

Artificial Science

– a simulation test-bed for studying the social processes of science

Bruce Edmonds

Centre for Policy Modelling
Manchester Metropolitan University
cfpm.org/~bruce

1 Introduction

Science is important, not only in the knowledge (and hence power) it gives humans, but also as an example of effective distributed problem solving that results in complex and compound solutions. For even though it is usual for one or two individuals to be credited for any particular discovery in science, their efforts almost always use a host of results and techniques developed by other scientists. In this sense all scientists "stand on the shoulders of giants" in order to "see a little further". Thus, contrary to the archtypal image of lone geniuses labouring to prove their ideas despite the opinions of thier colleagues, science is fundermentally a social activity. A collection of individuals, however gifted, that did not communicate would not be able to develop science as we know it. Even the earliest scientists such as Galileo were building on the ideas of others (Copernicus) and using the technology produced by others (the telescope). Indeed some philosophers (e.g. [18]) have claimed that the only things that distinguishes the process of science from other social processes are its social norms and processes.

These processes become the more remarkable, the more they are examined. It turns out that science manages to implement many features that have been difficult to achieve in distributed AI and multi-agent systems. These include: the spontaneous specialisation and distribution of skills accross the problem space; the combination of advances and results from many different individuals to form complex chains of inference and problem solving; the reliability of established results in comparison to the uncertain reliability of individuals' work; the spontaneous autopoiesis and self-organisation of fields and sub-fields, continually adapting to problems and degrees of success; the ability of science (as a whole) to combine "normal science", characterised by much cooperative work within a common framework and "revolutionary science" characterised by sharp competition between individuals and frameworks; and the ability of science to produce coherent developments of knowledge whilst, at the same time, maintaining variety and criticism so that it can quickly adapt to the failure of any particular developments. All of this is achieved with a relative lack of: explicit central coordination; use of market mechanisms; global and explicit agreement about norms or methods; or well-defined hierarchies.

Thus science is an important subject for study in its own right, and thus also its critical social processes. The question is not so much that it is worth modelling, but how one approach modelling it in a useful way. It is the aim of this paper to suggest a framework for a set of investigations that will advance such a project. Thus the framework will be described as well as a first implemented instantiation of the

framework. Although it is the framework which I consider more important, the exhibited simulation exhibits results that are interesting in their own right.

Traditionally there is the ‘building-block’ picture of science [11] where knowledge is slowly built up, brick by brick, as a result of reliable contributions to knowledge – each contribution standing upon its predecessors. Here, as long as each contribution is checked as *completely* reliable, the process can continue until an indefinitely high edifice of interdependent knowledge has been constructed. However other pictures have been proposed. Kuhn in [14] suggested that often science progresses not gradually but in revolutions, where past structures are torn down and completely new ones built.

Despite the importance of the social processes in science to society, they are relatively little studied. The philosophy of science has debated, at some length, the epistemological aspects of science – how knowledge is created and checked ‘at the coal face of the individual’. Social processes have been introduced mainly by critics of science – to point out that because science progresses through social processes it is ‘only’ a social construction, and thus has no special status or unique reliability.

Here I take a neutral view – namely, that it is likely that there are many different social processes occurring in different parts of science and at different times, and that these processes will impact upon the nature, quality and quantity of the knowledge that is produced in a multitude of ways and to different extents. It seems clear to me that sometimes the social processes act to increase the reliability of knowledge (such as when there is a tradition of independently reproducing experiments) but sometimes does the opposite (when a closed clique act to perpetuate itself by reducing opportunity for criticism). Simulation can perform a valuable role here by providing and refining possible linkages between the kinds of social processes and its results in terms of knowledge. Earlier simulations of this sort include Gilbert et al. in [10]. The simulation described herein aims to progress this work with a more structural and descriptive approach, that relates what is done by individuals and journals and what collectively results in terms of the overall process.

2 The Simulation

2.1 Motivation and Related Work

The aim of this simulation is to suggest a set-up within which the social/interactive aspects of collective knowledge discovery can be explored. It therefore contrasts with attempts to understand what a single scientist does, by modelling and philosophy. Computational models of aspects of the work of a single scientist include those of problem solving [21] and induction [12]. Implemented models which attempt to synthesise the essential processes of a single scientist more as a whole include BACON [17], Meta-DENDRAL [1] and PI [24] (this last providing the best general discussion on the project of computationally modelling science).

There is a similar tendency in the philosophy of science, with a historical concentration on what a single scientist does. Social aspects of science have been

brought in mainly as a critique of the “received picture” of science [11] – the argument is roughly that because social processes are involved in the construction of scientific theories, that scientific truths do not correspond to an objective truth.

