A computational approach to socially distributed cognition.

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Abstract. In most Interactive Learning Environments (ILEs), the human learner interacts with an expert in the domain to be taught. We explored a different approach: the system does not know more than the learner, but learns by interacting with him. A human-computer collaborative learning (HCCL) system includes a micro-world, in which two learners jointly try to solve problems and learn, the human learner and a computerized co-learner. This paper presents the foundations of this artificial co-learner.

The collaboration between learners is modelled as 'socially distributed cognition' (SDC). The SDC model connects three ideas: i) a group is a cognitive system, ii) reflection is a dialogue with oneself, iii) social processes are internalised. The key has been to find a computational connection between those ideas. The domain chosen for illustration is the argumentation concerning how some changes to an electoral system affect the results of elections. This argumentation involves a sequence of arguments and their refutations. The basic principle is that learners 'store' the structure of this argumentation (dialogue pattern) and 'replay' it individually later on. The verbs 'store' and 'replay' do not refer to a simple 'record and retrieve' process. Storage is implemented as the incremental and parameterised evolution of a network of arguments, here called a 'dialogue pattern'. The learning outcome is a structuration of knowledge (rules) into situation-specific models, used to guide reasoning.

We conducted experiments in two settings: with a human and an artificial learner or with two artificial learners. The common findings of these two experiments is that the SDC model generates learning effects provided that the discussion is intensive, i.e. that many arguments are brought into dialogue. The importance of this variable also appears in Hutchins' (1991) modelling of the evolution of the confirmation bias in groups. It is argued than computational models are heuristic tools, allowing researchers to isolate variables for designing empirical studies with human subjects.

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Introduction

Research on collaborative learning is inscribed within the "social versus individual" debate. For Butterworth (1982) and Resnick (1991), the opposition between the Piagetian and Vygotskyan streams have been exaggerated. Perret-Clermont, Perret and Bell (1991) state that "*... research paradigms built on supposedly clear distinctions between what is social and what is cognitive will have an inherent weakness, because the causality of social and cognitive processes is, at the very least, circular and is perhaps even more complex*" (p. 50). Our work goes in that direction. Instead of choosing the individual or the group as the primary unit of analysis, we concentrate on the similarities between individuals and groups. We consider both individuals and groups as instances of a more general class, called 'cognitive system'. We postulate that the similarities between the individual and social levels constitute a mechanism of internalisation.

An 'AI & Education' perspective

Many researchers in Artificial Intelligence and Education (AI & Ed) view the design of an ILE as an attempt to formalise some theory of learning or teaching. We attempted to ground our work in a computational model that goes beyond the particular implementation of a system. The specification, the implementation and the experimentation of this model are reported in this paper. However, in order to clarify the status of our computational model, we briefly describe the research context.

The model presented in this chapter results from a research project on ILEs. The initial goal was to explore HCCL as an alternative to learner modelling (Self, 1986). The idea was to apply machine learning techniques on the set of examples and counter-examples observed by a learner. The algorithm would then elaborate a concept that approximates the learner's concept. This approach raises two fundamental issues. First, the learning algorithm should be psychologically valid, which is not the case for most machine learning techniques. Second, the concept acquired by a human subject depends not only on the instances she observed, but also on her previous knowledge, e.g. her knowledge of close concepts. This prior knowledge must be provided as input to the learning algorithm, i.e. some diagnosis would be required anyway. Thus, the HCCL approach does not simplify the diagnosis task.

We were interested in exploring new architectures for ILEs. Traditionally, an ILE includes three components: (i) the 'expert model' includes the knowledge to be taught, (ii) the 'learner model' stores what the system knows about the learner, (iii) the 'tutor model' holds the knowledge necessary to run didactic strategies. This architecture is actually more conceptual than real. The expert model is generally the main system component, and the learner and tutor model are rather appendices to the expert kernel. The learner model includes some erroneous knowledge that may be combined with the expert's knowledge to reproduce the learner's behaviour. The tutor model contains the knowledge necessary to schedule and present the expert's knowledge.

This preponderance of the expert model has positively influenced the evolution of educational computing, by moving the focus from the learner's answers to her processes and by compelling system designers to perform the intensive analysis of content. However, this expert model has led to a normative view of expertise in ILEs. The implicit goal of most systems is that the learner acquires the expert's knowledge. Expert-centered systems are basically in contradiction with the dominant views in psychology: i) that knowledge must be individually constructed and ii) that knowledge is the shared product of social processes. The learner might wonder why she has to reconstruct knowledge that exists in an inspectable form in the system (Dillenbourg, 1992). The centrality of expertise is a bias towards pedagogical directivity and towards a normative view of knowledge. Researchers have addressed some issues related to expert-centred systems. For instance, they have developed systems that can adopt multiple viewpoints (Moyse, 1989) and apprenticeship systems (Newman, 1989). HCCL is a more radical alternative to the 'expert-learner-tutor trinity': it suppresses of course the domain expertise, but also the tutor model since there is no teaching and the learner model since a diagnosis is useful for selecting didactic strategies (which don't exist here). INTEGRATION KID (Chan and Baskin, 1988) occupies an intermediate place between the traditional structure and 'HCCL hard line', since this collaborative system still includes a tutoring component.

Role and focus of the model

An HCCL does not necessarily need a model of collaborative learning. In INTEGRATION KID (Chan and Baskin, 1988), the authors have a priori implemented a sequence of knowledge states; the co-learner does not learn incrementally, but jumps to the next knowledge state when the tutor decides it. We could have a system like ELIZA (Weizenbaum, 1966): even if a co-learner does actually not understand anything, it could still involve the learner in significant activities by randomly asking 'why?', 'please explain', etc. However, this weakens the HCCL idea, since it removes the causal relationship between social activities and learning. We believe a HCCL system must be built around a computational account of this causal relationship. This is precisely the role of our model of collaborative learning.

To some extent, the idea to implement this model is very naive. Since people do not have two brains, one to learn alone and one to learn with a peer, since most cognitive functions are involved in large labels such as 'learning' or 'collaboration', the model should hypothetically reproduce the whole human cognitive functioning. To remain within sensible limits of ambition, our model focuses on a particular feature of cognition. Hutchins (1991), who developed a model similar to ours, studied for instance how social processes influence the *confirmation bias*, i.e. the fact that subjects tend to discard empirical evidence that contradicts their hypothesis (Johnson-Laird, 1983; Klahr and Dunbar, 1988). We will report his work after the description of our model, in order to describe more easily the similarities and differences between our respective approaches. For our model, we have chosen to concentrate on the *internalisation of mutual regulation* skills. During collaboration, each peer is often requested by his partner to explain why he suggested or performed some action. This meta-knowledge, which he implicitely used to regulate his own action, is then made explicit to regulate the joint actions. Blaye (1988) observed that these social regulation processes are later mastered by individuals. Wertsch (1985) has established the communicative dimension of the internalisation process (Vygotsky, 1978), by showing that a change of language prepares, within the social stage, the transition to the individual stage. The central role of communication also emerges on the Piagetian side. Blaye (1988) suggests that the intensity of the socio-cognitive conflict (Doise and Mugny, 1984) is less important than the fact that it generates dialogue. Perret-Clermont, Perret and Bell (1991) reinterprets their socio-cognitive experiments in the light of implicit messages conveyed by the experimenter's questions.

It is interesting to notice that the relation between communication and regulation is also a core issue of *distributed artificial intelligence* (DAI). Gasser (1991) sets the goal of DAI as "understanding and modeling action and knowledge in collaborative enterprises" (p.108). Durfee, Lesser and Corkill (1989) refer to the "study of how a loosely coupled network of problem solvers can work together to solve problems that are beyond their individual capabilities" (p. 85). Designers of DAI systems noted that there is a trade-off between the need for central control (regulation) and the agents' ability to convince each other through argumentation. The convergence of psychological and computational approaches to social cognition led us to focus our work on the acquisition of regulation skills through communication. The place given to communicative processes within cognitive systems discriminates social from individual theories of mind.

