DIVERSITY AND COMMUNICATION IN TEAMS:

IMPROVING PROBLEM SOLVING OR CREATING CONFUSION?

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ABSTRACT

Despite the rich and interdisciplinary debate on the role of diversity and communication in group problem solving, as well as the recognition of the interactions between the two topics, they have been rarely treated as a joint research issue. In this paper we develop a computational approach aimed at modeling problem solving agents and we assess the impact of various levels of diversity and communication in teams on agents' performance at solving problems. By communication we intend a conversation on the persuasiveness of the features characterizing the problem setting. By diversity we mean differences in how agents build problem representations that allow them to access various solutions. We deploy the concept of diversity along two dimensions: *knowledge amplitude*, that is, the amount of available knowledge (compared to the complete representation of a problem), and *knowledge variety*, which pertains to the differences in agents' knowledge endowments.

Our results show the different impact of these two sources of variety on problem solving performance in teams, as well as their interplay. Regarding knowledge amplitude, when agents' representation of the problem is considerably incomplete, communication provides confusion as it is difficult to find a common language for sharing thoughts, and agents perform better alone. Adding knowledge variety to this scenario, the effects of communication are even more negative. Conversely, as the representation of the problem gets more and more complete, communication becomes more and more effective. Albeit displaying a clear non-monotonic effect: increasing the communication strength, performance increases until an optimal point, after which it declines and gets very rapidly worse than individual behavior. In this case, the introduction of knowledge variety further increases performance in teams, since benefits from integrating partial representations of the problem occur more frequently than communication clashes. Finally, highly diverse teams seem to be less sensitive to changes in communication strength, while as diversity declines, even small discrepancies from the optimal communication strength level might account for a strong variability of performance. In particular, overestimation of the required communication effort might cause severe performance breakdowns.

Our results suggest that organizations and firms should jointly consider communication intensity and different sources of diversity in teams, since interactions among these variables might result in problem solving groups resembling more a Tower of Babel than an effective and helpful workplace.

Keywords: Problem solving, diversity, heterogeneous agents, communication, constraint satisfaction, neural networks, causality.

INTRODUCTION

In this paper we analyze problem solving by a set of diverse agents with bounded abilities in collecting the relevant features characterizing a problem setting and we compare their individual performance to performance within a team for various levels of communication.
In the previous literature, the issue of effectiveness has been explored in teams of problem solvers along the dimensions of communication and diversity taken separately. Some studies (Hutchins 1995, Marchiori and Warglien 2005) investigated to what extent communication might play a corrective role for agents with limited exposure to information. Other contributions addressed the role of diversity in problem setting (Hong and Page 2001) or in solution strategies (Hong and Page 2004) but they modeled teams as collection of agents working sequentially on a common task, without introducing any form of communication. These studies have shown that communication alone or diversity on its own, might explain why groups of agents outperform individuals. Nevertheless, there is a clear interplay between these two variables that calls for further investigation, and our paper can be regarded as an attempt to address this gap.
Considering communication and diversity together, the contribution of diversity to collective problem solving turns out, in the existing literature, to be controversial. On the one hand, some authors (Hong and Page 2001) showed that diverse agents are meant to offer different perspectives on problems that increase problem solving success, others highlighted that communication can correct diverse or even wrong perspectives (Marchiori and Warglien 2005). On the other hand, other perspectives on diversity (we refer to the similarity-attraction paradigm – see Williams and O'Reilly 1998 or Mannix and Neale 2005 for a review), point out the limits of diversity: when diversity is taken too further, agents face obstacles in sharing thoughts, in finding a common language and in negotiating meanings that build upon a communal background knowledge. When agents are very diverse, irreconcilability or disregard of each other's ideas are more likely to appear and conflict is more likely to emerge. Accordingly, problem solving in teams displays outcomes worse than individuals' ones, meaning that exchange of ideas among too diverse people confounds thoughts instead of illuminating minds.
Communication per se, seems to display a non-monotonic relation with performance. In fact, over a certain level, communication strength impacts on the ability of the individual to think correctly. In some models, this effect has been represented as a high pressure to conform to the whatever shared outcome – as suggested, for instance, by the "Credulous Theorem" of

Marchiori and Warglien 2005 – similarly, in other models high levels of communication display the emergence of confusion in agents judgments up to the point of being unable to select one over many alternatives (Frigotto and Rossi, forthcoming). These models, though, have not highlighted to what extent communication effects depend on agents' diversity and, vice versa, if the role of diversity is affected by the strength of communication.