The philosophy of science has moved from *a priori* normative accounts (how science *should* work) to *a posteriori* descriptive accounts, largely due to Kuhn’s account of how revolutions (“paradigm shifts”) occur in science [14]. The exact nature of the social processes that occur in science are not, in general, considered. Exceptions include: Tolmin’s book [25], a recent paper by Giere [9] and a book by Knorr-Cetina [13]. However, these processes are even more rarely modelled – the only exception I know that touches on this being [10].

The individual agents in the specific simulation below are fairly simple compared to some of the models listed above – I have concentrated instead on the flow of information between agents via a publically accessible repository (corresponding to a journal) and how the agents select what knowledge to learn and use. This does not mean that a model with more sophisticated and realistic agents would not be better, just that I have not done this.

2.2 The General Structure

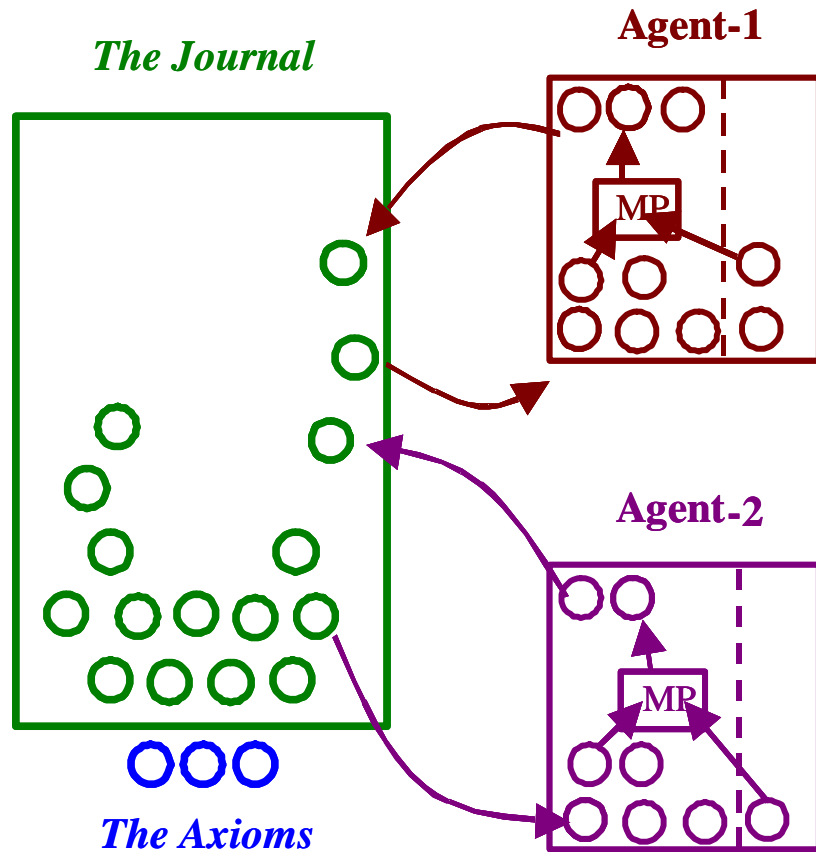


Figure 1. An illustration of the set-up with two agents (circles are items of knowledge, rectangles are agents)

The simulation involves a fixed number of agents (representing individual or closely collaborating teams of scientists) a journal (only one in the present simulation) which includes the set of formal sentences representing the knowledge that is discovered and published. Each agent has a private store of knowledge which may or may not be public (i.e. an axiom or published) – this store is their working knowledge. To use a public item of knowledge this must be added to their private store before they can use it to produce new items. They submit some of this to the journal which selects (according to some criteria) a subset which is then published and becomes available to others. The whole set-up is illustrated in Figure 1.

2.3 The Environment and Task

Science continually progresses into the unknown. In science sometimes the end points are known – for example, when it is known that a certain disease is passed on genetically, then the genes that are responsible may be sought. Often, however, scientific discoveries are a surprise to their discoverers. Thus it is often the case that scientists do not know exactly what it is they are searching for. This is in contrast to engineering where it is usual to know the problem for which an answer is sought. This poses a problem for a would-be simulator of the social and cognitive processes that contribute to science – *how can one simulate creative discovery of the unknown?*

The answer I have chosen is to use a formal system (logic) as the representation of knowledge, so that the agents work on the logical structures to produce new structures (theorems in the logical sense), but where it is impossible to know in advance how useful these will be. This decision has distinct consequences both in terms of the possibilities and limitations of the model and in terms of the assumptions on which it relies. These will be discussed later. This can be seen as following [17].