The 'Socially Distributed Cognition' Model

The 'socially distributed cognition' (SDC) model is based on three postulates. They are presented in increasing order of specificity with respect to the focus defined in the previous section. The first one specifies what we mean by 'socially distributed cognition'. Our model is loosely related to Minsky's (1987) "Society of mind". According to Minsky, intelligence emerges from the combination of mental agents, each responsible for a "smaller process". The number of agents is very large, but they are organised into a hierarchical structure that he called a "bureaucracy". We are interested in another kind of social organisation, its distribution over several individuals. We henceforth use 'agent' to refer to a cognitive process and 'device' for the place where agents are 'implemented ' (a human subject or an artificial system).

Postulate 1.
An individual is a society of agents that communicate.
A pair is also a society, variably partitioned into devices.

The individual and the group are cognitive systems, we represent both of them as a society of agents. The composition of this society does not depend on the number of devices (individual versus group), but on the problem being solved: several researchers have observed a spontaneous and unstable distribution of task among peer members (Miyake, 1986; 0'Malley, 1987; Blaye et al., 1991). We use the same computational representation for an agent, whether it belongs to a device or another.

Postulate 2.
The device border determines two levels of communication: agent-agent communication and device-device communication. Inter-agent and inter-device communications are isomorphic.

The border between devices defines two types of communication: communication between agents within a device and communication between agents from different devices (see figure 1). Postulate 2 claims that these two levels of communication are isomorphic. The precise meaning of 'isomorphic' will be clarified shortly.

Postulate 3.
Inter-device communication is observable by each device. Therefore, inter-device communication patterns generate intra-device communication patterns

Postulate 3 outlines an important difference between inter-agent and inter-device communication: the latter is observable. It becomes an observable object of the environment and, because it is observable, subjects can induce regularities (patterns). The duality of the isomorphism (postulate 2) and the difference between these two communication levels determine the mechanism by which intra-device and inter-device communication processes influence each other: *inter-device communication structures are internalised as intra-device communication structures*. This third postulate corresponds to our research objective: mutual regulation processes, encompassed in inter-device communication, create self-regulation processes.

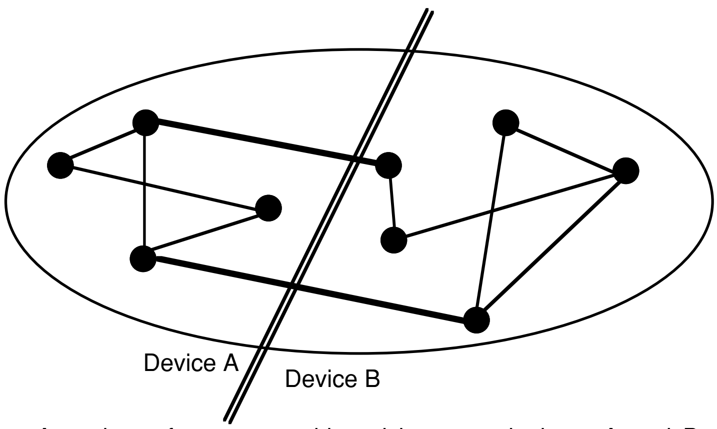

Figure 1: A society of agents partitioned into two devices, A and B. Thin lines indicate inter-agent communication and thick lines inter-device communication.

In short, this model relates three ideas. The first idea views a group of subjects as a single cognitive system. This implies that reasoning and collaborating are two instances of dialogue: reasoning is a dialogue with oneself and collaborating a dialogue with the peer. That is the second idea. It is not new, it has been proposed by several psychologists of the beginning of the twentieth century:

- "*Reflection is the transferal of argumentation to an internal level*" (Vygotsky, 1981, quoted by Wertsch, 1985)
- "*Logical reasoning is an argument we have with ourselves and which reproduces internally the features of a real argument*" (Piaget, 1928, p. 204).
- Mead (1934) refers to thought as a "*conversation with the generalized other*", in which the concept of conversation includes gestures and emotions.

Because of the isomorphism between the two dialogue levels (social and individual), each level influences each other. Especially, the social dialogue generates structures for the reflective dialogue. That is the third idea. The SDC model is thus based on classical ideas. Our contribution is to organise these ideas into a logical structure that has the consistency necessary for implementing a computational model.

A simple example

Before describing our implementation, we illustrate our approach with a simple example. Figure 2 shows an imaginary dialogue between two mountaineers. Lucil suggests carrying on to the top and Jerry suggests going down. This discussion can be represented in a simple way by the 'dialogue pattern' shown in figure 3. Lucil's goal is to *prove* that it's a good thing to go to the top. Jerry's first utterance (#2) refutes Lucil's argument (#1). By refutation, we mean a sequence of arguments that proves (in the AI meaning) the goal opposite to the speaker's goal. In this case, the refutation sequence has only one argument. Lucil's second utterance (#3) refutes Jerry's refutation, since it denies that clouds will reduce the view. Then Lucil continues her argumentation. We use the label 'continue' to refer to two consecutive arguments within a proof, Lucil's proof being constituted of two arguments (#1 & #4).

Lucil (#1)>	*Come on, the view is great from the top.*
Jerry (#2)>	*The clouds are coming.*
Lucil (#3)>	*The top is higher than the clouds roof,*
Lucil (#4)>	*... and snow is good, the risk of avalanche is low,*
Jerry (#5)>	*Yes, but it will be late when we'll return.*

Figure 2: A fictional dialogue among mountaineers.

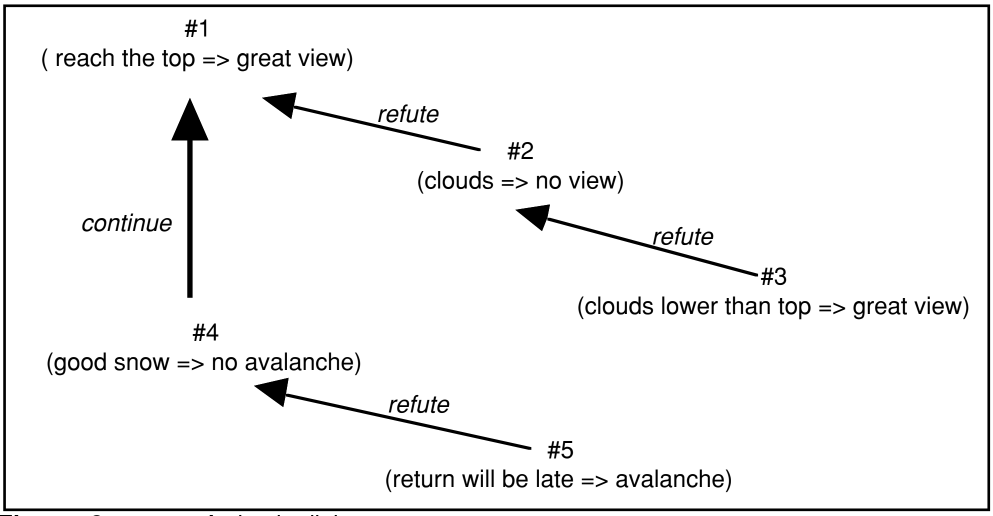

Figure 3: A simple dialogue pattern

Let us imagine that Lucil climbs another mountain, two weeks later, with no snow, and hesitates between continuing or not. She can roughly have the same discussion with herself that she had with Jerry. She can replay the first part of the dialogue (#1-3), but not the second part (#4-5) which is not appropriate to the new context (no snow).