This paper intends to tackle the reciprocal influence of communication and diversity in collective problem solving. Our research question is twofold. On the one side, we ask how much diversity supports collective problem solving allowing effective communication among agents or whether it adds confusion and noise in the interpretation of the problem setting. On the other side, we are interested in understanding if more communication can valuably support lower levels of diversity among agents.

We address these questions though a computational model deploying teams of diverse agents communicating with each other. The model shows two main novelties with respect to existing agent-based models.

First, we model diversity in terms of differences in how agents encode and approach problems. Hong and Page 2001 signed a shift between models in which problem representations were fixed among agents, to a model in which perspectives varied. In their model, agents' perspective on the problem is represented through an internal language of the agent, normally a binary string of a certain length. This binary string defines what points in the landscape the agent is able to see, and to evaluate, thus showing her view of the problem. Given the abstraction of these perspectives, many explanations are possible of what internal language is meant to represent: different perceptions of the problem, given the same set of information and the same knowledge information for interpreting them, or different interpretations of the problem referring to different knowledge basis, etc. In essence, the nature of diversity in this model has not been specified nor made explicit in model components and, even though abstraction adds interpretive power to simulated results, it also limits them, because does not enable to distinguish among different cases. In addition, this choice does not allow to evaluate how distant two diverse agents having different binary strings are in terms of representations. As a result, a measure of diversity and an assessment of the impact of its variability on performance are not possible. We address this limit modeling agents' diversity in terms of two different dimensions both referring to knowledge. We assume as the reference point the knowledge required for the complete representation of a problem and we model diversity in terms of different knowledge bases available to agents. We measure *knowledge amplitude* in terms of the level of completion in the problem representation, and *knowledge variety* in terms of differences in available knowledge constituents. We then explore how agents' interactions and problem solving outcomes vary along these two features of diversity.

Second, the class of models we refer to is a peculiar class of connectionist networks, namely constraint satisfaction (CS) networks, originally proposed by Rumelhart et al. (1986). Other contributions on team diversity have built upon the constraint satisfaction approach, assuming problem solving as a patterns matching activity (Hutchins 1995, Marchiori and Warglien 2005). One novelty of our model lies in that we suggest the use of such models abandoning the pattern matching perspective, thus extending the class of cognitive phenomena that might be represented though CS models.

We assume that agents, viewed as problem solvers, struggle for building convincing and internally coherent representations of problems, based on a satisfactory understanding of the nature and relationships of the constituents of the problem setting. This means that they try to give sense to the scraps of evidence they consider important for the issue at stake, to give an explanation to the causes of their manifestation in order to understand how to intervene on the situation. In fact, building on Simon (1991), we hypothesize that representations give access to alternative solutions (Figure 1 sketches a stylized model). Our perspective is particularly interesting if we consider problem solving in novel and inexperienced situations as opposed to familiar and more routinized cases in which stored solutions are ready to use and choice is based on an assessment on the similarity of the case at point with the one in memory.

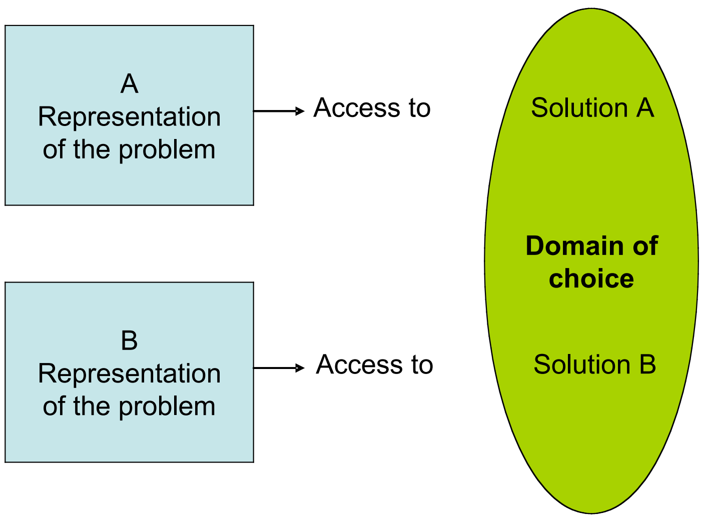


Figure 1: Problem Representations and Solutions.