Thus the universe of knowledge that the agents will explore in this simulation is the set of inferable formal sentences derivable from a given set of initial axioms. For ease of implementation I have restricted my self to logics formalisable as Hilbert Systems (that is, ones with a set of axioms and a single rule of inference, Modus Ponens, which is recursively applied, see an introduction to logic, e.g. [4]). The agents can produce new sentences by applying existing sentences to other sentences using Modus Ponens (MP). The form of this is if you know A and you know $A \rightarrow B$ then you can also conclude B (written $A, A \rightarrow B \models B$). An example of this is: when A is $((a \rightarrow a) \rightarrow (a \rightarrow a))$ and B is $(a \rightarrow a)$: from $((a \rightarrow a) \rightarrow (a \rightarrow a))$ and $((a \rightarrow a) \rightarrow b) \rightarrow b$ we can infer $(a \rightarrow a)$. This is illustrated in Figure 2.

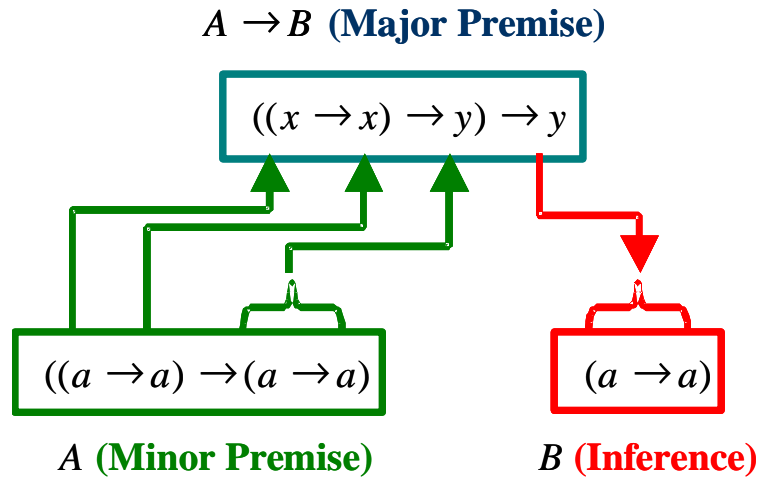


Figure 2. An illustration of the working of MP

The agents thus have the task of discovering new formal sentences. The advantages of this structure are that: (1) future developments from any item of knowledge are not known in advance; (2) knowledge is not only useful as an end in itself but can be used as a *tool*, acting upon other knowledge to produce new knowledge (as the major premise in MP, the A in Figure 2); (3) the programmer of the simulation does not necessarily know *how* one gets to any given theorem of the system, which reduces the temptation to bias the simulation to get specific results; (4) the task is suitably *hard*, as the development of automatic theorem-provers shows.

In order to set up the field of knowledge that the agents will collectively explore the simulator needs to list the symbols being used and list the axioms of the relevant logic. Optionally the simulator can also list a number of known theorems that are considered important by logicians and give them a value, though *how* one derives these is not needed to be specified (this is for the agents to find out). These 'target theorems' are unknown to the agents until they discover them. They represent (in the loosest possible way) useful technologies that may come out of science. Counting how many of these have been discovered (and the total value of their 'worth') is an indication of the effectiveness of the collective discover effort, and can be a better measure than simply counting how many new sentences have been discovered since it is easy to develop trivial elaborations of already known sentences.

2.4 The Agents

In this simulation the agents have a very simple-minded approach to the production of new knowledge: agents select two items in its own store of knowledge and apply the MP rule to it, which may or may not result in a new item of knowledge which is added to their store. Each agent has two private stores of knowledge: *firstly*, a store

of formal sentences that are candidates as the minor premises for the MP rule and *secondly*, store composed of candidates for the major premises. The former roughly corresponds to the primary knowledge of a scientist and the second as the set of techniques of the agent since it determines which transformations can be applied to which items and what can be produced.

Each time period the agent does the following:

1. Decide what new items of knowledge (both major and minor) to add to its private store from the published set, also which to drop.
2. Decide which major premise and what set of minor premises it will try with the MP rule and add any results to its (minor) store.
3. Decide which of its private knowledge (that is not already public) it will submit to the journal.

There are obviously many different ways of making these decisions. Each of these ways will have a (varying) impact upon the development of the collective knowledge. In addition to the above, gradual, update policy if the agent fails to discover any new sentences during a given number of consecutive time periods it may 'panic' and completely replace one of its stores with a new set of sentences.

Key parameters and setting of the agent are as follows. For each of its private knowledge stores (minor and major) the update policy includes the following: its size; the rate at which it adds or drops knowledge from this store; *how* it does either the addition; the dropping; or the panic replacement (at random/probabilistically the best/the best judge either on raw past fertility or past fertility with a bias towards simplicity); whether it panics and how long it endures lack of success before panicking; which to try (the best/probabilistically the best/untried/random); and how it judges what it knows (personal fertility/lack of failure to produce new knowledge). Also its submission policy: whether it submits all novel (i.e. unpublished) sentences to the journal or only the simplest/best ones.