The technique we have implemented consists of storing and replaying dialogue patterns. A pattern is a network of relationships between arguments. A pattern is stored with some knowledge about the context in which it has been expressed. The probability that Lucil replays individually such a dialogue depends on two factors. The first one is her confidence in Jerry, hereafter, the *social sensitivity*: there are more chances that Lucil pays attention to this pattern if Jerry is a guide. The second factor is the environmental feed-back. If Lucil convinces Jerry to continue, and if it occurs that there is no view at all, it is more likely that Lucil will pay attention to Jerry's counter-arguments in the future. These two factors modify the patterns by updating the strength of links between arguments. This example describes, modus modendi, the implementation of the SDC model.

The HCCL implementation: PEOPLE POWER

The SDC model has been implemented within an HCCL. The HCCL system, named PEOPLE POWER, concerns political science. The goal is that learners discover the mechanisms by which an electoral system is more or less proportional. The system includes four components (see figure 4) : (i) a micro-world in which the learner can design an electoral experiment, run it and analyse the results; (ii) an interface by which the human learner (and conceptually the co-learner) plays with the micro-world; (iii) the co-learner, i.e. the implementation of the SDC model plus the co-learner's initial knowledge base; (iv) an interface that allow learners to communicate with each other. The co-learner, named Jerry Mander, interacts to solve problems. It has no access to any hidden expertise and it has no hidden didactic goals: it asks questions to get the answers, not to check if the learner knows the answers.

PEOPLE POWER is written in object-oriented Common Lisp (CLOS) and runs on a Macintosh. The learners' activities cycle is (i) design an electoral experiment (i.e. choose parties, candidates, laws, organise the country map into constituencies, allocate seats to constituencies, etc.); (ii) run the electoral experiments; (iii) observe, analyse and compare electoral results with various interface facilities. We concentrated on the collaboration occuring during the first stage, i.e. the design of an electoral process. The visible part of collaboration is the dialogue by which learners agree on the features of the electoral system.

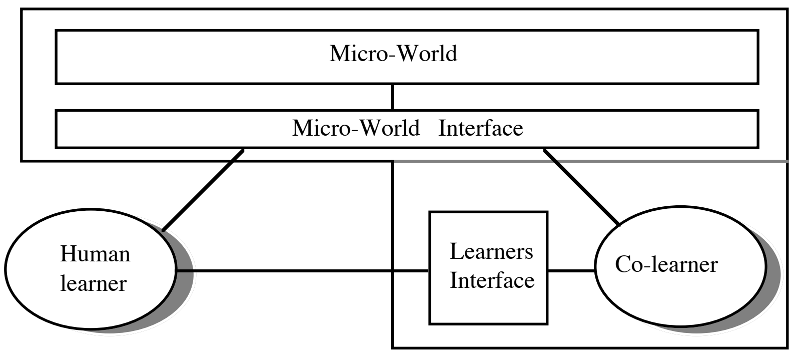

Figure 4: Components of People Power

PEOPLE POWER supports a free exploration of the micro-world. However, in order to test the SDC model and measure learning, we have reduced the scope of activities to a game, named the 'Euro-Demago' game. Twelve countries are presented to learners. For each country, learners have to reorganise the map. The goal is to get at least one more seat for their party (the Demagogic party). Learners are allowed to move only one ward from one constituency to another. When they have modified the map, they run the elections and check whether they have gained seats or not. If not, they try another change. We measure performance as the number of attempts necessary to gain seats in one country. Learning should lead to a decrease in this number of attempts.

At the knowledge level, what the co-learner will acquire is some structure of arguments. Initially, the co-learner has some naive knowledge about elections. Nobody learns from scratch. Machine learning research has clearly shown the importance of prior knowledge in learning (Michalski, 1986). Jerry Mander has a set of arguments, represented by rules, to reason about elections. For instance, a rule says "If a party gets more votes, then it will get more seats". This rule is naive. While not basically wrong, it is only true in some circumstances. Jerry learns when it may apply this rule, essentially with respect to the arguments that have been used before.

Monologue and dialogue

Traditionally, AI has clustered cognitive activities into research streams such as machine learning, expert systems or computational linguistics. This artificial clustering was necessary but costly. For instance, knowing how the concept to be learned will serve in problem solving is a powerful heuristic that has been neglected in inductive learning. The SDC model by-passes the boundaries between learning and problem solving, and those between reasoning and communicating. Jerry Mander uses a single process for both searching for a solution and dialoguing with the real-learner. This procedure uses two arguments, the proposer and the criticiser. If two different learners are respectively assigned to each argument, the procedure performs a real dialogue. If the same learner is used for both arguments, the procedure does monologue, i.e. reasoning.

The procedure is a theorem prover: in the context of PEOPLE POWER, it must prove that some change in the country map will lead to a gain of seats for the Demagogic party. Because this theorem prover must interact with a human learner, we prefer a natural deduction system to a resolution-based prover: "*The advantage of natural deduction is chiefly that the proofs it produces are relatively easy to understand. This is very important whenever there is interaction between an automatic theorem prover and a human.*" (Cohen and Feigenbaum, 1982, p. 101). It may function forward or backwards. It runs backwards when Jerry searches for a change to perform or searches to disprove the change proposed by its partner. It runs forward when Jerry 'replays' its argumentation to justify its choice to its partner.

The procedure explores a tree of rules (or arguments), in depth-first search. In the simple monologue mode, a learner explores the tree backwards until it proves that some map change leads to gaining seats. In the dialogue mode, this learner (the proposer) shows its inference path step-by-step to the other learner (the criticiser). The dialogue structure is analogous to the mountain climbers example. When a learner proposes an argument, the criticiser attempts to prove that this argument does not guarantee a gain of seats. If the criticiser does not find any counter-argument, the proposer continues its argumentation. If the criticiser finds a counter-argument, it initiates a new sub-dialogue in which the proposer and criticiser roles are inverted. This recursive procedure could theoretically lead to a large number of embedded sub-dialogues, but practically, our rule base did not generate a dialogue depth superior to 3.

Figure 5 shows an example of dialogue 'purely' generated by the model ('purely' indicates that it is a dialogue between two artificial learners - see the experimentation section - both based on the SDC mode). One can observe that the dialogue structure is quite simple and rigid. As in the mountaineers example (figure 3), each learner may only perform two dialogues moves: *continue* or *refute* (see prior definitions). This set of dialogue moves is very restricted with respect to the richness of human-human dialogue. For instance, it does not include disambiguation sub-dialogues which are very important in human functioning (Suchman, 1987). This feature constitutes one of the simplifications we had to concede to obtain a relatively transparent model. Moreover, in order to avoid processing natural language, the human learner does not enter freely his sentences. He produces arguments by selecting and instantiating rules through a graphical interface.

Marc > I suggest to move ward1 from Nord to Rhone-Alpes
Jerry > Why ?
Marc > If When We Remove "ward1" From Nord
Marc > The Demagogiques Get More Preferences Than Ringards In Nord
Marc > Then Demagogiques Will Take A Seat From Ringards In Nord
Jerry > OK, continue.
Marc > If Demagogiques Takes A Seat From Ringards In Nord
Marc > Then Demagogiques Will Have More Seats In Nord
Marc > And Ringards Will Lose One Seat
Jerry > OK, continue.
Marc > If Demagogiques Get More Seats In Nord
Marc > Then Demagogiques Will Have More Seats In France
Jerry > I disagree with that...

> Marc > Why ?
> Jerry > If Demagogiques Has Less Preferences In "ward1" Than In Rhone-Alpes
> Jerry > And If One Add "ward1" To Rhone-Alpes
> Jerry > Then Demagogiques Will Lose Preferences In Rhone-Alpes
> Marc > OK, continue.
> Jerry > If Demagogiques Get Fewer Preferences In Rhone-Alpes
> Jerry > Then Demagogiques Will Get Fewer Votes In Rhone-Alpes
> Marc > OK, continue.
> Jerry > If Demagogiques Party Gets Fewer Votes In Rhone-Alpes
> Jerry > Then It Will Get Fewer Seats In Rhone-Alpes
> Marc > I disagree with that...
>
> > Jerry > Why ?
> > Marc > If Demagogiques Has No Seats In Rhone-Alpes
> > Marc > Then It Cannot Lose Seats
> > Jerry > OK, continue.
> > Marc > Let's resume where we were.
> > Jerry > Let's resume where we were.

