 0.5
1	2.6 (0.000)	61.0 (0.079)	61.0 (0.076)	0.017 (0.000)	0.035 (0.157)	0.038 (0.107)
2	2.2 (0.000)	80.0 (0.011)	69.3 (0.083)	0.012 (0.000)	0.019 (0.050)	0.055 (0.182)
3	2.3 (0.000)	85.6 (0.048)	73.9 (0.052)	0.010 (0.000)	0.090 (0.216)	0.044 (0.147)
4	6.4 (0.064)	85.8 (0.031)	76.8 (0.061)	0.010 (0.000)	0.057 (0.147)	0.062 (0.172)
6	30.3 (0.007)	87.7 (0.046)	77.9 (0.008)	0.021 (0.021)	0.111 (0.217)	0.013 (0.013)
8	32.8 (0.001)	90.5 (0.062)	80.6 (0.043)	0.024 (0.024)	0.225 (0.290)	0.049 (0.136)
10	33.8 (0.015)	89.3 (0.056)	81.1 (0.039)	0.043 (0.043)	0.180 (0.279)	0.040 (0.132)
20	35.5 (0.034)	89.5 (0.057)	82.0 (0.003)	0.106 (0.078)	0.189 (0.274)	0.012 (0.005)
40	36.0 (0.047)	91.3 (0.047)	83.1 (0.015)	0.241 (0.241)	0.268 (0.305)	0.025 (0.049)

Table 1

Donation rates and tolerance levels for different numbers of awards in a 2-skill scenario (i.e. when S ε {1,2}) for different search strategies and costs. The values in brackets are standard deviations over the 30 replications.

[4] The standard deviations are not calculated over the percentages given but proportions (i.e. percentages scaled within [0..1] – so 100% would count as 1 and 50% as 0.5 etc.)

As can be seen in Table 1, the donation rate for the smart strategy (when c=0.1) increases dramatically when P=2 awards and then increases modestly (though non-monotonically) as P is increased. In comparison with the previous results for the *dumb* searching strategy the donation rate is substantially higher (61% to 2.6% for a single award). Note also that the tolerance values are higher too and the standard deviation of tolerance (over the 30 runs) is much higher (indicating a high heterogeneity over the runs)[5].

When the cost, c, is increased to 0.5 the smart strategy does not increase as dramatically when P=2. But still shows substantially higher donation levels than the dumb strategy. The increase in donation rate as P is increased follows a more linear (monotonically increasing) path than when the cost was c=0.1 and the tolerance levels are generally reduced. The variance of the tolerance is reduced by still higher than for the dumb strategy.

Awards (P)	Donation Rate – Ave % (st.dev. in brackets)			Tolerance – Ave (st.dev. in brackets)		
	Dumb c = 0.1	Smart c = 0.1	Smart c = 0.5	Dumb c = 0.1	Smart c = 0.1	Smart c = 0.5
1	1.5 (0.001)	29.5 (0.081)	29.5 (0.081)	0.028 (0.002)	0.021 (0.118)	0.021 (0.084)
2	1.1 (0.000)	75.3 (0.016)	47.9 (0.087)	0.019 (0.001)	0.023 (0.034)	0.030 (0.111)
3	1.0 (0.000)	81.8 (0.037)	59.9 (0.035)	0.015 (0.001)	0.056 (0.110)	0.017 (0.048)
4	0.9 (0.000)	84.3 (0.060)	66.3 (0.046)	0.013 (0.000)	0.104 (0.222)	0.028 (0.105)
6	0.9 (0.000)	84.4 (0.051)	70.9 (0.010)	0.011 (0.001)	0.099 (0.210)	0.011 (0.014)
8	0.9 (0.000)	88.5 (0.077)	73.1 (0.002)	0.010 (0.000)	0.250 (0.319)	0.009 (0.000)
10	2.1 (0.002)	84.1 (0.049)	74.5 (0.002)	0.010 (0.000)	0.099 (0.208)	0.009 (0.000)
20	12.9 (0.000)	85.8 (0.070)	77.3 (0.002)	0.025 (0.003)	0.170 (0.261)	0.010 (0.001)
40	13.9 (0.015)	91.0 (0.015)	79.3 (0.033)	0.098 (0.190)	0.370 (0.341)	0.038 (0.107)

Table 2

Donation rates and tolerance levels for different numbers of awards in a 5-skill scenario (i.e. there are 5 skill types, such that each agent has a skill S ε {1,2,3,4,5}) for different search strategies and costs. The values in brackets are standard deviations over the 30 replications.

[5] This result suggests that there may not be a "single story" (i.e. evolutionary trajectory) here. This means that increases in donation and tolerance might be highly contingent on initial conditions and on-going stochasticities (this is discussed later).