2.5 The Journal

The journal (*the Journal of Artificial Sentences and Successful Syllogisms*) is the gatekeeper to the repository of public knowledge. The key aspect of the journal is the criteria it uses for assessing the items submitted to it, so as to decide what (if any) it will publish. This occurs in three basic stages: the short-listing of those that met basic criteria; the evaluation of those short listed; and their ranking. The journal then published a selection of the top n in the ranking (if there were more than n short listed), otherwise all of them. This final selection could be the best (from the top); probabilistically on the weighted score (the higher the score the more likely it is to be selected); randomly or simply all of them. The evaluation of the submissions was done as a weighted sum of scores for a number of aspects: the number of variables in the sentence, its brevity, the extent to which it shortens sentences when used in MP, and the past success of the author. The weights and selection policies can be set by the programmer.

2.6 Methods of evaluation

Key to many of the decisions made by the agents or the journal is the evaluation of the existing knowledge. Ultimately this can be considered as a guess at the future usefulness of that knowledge, in terms of either: its productivity in producing new knowledge; reaching the hidden ‘target theorems’; or in getting published. This may be done in a number of ways. One way is by looking at the historical record of how productive the sentence has been in the past in resulting in new published knowledge (this can be done in a recursive way to value sentences that have produced productive sentences etc.). Another way is to look at the most published agents and see what knowledge they have used (in published work). Other ways include considering features of the sentences themselves, for example measures of their simplicity (how many variables they have, how long they are, to what extent the sentence results in a shortening of sentences when applied using MP, etc.)

3 Preliminary Results

At the time of writing only preliminary results are available, which explore only a very small proportion of the possibilities inherent in this model.

Many of the settings do affect the outcomes to a significant degree. However many which increase the short-term success (measured in a number of different ways) of the scientific progress also have the effect of reducing the longer-term maintenance of new results. Thus, for example, adding new sentences *at random* to an agent’s private knowledge (i.e. regardless of the agent’s evaluation of sentences) decreased the short-term level of discovery markedly, but then that level of discovery lasted a longer time. In contrast where agents follow other agents closely (preferentially adding sentences used successfully by others) results followed much more quickly to begin with but then petered out to zero after 40-60 time periods (only then deviating from zero when an agent panicked and hit lucky with its new set of knowledge). Such a result would indicate that a process of fairly frequent, but collective revolution was one of the most efficient collective modes of discovery.

In general most of the targeted sentences were either discovered very soon, or never. This suggests that “deep” sentences (those difficult to reach in this collective but individually stupid manner) require guidance from a deeper knowledge of the individual logics concerned, and is not so amenable to a generic approach (collective or otherwise).

3.1 Varying the rate of publication

The set of results I will exhibit here are those concerning the effect of the journal’s policy on the whole discovery enterprise. The number selected by the journal to publish were varied from the set $\{1, 2, 3, \dots, 10\}$ in 250 independent runs with 20 agents and 50 iterations. The journal selected according to a number of factors, which were (in order of importance): the extent to which a formula had the effect of

shortening formula when applied as the major premise in MP; the shortness of the formula itself; the past publishing success of the author; and the fewness of the number of distinct variables in the formula. The journal ranks all submissions according to a score composed of a weighted sum representing the former priorities. Agents submit all formula they discover to the journal if they have not been previously published. Each agent has a store of 4 major premises and 27 minor premises and tries 9 different combinations of major and minor premises with MP each iteration. Generally agents change 1 major and 2 minor premises each time. New major premises are chosen probabilistically according to a formula's past fertility in producing formula that are published. Minor premises are chosen at random. If an agent is completely unsuccessful for a certain length of time they panic and replace all of their premises with new ones. The exact settings are those listed in section 6.1 in the appendix, and were those found in unstructured experimentation to be one of the more productive settings for agent behaviour.

The journal was never short of material to publish even when it was publishing 10 formulae each iteration. Thus the rate of publishing is directly related to the size of the body of publically known formula accessible to agents, as is shown in Figure 3.