Marc > Let's resume where we were.

Figure 5: Example of dialogue between two artificial learners. The indentation indicates levels of refutation. The task was to move a ward from a constituency to another in such way that the new regrouping of votes leads the 'Demagogics' party to gain seats.

As we said, reasoning is implemented as a dialogue with oneself. This means that the same learner plays simultaneously the roles of proposer and criticiser. When the learner reaches some node (an argument) in exploring the solution tree, it tries to refute it before continuing. If it fails to refute, it goes one level deeper. If it refutes its own argument (self-refutation), it backtracks and explores another branch of the tree. The process is recursive as in dialogue: the learner attempts also to refute its own refutation, and so forth. The obvious criticism is that such an approach would impose an enormous cognitive load on the learner, who should be able to verify all the possible refutations for all its arguments. Therefore, in our model, the learner only tries to refute Rule-X by Rule-Y, if it previously occurred in dialogues that Rule-Y was used to refute Rule-X.

Learning mechanisms

The learner will learn relations between arguments. Arguments are stored as rules. Although it is a source of learning in collaboration, we did not model the fact a learner may reveal new arguments to the other one. We concentrated on the structuration of arguments into patterns that guide reasoning. A dialogue pattern is a set of relations between arguments. According to the second postulate (isomorphism of communication), we do not discriminate patterns according to who produced them: inter-device and intra-device patterns are both represented as a network of relations between agents. The type of links is determined by the dialogue moves: a 'continue-link' relates two rules that have been consecutively verbalised in an explanation; a 'refute-link' relates two rules such that one has been verbalised to refute the other. The word 'verbalised' is important because Jerry Mander only records rules which were verbalised, i.e. whose association is observable by both learners (postulate 3). The representation of patterns is distributed: we don't have a specific object which represents a pattern, each agent stores its links with other agents.

Some additional information is stored for each link: the link strength, a numeric parameter whose role will be described later on, the context (features of the country being discussed) and the relation between variable bindings in each rule (e.g. 'the instantiation of the variable _Candidate in rule-Y must belong to the party stored in the variable _Party in rule-X').

In monologue, the learner uses continue-links as a heuristic for exploring the tree. If rule-X has a continue-link rule-Y, this means that, after having applied rule-X, Jerry Mander considers rule-Y before any other one. If rule-X has several continue-links, the connected rules are sorted by increasing order of strength. Acquiring 'continue-links' corresponds to some incremental and context-sensitive form of knowledge compilation: the pair (rule-X rule-Y) is now some kind of 'chunk' that speeds up reasoning.

Example: Rule-6 ('If a party gets more preferences, then it will get more votes') is often followed by Rule-8 ('If a party gets more votes, then it will get more seats'). Their association corresponds to the rule 'If a party has more preferences, then it will get more seats')

In monologue, the refute-links bring attention to rules that should be considered before continuing inference. If rule-X has a refute-link to rule-Y, Jerry will check out rule-Y before continuing. If it occurs that rule-Y is verified, Jerry will backtrack, otherwise it will continue its search. If several refutation-links exist, they are sorted by increasing order of strength. The refutation (rule-Y) may of course itself be refuted. If it is the case, Jerry may continue its inference from rule-X. Adding refute-link constitutes a special form of rule specialisation. Creating a refute-link is identical to adding a rule condition. Let us imagine two rules, rule-X: p1 => q, and rule-Y: p2 => (not q). The refute-link rule-X/rule-Y (i.e. rule-Y refutes rule-X) corresponds indeed to a specialized version of rule-X: p1 and (not p2) => q.

Example: Rule-9 ('If a party gets fewer votes (p1), then it will get fewer seats'(q)) is refuted by Rule-13 ('If a party has no seats (p2), then it cannot lose seats' (not q)). The association Rule-9 / Rule-13 corresponds to a specialised version of Rule-9: 'If a party gets fewer votes (p1) and has seats (not p2), then it will lose seats (q)'.

Patterns evolve with time, namely the strength of each link is changed according to dialogues and to the results of experiments with the micro-world. Two mechanisms modify the strength of links, these mechanisms do modify the pattern by changing the strength of one link at a time.

The first strengthening mechanism corresponds to *social sensitivity*. This factor represents the extent to which the real learner influences the co-learner, especially the confidence that the co-learner has in its peer. When a new link is proposed by the real learner, its initial strength is set to the value of this social factor. If the real learner proposes an existing link, the strength of this link is increased by the same value. This strengthening process gives an inductive dimension to the learning process: patterns that are frequently verbalised become 'stronger'. We initially envisaged that the social factor would evolve with time. It seems natural that the co-learner's confidence increases if the real learner makes suggestions which often lead to obtaining more seats. Although this was trivial to implement, we have not done it in order to maintain the transparency of the system.

The second mechanism modifies the link strength according to the results of the simulated elections. Given the 'confirmation bias', if a pattern leads to a loss of seats, we do not simply erase the pattern, but we reduce its strength. Conversely, we increase the strength if the experimental feedback is positive. This increment value is referred to as the '*environmental factor*'. If Jerry drives the dialogue and if its proposal leads to a gain of seats, the links that Jerry verbalised are strengthened and those verbalised for refuting Jerry are weakened. Conversely, if some seats are lost, the verbalised continue-links are weakened and the refute-links are strengthen. This corresponds to a simplified 'learning by experimentation' strategy.

The absolute value of the social and environmental factors is less important than the ratio between these parameters. Let us imagine that a pattern is confirmed twice by the real learner and invalidated once by the simulation results. The issue is to know if the strength of this pattern after these three events must be lower or higher than originally. The answer to this question depends on the proportional value of the social and environmental factors. In the experimentation section, we analyse the effect of changing the *social-environmental ratio* (SE-ratio).

Experimentation

Learners are represented as examples of the class 'learner', which has two subclasses, 'artificial-learner' and 'natural-learner'. This allows us to create two kinds of experiment: (i) a natural learner collaborates with a human learner and (ii) two artificial learners collaborate. The dialogue process is identical in both cases. Some dialogue procedures, such as 'ask' or 'tell', are specialized on the subclasses. For instance, the generic method 'ask' will appear differently on the screen according to the dialogue participant: an artificial learner asking a natural learner, a natural learner asking an artificial learner, or an artificial learner asking another artificial learner.