Run	Donation Proportion	Tolerance Ave	Tag Clone Donations
1	0.811	0.020	0.768
2	1.000	0.779	0.013
3	1.000	0.673	0.015
4	0.881	0.188	0.429
5	0.998	0.600	0.018
6	1.000	0.669	0.015
7	0.861	0.109	0.499
8	0.811	0.021	0.750
9	1.000	0.659	0.015
10	0.829	0.045	0.699
11	1.000	0.768	0.013
12	1.000	0.901	0.012
13	0.917	0.418	0.297
14	0.834	0.046	0.641
15	0.813	0.022	0.760

Table 3

The first 15 individual runs for the smart strategy (c=0.1) in the 5-skill scenario. Each run represents a single execution of the model to 30,000 generations starting with a different pseudo-random number seed. The Donation Rate shows the proportion of awards that resulted in a successful donation. The Tolerance Average shows the average tolerance over all agents over each generation. The Tag Clone Donations shows the proportion of successful donations made to an agent with an identical tag value.

In a 5-skill scenario (Table 2) a similar (though even more dramatic) pattern is seen for the smart strategy when c = 0.1. Again a big increase in the donation rate takes place when P=2 followed by a much slower (non-monotonic rise) as P is increased. Again the variance over the 30 runs for each P value is much higher than the dumb strategy (evidenced by the standard deviation values).

When c = 0.5 the results are broadly similar to those for the 2-skill scenario. Again notice that for the smart strategy when c = 0.5 the increase when P = 2 is less dramatic, and as P increases the donation rate increase in a more linear (and monotonic) way. We note here however, that tolerance values and the variance of those values is lower than in the 2-skill scenario – almost comparable to the dumb strategy.

Discussion

Let us be clear about what is being demonstrated by the model: Agents form groups based on tag similarity contain a diversity of skills. Agents donate resources, requiring skills that they do not posses, to other agents within their group *even though this causes them to incur a substantial cost.* This behaviour persists even though the agents are reproduced on the basis of individual utility. Since agents can only pass resources to others within their group who posses a required skill, the high-level of donation rate

produced indicates that *high levels of skill diversity are being maintained within groups*. This is exactly the kind of group organisation that can best exploit the environmental scenario. So, *agents are forming into very efficient, skill diverse groups*. Since skill diversity means that agents cannot be clones, this evolved structure cannot be the result of simply kin based selection.

The results presented here indicate that "smart searching" strategies, i.e. efficient methods of find an appropriate in-group recipient for donation, substantially increase the efficiency of specialisation within groups. Since smart strategies would seem to require a higher cognitive ability within agents, can we conclude that there is strong selection pressure for such cognitive abilities?

So far, we cannot, since *the results presented here do not pit dumb strategies against smart ones in the same evolving population*. We hypothesis, however, that smart agents would indeed out compete dumb agents – even when the cost of donating for smart agents was substantially higher. We put this hypothesis to the test in the forthcoming paper.

As stated previously, in some of the results, very high levels of tolerance were produced. This tended to occur when P (awards) was high and a smart strategy was employed (though not when costs were high). In those cases where the tolerance was high, the variance (over the 30 replication) of tolerance was also high. This indicated heterogeneity of evolutionary trajectories taking place over replications. To investigate this we examine the average tolerances and donation rates of the individual replication runs when P=40 in the 5-skill scenario for the smart strategy when cost c=0.1.

Table 3 shows the results of the first 15 individual runs. Note that the runs fall into two categories: a) runs with low average tolerances and b) runs with very high average tolerances. The b-type runs produce almost 100% donation rates (the results are rounded to 4 significant figures in the table - the actual results are slightly less than 100%). The a-type runs have lower (yet still high) donation rates. The column labelled "Tag Clone Donations" shows the proportion of awards that resulted in a donation to a recipient agent with an *identical tag* value to the donor. As would be expected, runs that average high tolerances result in high non-tag clone donation, even though donation rates are almost at maximum. Such results indicate that all agents donate to all others and maintain the required skill diversity to exploit each resource type.

But how is this happening? Intuitively, it would appear that, in the b-type runs the population should be invaded by "cheating" agents with a low tolerance that would restrict donation to agents with tag values much closer to their own while benefiting from donations from more tolerant agents. But a moment's reflection indicates that agents may not benefit by reducing tolerance in the small decrements produced by the gaussian mutation method (described above) when the cost of donation is low and the initial tolerance is high. This is because a small decrement in the tolerance would mean that agents with higher tolerances could still be recipients of donations. Only if an agent was produced (via mutation) that had a very uncommon tag and a very low tolerance could a

substantial increase in fitness be produced. It should be noted that when the cost is increased to c=0.5 the b-type runs disappear. This could be explained by the additional evolutionary advantage that the extra cost gives to "cheaters". But do these reflections explain the results? In tables 1 and 2, the b-type runs only occur in resource rich (i.e. when awards (P) are high) environments. We currently do not have an explanation for this. Consequently the b-type runs are currently under closer investigation.

The forms of interaction and specialisation possible in the model presented in this paper are limited. The assumption that donation only takes place between two individuals (i.e. donation results from dyadic pairing of a donor and recipient) precludes the possibility of an agent donating to several agents at once. The environmental scenario, in which agents are rewarded individually for diverse skills, does not allow agents to become *full-time* specialists in other roles – such as internal group organisation roles (e.g. redistribution agents, that collect and redistribute resources to the in-group or policing agents that punish potential free-riders within the group). Intuitively, it would seem, agents would need to have *smart redistribution* (or donation) strategies than those presented in the model and richer interaction abilities. A forthcoming paper will explore the evolution of smarter redistribution strategies.

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