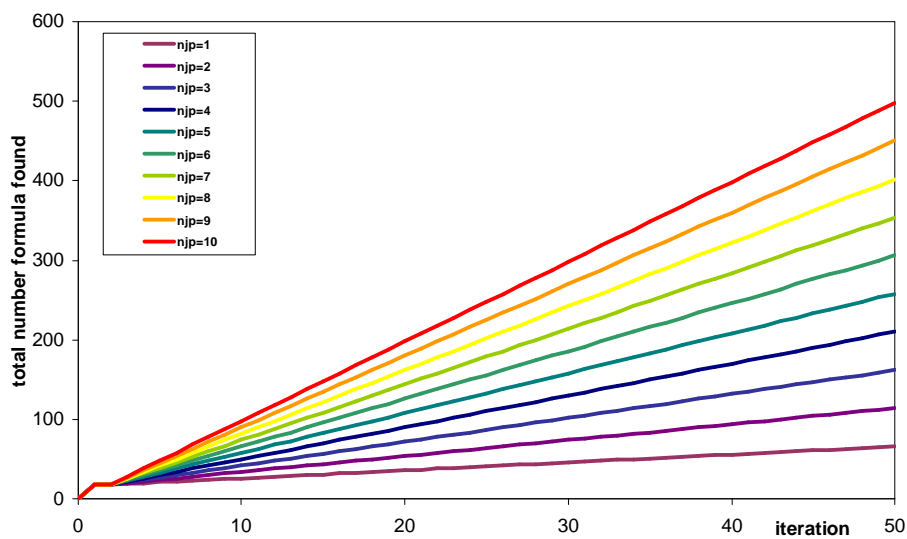


Figure 3. Total number of formulas publically known at each iteration (averaged over 25 runs) for different journal publication rates (njp)

However, this does not mean that a higher publication rate results in finding more useful knowledge, for this does not tell us how useful these are. The system was given a list of 110 target theorems – those listed as significant in logic textbooks. Figure 4 shows the average number of these theorems that the system discovers for different publication rates (averaged over 25 runs). The publication rate did not make a big difference to the number of discovered targets and that almost all discovery

occurred early on. Usually 11-12 targets were found. Only once 20 were found at publication rate of 2 (this explains why this line is higher than the others).

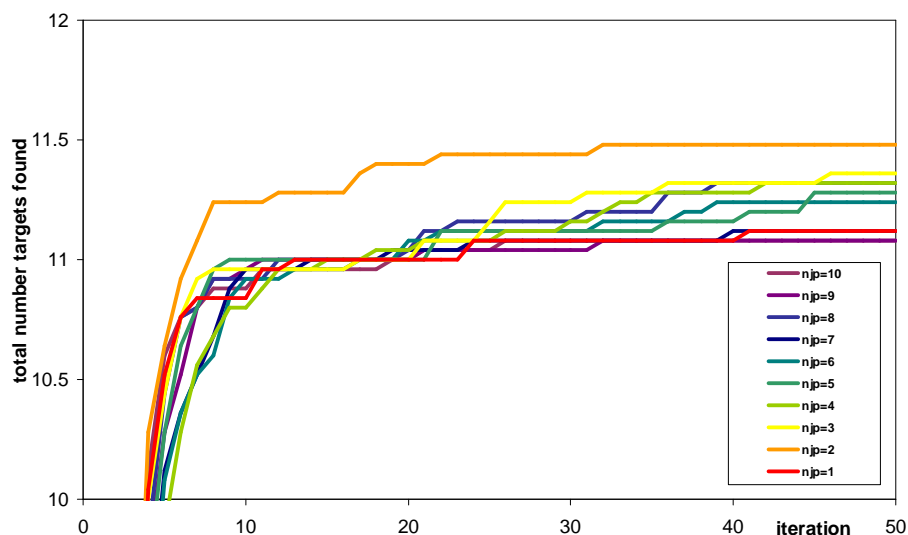


Figure 4. Total number of target formulas discovered (averaged over 25 runs) for different journal publication rates (njp)

What is interesting is that this discovery rate was fairly independent of the number of submissions to the journal. Roughly, the higher the publication rate, the lower the number of submissions as Figure 5 shows. Whilst at first sight this seems counter-intuitive, it is less so given that the more knowledge has been published, the more difficult it is to find something new to submit. Although in each case the system did learn to find very many of the target formulae. Clearly, in this particular case, published knowledge was not so useful in producing new kinds of knowledge.

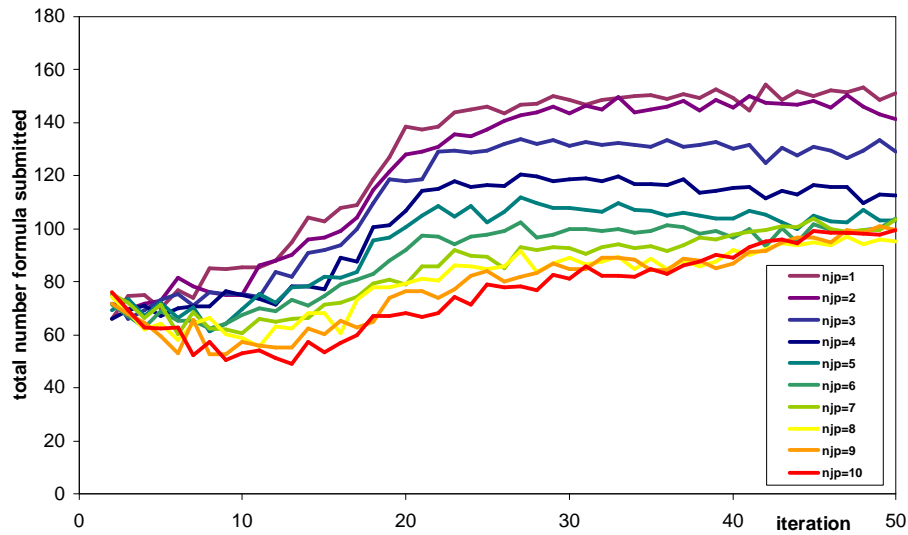


Figure 5. Total number of formulas submitted at each iteration (averaged over 25 runs) for different journal publication rates (npj)

Also interesting is the disparity between agents in terms of the number of new formula discovered (i.e. unpublished and not known by the agent concerned). Whilst initially a higher publication rate meant less disparity between agents, after a while some agents learnt to do so much better than others and dominate (Figure 6).