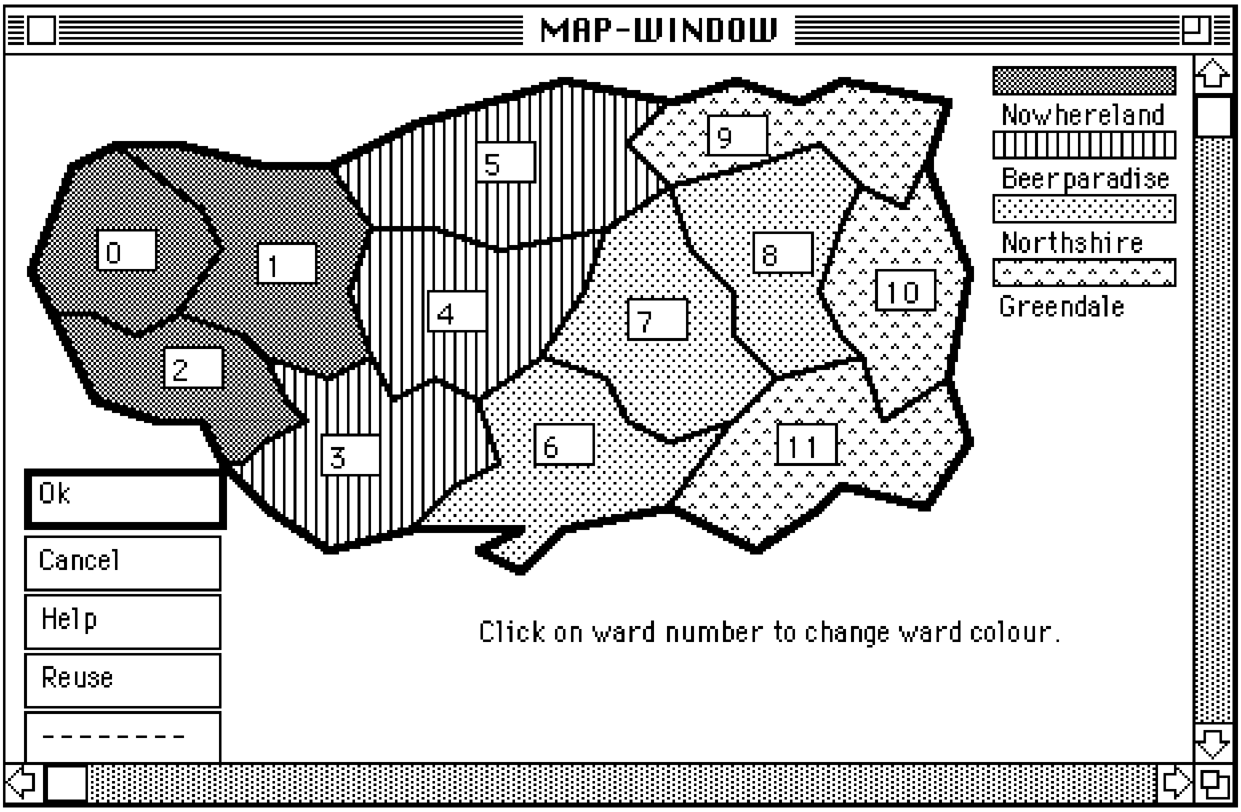

Figure 6: The window used for moving wards from a constituency to another one. Wards are referred by numbers. The filling pattern indicates to which constituency belongs each ward.

The experimentation was based on the 'euro-demagogic game'. In each of twelve pseudo-countries, there is a 'demagogic' party. The learner's goal is to gain one seat for this party. The only change they are allowed to do is to move one ward from a constituency to another one (by using the window shown in figure 6). Let us assume that, in Northshire, the Liberals have 33% of votes and the Demagogics 29% and that, in ward W9 (in Greendale), the Demagogics have 45% against 32% for the Liberals. Then, if the learners move ward W9 from Greendale to Northshire, the Demagogics might beat the

Liberals and take their seat in Northshire. The argumentation about this move will consider whether the Demagogics won't lose a seat in Greendale, whether the Liberals actually have a seat in Northshire, and so forth. When they agreed on a change, the micro-world simulates elections and produces the new distribution of seats in the parliament. Learners observe whether the Demagogics have gained a seat or not. If it is the case, they consider the next country. Otherwise, they attempt to do another change. The number of attempts necessary to gain a seat is our measure of the learners' performance.

We conducted experiments with a human and an artificial learner, for five subjects. The experiments revealed the limitations of the interface through which learners communicate. This interface is based on the usual set of Macintosh dialogue widgets (buttons, scrolling lists, etc.). We avoided natural language processing for pragmatic reasons. The human learner expresses his arguments by selecting one of Jerry's rules and instantiating it with micro-world data. Technically, human learners manipulated the interface with ease very quickly. However, they complained about the need to know Jerry's rules (they were inspectable) and to express themselves in its logic. Because the cost of interaction with Jerry was very high, subjects reduced the number of interactions. Since Jerry's learning output depends directly on the amount of interactions, Jerry learned slowly. All dialogue patterns elaborated by Jerry during these one-hour sessions included less than 10 inter-agents links, while machine-machine dialogue patterns become efficient around 25 links. Hence, Jerry continued to provide the learners with suggestions that were not very good, and hence decreased the subjects' interest in its suggestions.

In order to observe the model functioning independently from the interface quality, we then conducted experiments with two artificial learners. This allowed us to repeat many experiments with various values of the parameters describing each artificial learner. We could tune four parameters influencing the behaviour of each artificial learner:

- background knowledge: this is the set of rules initially provided;
- working memory limit: the maximum depth of backtracking for the inference engine ;
- systematicity: the percentage of cases when, if Jerry disagrees, it expresses its disagreement (a learner that would be 100% systematic would be very boring);
- socio-environmental ratio: the ratio between the social influence on Jerry and its sensitivity to environmental feed-back.

Jerry acquired dialogue patterns and used them to solve problems. The patterns created at the end of an experiment include between 26 and 33 links, according to the order of problems and the value of the SE-ratio. Figure 7 shows the most complete pattern (33 links) developed by Jerry during the various experiments.This pattern shows three main explanation lines: left (rules 15,7,9,3,0,3), the central (rules 14, 6,8,2) and the right (rules 19/20,23,2). Each line has specific refutations: rule13 for the left line, 30 for the central line and 25/26 for the right line. An auto-link is a link between two consecutive instantiations of the same rule, e.g. when we prove that party-X is the first one by asserting that party-X beats party-Y (first instantiation) and that party-X beats party-Z (second instantiation).

We conducted a few pre-experiments along several factors and decided to focus on the order of problems and on socio-environmental ratio. We controlled the other factors. We used the same set of rules for each artificial learner in order to neutralise the effect of the discrepancy between the prior knowledge of each learner. The systematicity was fixed to 100 in order□to eliminate chance from the process. The working memory limit was set to 7, a compromise between speed and power that has been empirically determined (but this arbitrary value is not related to the 'magic number seven'). Figure 8 compares the solutions of Jerry with or without using dialogue patterns. The dependent variable is the number of trials necessary for gaining seats in a country, i.e. the number of times a learner makes a change in the country map and runs an electoral simulation.

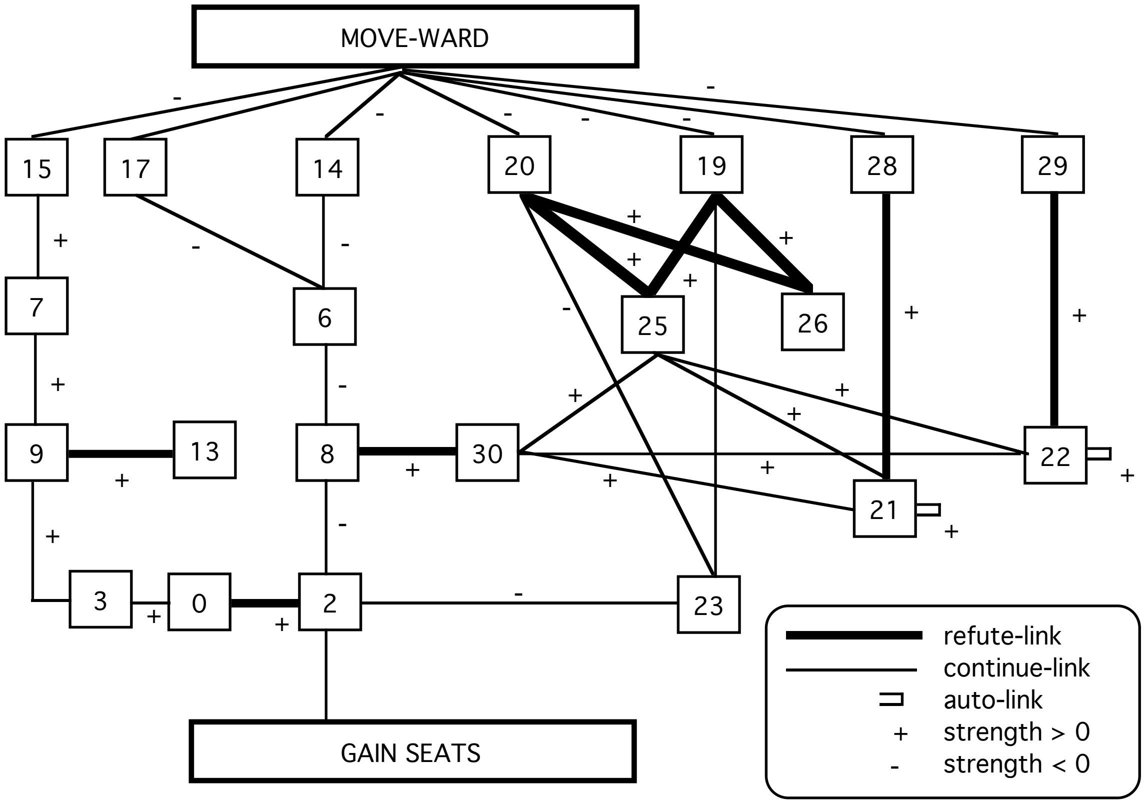

Figure 7: Jerry's dialogue pattern at the end of country sequence ADBC (explained later on), with SE-ratio of 0.5 for each partner. Each number in a box represents a rule, i.e. an argument.

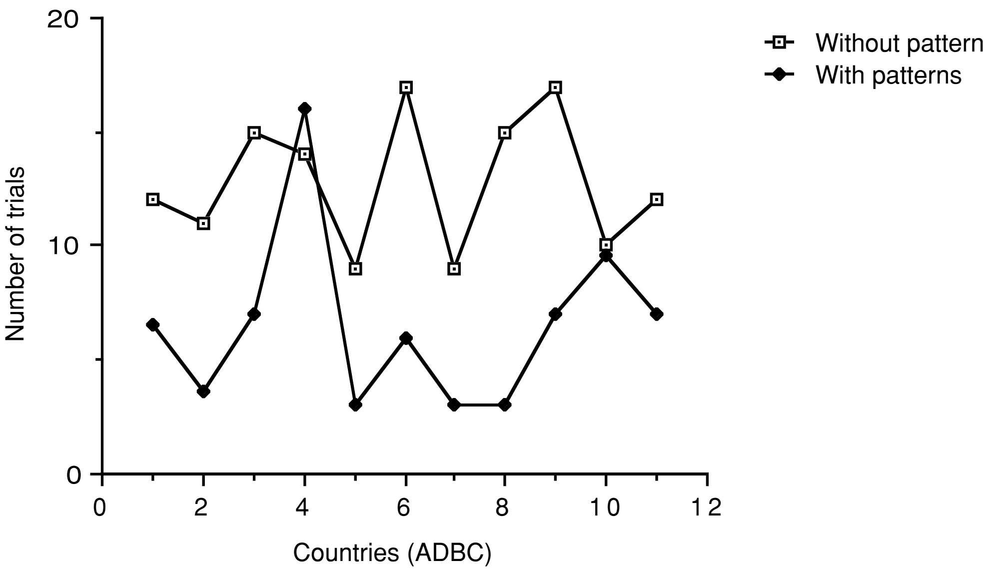

Figure 8: Comparison of the number of trials necessary to gain seats with or without using dialogue patterns, with sequence ADCB .The values of the 'with patterns' curve (black dots) are the mean of the number of trials for each country in five experiments, using the following SE-ratio values for the two learners: 1 and 1, 0.5 and 0.5, 1 and 0.5, 0.5 and 0.8, 1.5 and 2.

The global result is that Jerry needs fewer trials to solve the problem with dialogue patterns. This improvement is limited to some threshold (around 3 trials). The presence of a threshold is a classical observation in machine learning. For some problems Jerry's performance with patterns deteriorates and can even be lower than without dialogue patterns. The effect of problem ordering is another classical phenomenon in machine learning. We tackled this issue by controlling the difficulty of transferring knowledge from a sub-class of problems to another sub-class. The set of countries is partitioned into four subsets (A, B, C and D) according to two features: the number of seats in each constituency and the number of constituencies in the country. The order is indicated for each graph by a sequence of letters (e.g. ADCB).

Figure 9 shows that these criteria are not sufficient to explain the order effect, since the variations within a group of countries (A,B,C,D) are sometimes more important than the variation between two groups. The transfer issue should explain an increase of failure for the first country of a new group, but this increase should have been followed by a decrease stage (within the same problem sub-class). We then looked at the links elaborated by Jerry and observed that the generalisation/specialisation process did not lead it to create distinct links for distinct contexts. In other words, the criteria relevant for discrimination where not those used for describing the context.

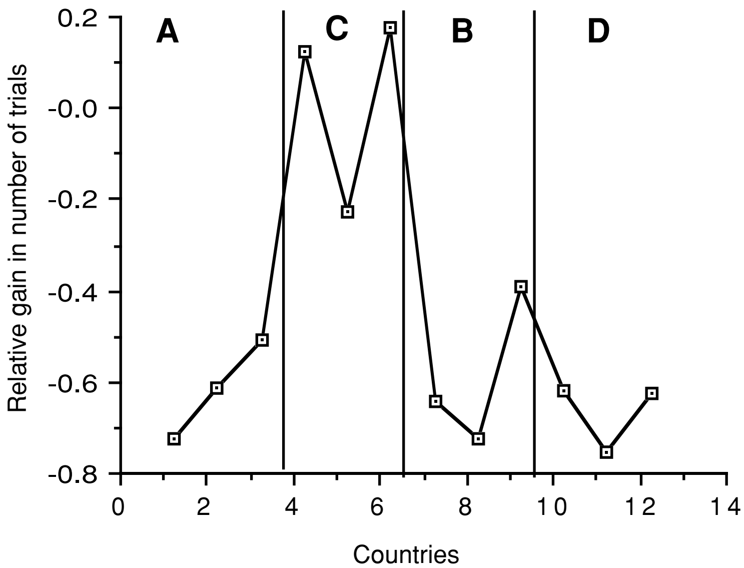

Figure 9: Effect of transfer (Sequence ACBD, SE-Ratio = 1/1). In order to compare performance on various country orders, we define Jerry's relative gain as the difference between the number of trials with and without patterns, divided by the number of trials without patterns. The maximal relative gain is -1.

In order to analyse the effect of order, we carried out experiments based on various permutations of Group A countries. The experiments showed that the order effect within a sub-class of countries was important. For instance, the number of trials necessary to gain a seat in Belgium was 5 when Belgium followed Netherlands, but 9 when it came after Portugal, with a SE-ratio of 1. With a SE-ratio of 0.5, the difference was even greater, respectively 5 and 15.

We can explain this effect by the fact that the actual distribution of preferences among parties is more important for determining Jerry's reasoning than the factors we considered (number of seats, number of constituencies). We did not want to explicitly represent this distribution, because it is precisely the type of knowledge that Jerry should acquire through collaboration. By providing him with this knowledge, we would escape from the idea that Jerry is a genuine learner. We observed that the human subjects who used People Power lacked such knowledge, their main difficulty being to construct it. For instance, two of them stopped summing preferences by party and started to count differences of preferences: "*... party-X has 10% less here than party-Y, but 5% more there, this makes -5% ,... so we should try to find a difference superior to 5%,...*". This new descriptive language identifies indeed the relevant relations among the numerous data.