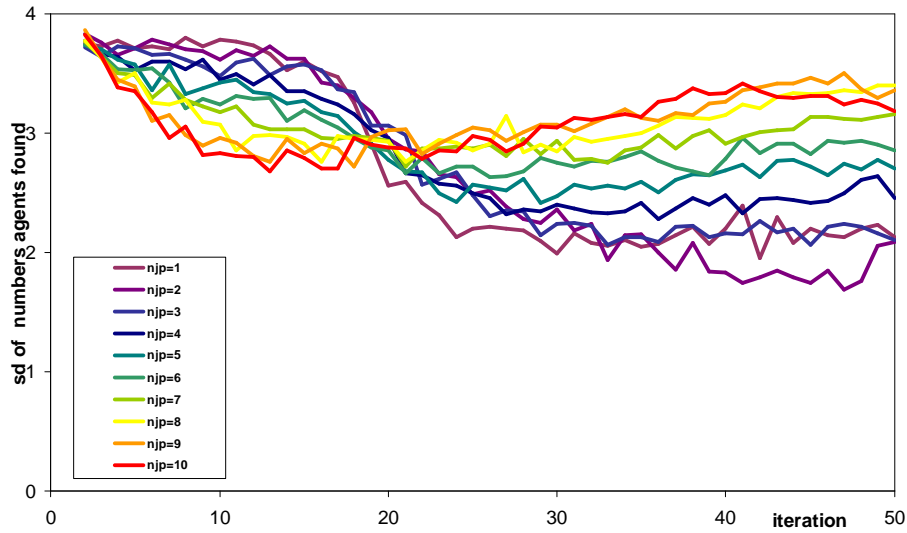


Figure 6. Spread (standard deviation) of the number of unpublished formula found by agents each iteration (averaged over 25 runs) for different journal publication rates (njp)

Now to look at a particular run (the one which discovered 20 formulae). Figure 7 shows the number discovered the 20 agents – the thickness of each band represents the number that agent found. Note the variation in terms consistency in performance.

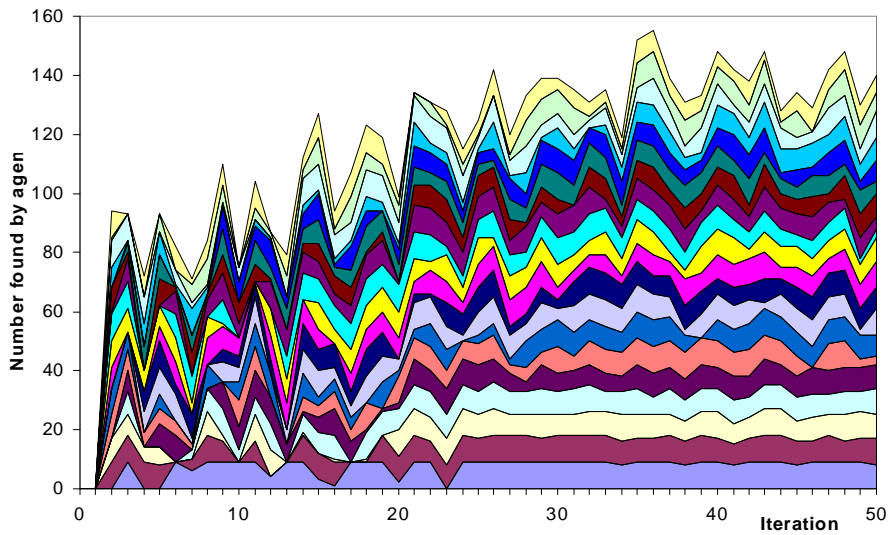


Figure 7. The number of unpublished formula found by each agent in a single run (each agent is represented by a single 'band' in the chart, the best on average at the bottom)

Figure 8 shows the average and the standard deviation of the number discovered by each agent in the same run as above. The number generally increases, and the standard deviation (in terms of raw discovery) tends to increase. It may be that the initial diversity facilitated the early, relatively high target discovery rate.