Nevertheless, we found that the order effect decreases later on in the game. For instance, when Denmark was placed at the fourth, seventh or tenth position in the sequence, the number of trials was respectively 11, 10 and 10 with a SE-ratio of 1. Similarly, with a SE-ratio of 0.5, the number of trials was respectively 11, 9 and 9. It appears that the effect of order tends to disappear when the learner has developed a stable dialogue pattern. We hence paid attention to the evolution of dialogue patterns. We describe a pattern by the number of its links. This intermediate variable partly explains the relation between the position of a problem in the sequence and Jerry's performance on this problem. This relation is illustrated by figure 10.

An interesting feature of figure 10 is the emergence of 'locks'. A lock occurs when Jerry finds no solution, i.e. when it has refuted all the solutions. We analysed the genesis of such phenomena. Let us imagine that the partner refutes Jerry's rule-A proposition with Rule-B. Jerry then attempts to refute the refutation with Rule-C. If Jerry finds that Rule-C is not relevant in the considered country, it will not refute the refutation. Jerry now has a link 'Rule-A is refuted by Rule-B', but has no link 'Rule B is refuted by Rule-C'. Later on, it will prevent itself from using Rule-A each time Rule-B is verified, without ever considering Rule-C, and hence it will discard the solutions related to Rule-A.

We added an 'unlock' mechanism: if Jerry finds no solution, it resumes the search without following dialogue patterns. This unlock mechanism has a positive effect on the development of Jerry's network of links. When there is no lock, Jerry tends to reuse the same rules, since it follows the links. During the 'unlock' stage, Jerry has the opportunity to use rules that it did not use before and thereby to enrich its dialogue pattern.

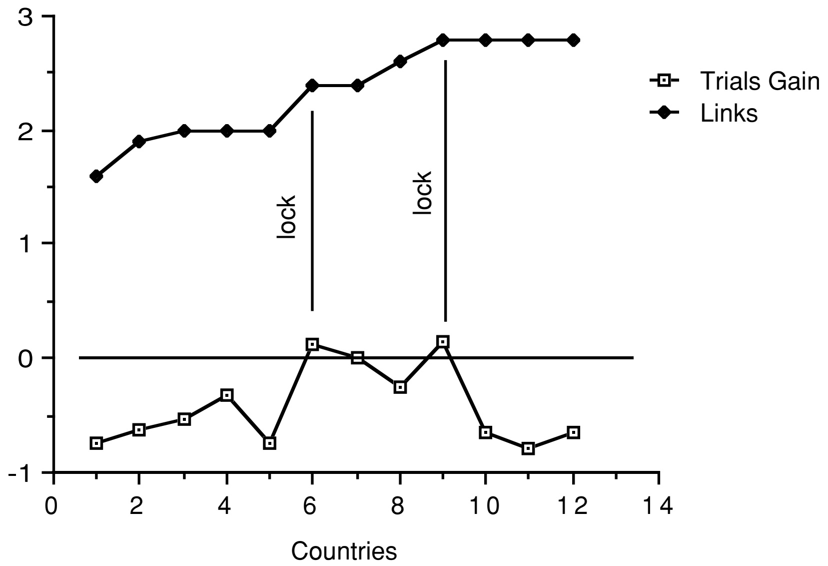

Figure 10: Comparing Jerry's performance and Jerry's number of dialogue links.The vertical axis supports two scales. The performance (lower line) is measured by the relative gain (see figure 9). The number of links in the dialogue pattern (upper line) is divided by 10 for supporting comparison. These data have been collected with the sequence ABCD, with SE-ratio equal to 1.

An interesting finding is that the locks occur sooner when the SE-ratio is lower than one, i.e. when the environmental influence is greater than the social influence. The first experiment always begins with a certain number of failures. When there is a failure, we decrease the strength of the links used for arguing in favour of the change and strengthen the links that refuted that proposal. The importance of this decrement / increment feedback is greater when the SE-ratio is smaller than 1. Hence, the refutation links quickly gain a considerable importance and lead Jerry into an early lock. The effect of the SE-ratio has been observed on various sequences of countries (ABCD, ACBD, ADBC). Figure 11 shows the average curve for two values of the SE-ratio, 1 and 0.5. When the SE-ratio is lower than 1, the number of links immediately reaches 23, while it takes usually 4 countries before reaching that level with a SE-ratio equal to 1. Moreover, when the SE-ratio is lower than one, the number of links remain higher along the whole sequence.

Related work

There are interesting similarities between our work and Hutchins' (1991). Both models are based on the view that the individual and the group can be represented in a distributed way (a network). He uses a constraint satisfaction network in which each unit represents a hypothesis. Connections between consistent hypotheses are labelled 'positive' and those among inconsistent hypotheses are 'negative'. An interpretation of some event is represented by a pattern of activation among the units. This maps closely with our weighted 'continue' and 'refute' links.

While our model focuses on similarities between intra-network and inter-network communications, Hutchins concentrates on differences between two kinds of communication: patterns of communication between networks (who talks to whom) and patterns of interconnectivity between nets connected to each other (what hypotheses are discussed). This divergence can be explained by the divergence of our goals. Our model belongs to a learning environment and therefore is oriented towards learning skills, more precisely the internalisation of mutual regulation skills. The isomorphism between levels of communication has been hypothetized as the engine of learning. But Hutchins studies how groups have cognitive properties that differ from those of their members. He has chosen the 'confirmation bias' as the property to observe.

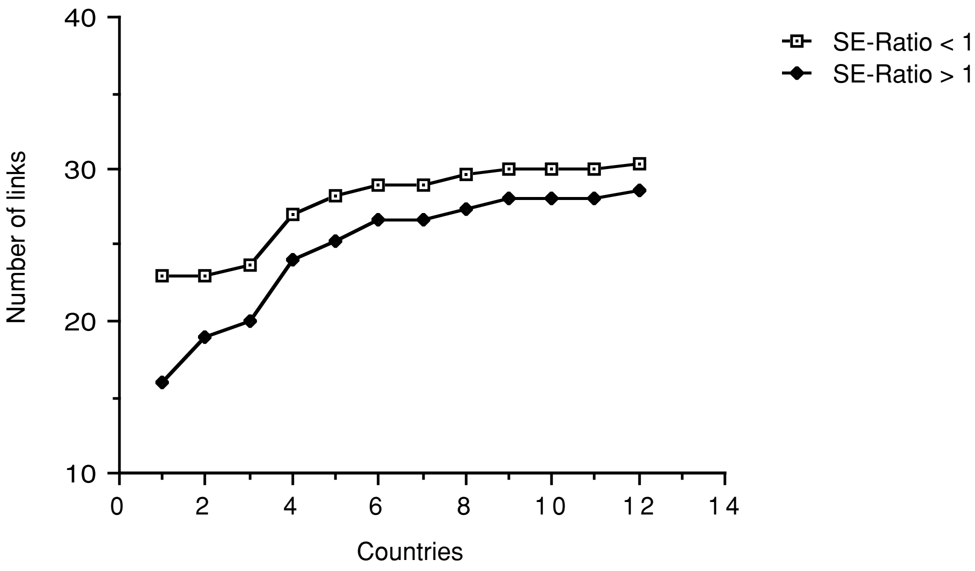

Figure 11: Average evolution of the number of links in sequences ABCD, ABCD and ABDC, with SE-Ratio equal to 1 and to 0.5.

Hutchins conducted experiments by changing values to a parameter, the 'persuasiveness', which is conceptually close to our 'social sensitivity' factor. In computational terms, the persuasiveness is the fraction of the activity in one network (individual) which becomes the external input for the corresponding unit in another network. High levels of persuasiveness lead to a very high confirmation bias (for the group itself). The explanation is that *each network has its own source of external evidence* which is propagated internally. With high level of persuasiveness (influence between networks), the strength of connection between networks becomes higher than the strength of connection within networks. All the nets move then to a consensus, but this consensus is incoherent and poorly sensitive to external evidence. This phenomenon is quite similar to our 'locks' which resulted from a too early convergence of ideas. The confirmation bias is reduced when persuasiveness rises gradually: the persuasiveness level is initially low, each network develops an interpretation that satisfies its evidence; when the persuasiveness level increases, the consensus emerges around the best supported hypothesis. The outcome is that "the group, as a cognitive system, has considered many kinds of evidence, whereas each individual considered only one" (ibid, p. 302). Hutchins establishes that the persuasiveness should increase before networks form well-supported hypotheses, otherwise networks might be unable to resolve conflicting hypotheses.

These experiments and Hutchins' experiments identify a variable that was not explicit in our model: the '*communication curve*', i.e. the frequency of communication between subjects and how it is distributed over time. The criterion for distinguishing time periods for that curve are, for us, the elicitation of counter-counter-arguments, and for Hutchins, the elaboration by each subject of an hypothesis consistent with his own evidence. Experiments with human subjects are needed to confirm the relevance of this variable. The computational mechanisms by which this variable has affected the performance of our networks may guide the explanation of future empirical results. If our model helps empirical research to prune the experimental space, to spare empirical research resources (Hutchins, 1991) and to suggest explanations, then it would have been scientifically useful.

Conclusions and Further Work

We do not believe that our model or Hutchins' work provides the reader with a theory of how human cognition is distributed. Our work has a modest metaphorical function; we view our model as an 'object to think with'. It allows researchers to state a certain number of hypotheses and to explore their logical implications. The computational nature of such models coerces the researcher to state clear hypotheses, but it overall allows them to execute models. It is often easier to understand complex processes by observing the effect of some parameter changes. Such models may help researchers to come out with new hypotheses. Computational experiments may lead to pruning the space of needed experimentations with human subjects, but it will not replace human experimentation.

The SDC model enabled us to connect three ideas: i) a group is a cognitive system, ii) reflection is a dialogue with oneself, iii) social processes are internalised. The key has been to find a computational connection between those ideas. The domain chosen for illustration is the argumentation concerning how some changes to an electoral system will affect the results of elections. This argumentation involves a sequence of arguments and their refutations. The basic principle is that learners 'store' the structure of this argumentation (dialogue pattern) and 'replay' it individually later on. The verbs 'store' and 'replay' do not refer to a simple 'record and retrieve' process. Storage is implemented as incremental and parameterised evolution of a network of arguments, here called a dialogue pattern.

Experiments have been conducted to explore how some parameters influence the evolution of dialogue patterns and how the evolution of patterns affects the artificial learner's performance. These experiments and the work of Hutchins lead to identify an intermediate variable, the 'communication curve', i.e. the frequency of communication between subjects and how it is distributed over time.

The main limitation of our work lies in the simplicity and rigidity of conversation among learners. In our implementation, dialogue is restricted to agreement and disagreement utterances. Real dialogue involves the much more complex process of elaborating and maintaining a shared understanding. This process involves a set of operators, such as 'specification', 'elaboration', 'reformulation', restrictions' and 'reasons'

(Baker, 1992). Such a rich set of operators is required to reach '*social grounding*', i.e. the participants belief that his partner has understood his utterance (up to some acceptability criterion) (Clark and Brennan, 1991). It would be interesting to adapt and test the SDC model with a larger set of dialogue operators, supporting dialogue repair. With respect to the specificity of HCCL, we should modify the interface in order to support '*physical grounding*', i.e the possibility of peers to use the environment (the micro-world) for comparing their mutual understanding (Roschelle, to appear). We could then conduct experiments for observing the emergence of shared meaning, a dependent variable which is probably more informative than the number of trials per problem.

Acknowledgments

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APPENDIX: Jerry's Rule Base

Note that the rules that are not relevant for reasoning about the map have not been used during the experiments.

Rule 0	If _Owner lose _Data in _Area then _Owner does not gain _Data in _Area

Rule-2	If _Party gets more _Data in _Constituency then _Party will have more _Data in _country
Rule-3	If _Party gets fewer seats in _Constituency then _Party will have fewer seats in _country
Rule-4	If _Candidate is a candidate of _Party in _Constituency and If _Party has fewer candidates in _Constituency then _Candidate will receives more preferences
Rule-5	If _Candidate is a candidate of _Party in _Constituency and If _Party has more candidates in _Constituency then _Candidate will receives fewer preferences
Rule-6	If _Owner gets more preferences in _Constituency then _Owner will get more votes in _Constituency
Rule-7	If _Owner gets fewer preferences in _Constituency then _Owner will get fewer votes in _Constituency
Rule-8	If the _Party party gets more votes in _Constituency then it will get more seats in _Constituency
Rule-9	If the _Party party gets fewer votes in _Constituency then it will get fewer seats in _Constituency
Rule-10	If _Candidate gets more _Data and If _Candidate is a candidate of _Party in _Constituency then _Party will get more _Data in _Constituency
Rule-11	If _Candidate gets fewer _Data and If _Candidate is a candidate of _Party in _Constituency then _Party will get fewer _Datain _Constituency
Rule-12	If the _Party has all the seats in _Constituency then it cannot gain seats
Rule-13	If the _Party has no seats in _Constituency then it cannot lose seats
Rule-14	If _Party has less preferences in _Ward than in _Constituency and If one remove _Ward from _Constituency then _Party will gain preferences in _Constituency
Rule-15	If _Party has more preferences in _Ward than in _Constituency and If one remove _Ward from _Constituency then _Party will lose preferences in _Constituency
Rule-16	If _Party has less preferences in _Ward than in _Constituency and If one add _Ward to _Constituency then _Party will lose preferences in _Constituency
Rule-17	If _Party has more preferences in _Ward than in _Constituency and If one add _Ward to _Constituency then _Party will gain preferences in _Constituency
Rule-18	If _Party has no more candidate available in _Constituency then _Party wont gain seats in _Constituency
Rule-19	If when we add _ward to _constituency the _Party-X get more preferences than _Party-Y in _Constituency then _Party-X will take a seat to _Party-Y in _Constituency
Rule-20	If when we remove _ward from _constituency the _Party-X get more preferences than _Party-Y in _Constituency then _Party-X will take a seat to _Party-Y in _Constituency
Rule-21	If when we add _ward to _constituency the _Party-X dont get more preferences than _Party-Y in _Constituency then _Party-X wont take a seat to _Party-Y in _Constituency

Rule-22	If when we remove _ward from _constituency the _Party-X don't get more preferences than _Party-Y in _Constituency then _Party-X wont take a seat to _Party-Y in _Constituency
Rule-23	If_Party-X takes a seat to _Party-Y in _Constituency then _Party-X will have more seats in _Constituency
Rule-24	If_Party-X does not take a seat to _Party-Y in _Constituency and if there are only two parties in the country then _Party-X will not have more seats in _Constituency
Rule-25	If _Party-Y has no seat in _Constituency then _Party-X cannot take a seat from _Party-Y in _Constituency
Rule-26	If _Party-X add already more preferences than _Party-Y in _Constituency then _Party-X wont take a seat from _Party-Y in _Constituency
Rule-27	If_Party does not take a seat from _Party-Y in _Constituency but that it takes a seats to _Party-Z in _Constituency then _Party will have more seats anyway in _Constituency
Rule-28	If when we add _ward to _Constituency the _Party-X obtain more than the half of _Party-Y votes and if _Party-Y has more than one seat then _Party-X will take a seat from _Party-Y _Constituency
Rule-29	Ifwhen we remove _ward from _Constituency the _Party-X obtain more than the half of _Party-Y votes and If _Party-Y has more than one seat then _Party-X will take a seat from _Party-Y _Constituency
Rule-30	If_Party-X does take a seat neither to _Party-Y nor to _Party-Z in _Constituency Then _Party-X will not have more seats in _Constituency