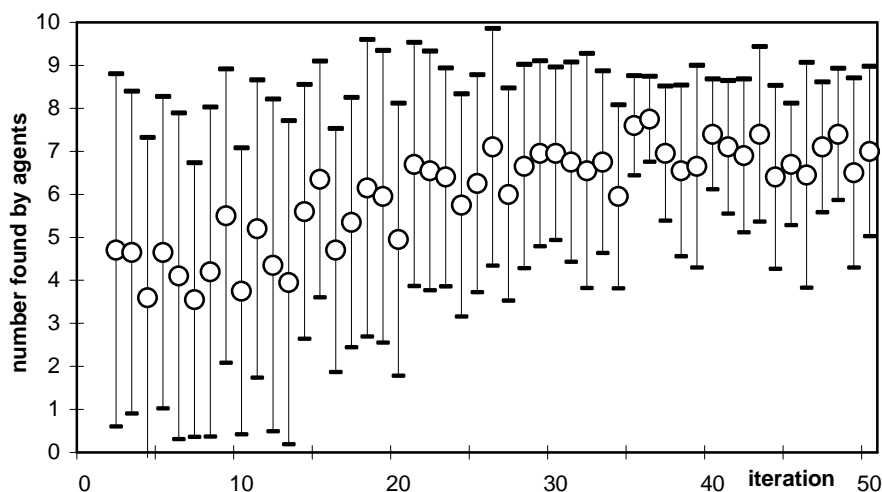


Figure 8. The average number of unpublished formula found by each agent in the particular run (average is show by the circles and the vertical lines show +/- one standard deviation)

The purpose of these results is *not* to conclusively show anything in particular about how many papers a real journal should publish, or even how many might be optimal. Rather it is to show how such a set-up can illuminate and explore such questions.

4 Discussion

4.1 The Possibility of Limited Validation

Following [10], it may be possible to compare the structure of the published knowledge that results in this simulation (i.e. which authors/items are derived from which previous items by which authors) might be compared with the structure found in citation indexes such ISI using a number of measures, statistics or structural comparisons. Unfortunately negotiations with ISI indicate that they are only prepared to part with the structural information of their databases (suitably anonymised) for rather large quantities of money (i.e. around \$30000). If anyone knows of an alternative source, please contact the author.

4.2 Limitation and Extensions

Clearly many of the limitations in this simulation are arbitrary: Thus I list a few possible extensions as examples:

- decision methods of arbitrary complexity can be implemented in agents (indeed these methods could themselves be evolved by GP) – in particular they might do more reasoning about causality [22];
- there could be many journals so that the: prestige of a journal; its topics; its impacts and the quality of its submissions could be allowed to co-develop inside the simulation;
- instead of inferring new knowledge the agents could hypothesise and test candidate sentences performing tests on the logical semantics (e.g. a row of the truth tables in classical logic) – this would introduce levels of uncertainty as to the reliability of any particular item of knowledge;
- a peer review system could be implemented whereby reviewers are selected depending on their past publishing success and impact; they could use their own experience of what is useful as their criteria for judging entries and their own tests; and items could be selected resulting on the votes of reviewers;
- informal social networks could be introduced to pass knowledge from agent to agent other than via official journals;
- agents should be allowed to reproduce in terms of the students they teach and retire after a suitable time (or if they are spectacularly unsuccessful).

More fundamentally the present structure of the simulation assumes that there *is* some independent ‘correct’ knowledge to be discovered and that it is checkable. This could be corrected by providing some database of atomic facts (e.g. the linkage structure of part of the web) and then hypotheses about these could be attempted to be induced (as in inductive data-mining techniques). The journal (or journals) would not be able to 100% check the veracity of any knowledge but have to rely on some fallible process to come to a judgement upon the knowledge. However, a disadvantage of such an approach is that it would lack the tight inter-dependency of knowledge that seems to be such a characteristic of some sciences¹.

4.3 Relationship with Distributed Theorem Proving (DTP)

The simulation *is* a forward-chaining theorem prover, and can be seen as an answer to [8] since it could be truly distributed. However it is a very inefficient one – it is deliberately *generic* in that it has not been ‘tuned’ for performance (by using deep properties of the particular logic being investigated), since this is not its goal. Despite this, lessons learned in this simulation do have potential in terms of informing the design of distributed theorem provers and *vice versa* from what is discovered about efficient DTP to this simulation (and potentially science itself²).

¹ Of course it *may* be that this *is* more appropriate for the social sciences.

² One can but dream!

OTTER [26], a particular and quite successful theorem prover is quite close to the how a single agent works in the above simulation. It has a list of candidate minor and major premises and works on these to extend the set of known sentences until it reaches the target theorems. It allows for a large range of techniques in re-writing formulas, guiding search and applying rules that are not touched upon here.

4.4 Key Questions and Issues

Perhaps most the important aspect of this paper is that it shows how a host of important issues and questions concerning the social processes of science (and science-like processes) may be investigated. Is Feyerabend's thesis that any imposed method for constructing scientific hypotheses is counterproductive [7], and the best way forward is "anything goes"? To what extent does the particular formal system affect the progress in any particular field [5]. In what circumstances and in what ways can inter-scientist processes contribute to the reliability (or otherwise) of the knowledge produced [9]? Is it helpful to have an inviolate core of unquestioned truths and techniques in a field or is it better that everything is open to revision [15]? Do scientists, in effect, create blind variations to then be tested as suggested in [2]? Are scientific norms the key characteristic that distinguishes science from other human institutions **Error! Reference source not found.**? When is it better to use a simplicity bias in the search for useful knowledge [6]? Answers to these questions may be suggested in functional terms by studying simulation models on the lines of the one discussed.

4.5 Conclusion

I hope to have shown how it is possible to capture some aspects of the social processes that contribute to the construction of science. Such modelling has the potential to intermediate between observations concerning how science works and areas of distributed knowledge discovery in computer science, e.g. automated theorem proving. It could help sort out the roles of the different processes in science confirming or disconfirming philosophical speculations as well as provide productive ways to parallelise computational tasks such as theorem proving.

5 References

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6 Appendix

6.1 Parameter settings

```
addRateMajor = 1
dropRateMajor = 1
```



```

addRateMinor = 2
dropRateMinor = 2
numInitialSAgents = 20
maxIteration = 50
maxRun = 250
numMajor = 4
numMinor = 27
interalScoreDecay = 0.9
fertilityDecay = 0.9
numToTry = 9
panicSoonTime = 4
panicLaterTime = 12
maxNumberToPublish = [1,...10]
minNumberOfVariablesForPublication = 1
shorteningWeight = 0.1
shortnessWeight = 0.01
sourceWeight = 0.001
numVariablesWeight = 0.0001
modelBehaviourList = [fertilityIsInverseLength
matchTargetGenerically publishBest]
behaviourList = [submitAll]
majorBehaviourList = [addFertileProb dropWorst
feedbackOnUsedFailure panicLater replaceBestIfBad tryBest]
minorBehaviourList = [addRandom dropWorstProb
feedbackOnFertility panicSoon replaceProbFertileIfBad
tryUntried]

```

6.2 Sample output from selected run

```

Iteration 1
Iteration 2
agent 2 found '->' A ('->' A ('->' A A))
agent 2 found '->' ('->' A B) ('->' ('->' C B) ('->' A ('->'
C B)))
agent 2 found '->' ('->' A B) ('->' ('->' B A) ('->' B A))
agent 2 found '->' ('->' A B) ('->' ('->' A B) ('->' A B))
agent 2 found '->' ('->' A A) ('->' A A)
agent 2 found '->' ('->' A A) ('->' ('->' A A) ('->' A A))
agent 6 found '->' A A
agent 6 found '->' ('->' A A) ('->' A A)
agent 10 found '->' ('->' A A) ('->' A A)
agent 12 found '->' A ('->' A ('->' A A))
agent 12 found '->' ('->' A B) ('->' ('->' C B) ('->' A ('->'
C B)))
agent 12 found '->' ('->' A B) ('->' ('->' B A) ('->' B A))
agent 12 found '->' ('->' A B) ('->' ('->' A B) ('->' A B))
agent 12 found '->' ('->' A A) ('->' A A)
agent 12 found '->' ('->' A A) ('->' ('->' A A) ('->' A A))
agent 18 found '->' ('->' A A) ('->' A A)
agent 19 found v A ('->' A)
agent 19 found '->' ('->' A B) ('->' ('->' B C) ('->' A C))

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agent 19 found '->' ('->' A A) ('->' ('->' A A) ('->' A A))
agent 19 found '<->' ('&' A ('¬' A)) F
Iteration 3
agent 3 found '->' ('->' A ('->' B C)) ('->' B ('->' A C))
agent 3 found '->' ('->' A ('->' ('->' B C) D)) ('->' ('->' B
C) ('->' A D))
agent 6 found '->' ('->' A ('->' B B)) ('->' A ('->' A ('->'
B B)))
agent 6 found '->' ('->' A ('->' A B)) ('->' A B)
agent 6 found '->' ('->' A B) ('->' ('->' B A) ('->' A B))
agent 17 found '->' ('->' A ('->' A B)) ('->' A B)
agent 19 found '->' ('->' A B) ('->' ('->' C A) ('->' C B))
agent 19 found '->' ('->' A B) ('->' ('->' C ('->' ('->' A B)
D)) ('->' C D))
Iteration 4
agent 7 found '->' ('->' A B) ('->' ('->' ('->' A B) C) C)
agent 7 found '->' A ('->' ('->' A B) B)
agent 13 found '->' ('->' A ('¬' A)) ('¬' A)
agent 15 found '->' ('->' A ('¬' A)) ('¬' A)
Iteration 5
Iteration 6
Etc.
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