We hypothesize that representations are built through causality and that they are evaluated according to their ability to offer a persuasive explanation of the situation.

Our view of agents as solvers building explanations of problems is new, but is not without foundation. We refer to Paul Thagard's works on explanatory coherence (1989, 1992b, 2000) and we draw the idea of expanding his theory to problem solving from the numerous applications he proposed in the domains of scientific revolutions (1989), scientific discoveries (1998a), medical discoveries (1998b), adversarial problem solving (1992a), juror's decisions (2004).

The psychological literature (Keil 2006 for a review) displayed that explanation is ubiquitous and used for a variety of purposes. Also children and lay people provide and ask for explanations, not only experts: they explore phenomena that puzzle them attempting to uncover an explanation of why an effect occurred. They are willing to see the events they face as the result of causes; the identification of these causes is necessary to understand what is going on and how they may intervene on that situation for reaching their goal.

Explanations are relevant in the past perspective, in order to justify and rationalize action. Our explanations are attempts to represent our actions to others or to ourselves as logical, well intentioned or appropriate. In this view, explanation can be seen as a form for retrospective rationality (March 1975; 1994).

Among various functions, the most interesting one for the purpose of our discussion, is the use of explanations in diagnosis. Typically one asks why a system failed and the aim is to identify the causally critical component and to bring it back to its normal function. Patriotta's (2003) analysis of accidents on the shop floor of a traditional pressing plant at Fiat Auto displayed the use of explanations in the form of detective-stories, for repairing disruptive occurrences. He disclosed the role of such narratives in solving problems and eventually, in shaping knowledge creation, utilization and institutionalization, in a forward looking perspective. Psychology clarified that explanations also serve to help people know how to weight information or how to allocate attention when facing a situation (Keil 2006).

Organizations working in highly risky environments, such as military organizations, nuclear companies, aviation safety organizations (grouped under the name of High Reliability Organizations – HRO), deploy the practice of building narratives and exploring explanations of their everyday experience in order to expand their knowledge and preparation for the more risky events they will face (March, Sproull and Tamuz 1991; Morris and Moore 2000; Weick and Sutcliffe 2001). This evidence can contribute to the idea of explanation as a form of rationality that is not only useful in the past perspective, as justification, but also in the perspective of the future.

The role of explanations as a form in which forward looking rationality happens, has also been investigated by the experimental literature (Shafir et al. 1993). Through typical laboratory methods and tools, though, it is not easy to distinguish the justification use from the supportive use of explanations; thus, this function of explanation has remained partially unexplored.

Moreover, it is interesting noting that, traditionally, psychological studies presented explanation-based processing information as slow and later in tasks, whereas early processing was more associative and fast. Recent findings illustrate that in many cases, explanation based effects occur in the early steps of processing (Keil 2006).

Our agent-based model also adds to extant managerial literature on team performance. Studies on the field have addressed the issue of diversity and communication in the context of top management teams and, more broadly, in the perspective of the collective working place. One of the main assumptions that was tested, is the one linking diversity in team members' cognition to problem solving performance. Demographic and educational differences have often been used as proxies for cognitive diversity, for the difficulty in grasping real cognitive characteristics, though displaying apparent limits (Kilduff et al. 2000; Pitcher and Smith 2001; Jackson et al. 2003). Simulation models, as ours, can contribute to shed some light on the impact of cognitive diversity in managerial teams, offering a stylization of cognition in action.

Before proceeding with the rest of the paper, it might be worth mentioning several features that are not included in our model. Foremost, our model is not a model of search for solutions. We ignore problems of search since our purpose is to focus on how diverse solutions can circulate among agents in a way in which each can benefit from one another's ideas and knowledge, and eventually take a wiser decision. Our agents have already searched for their solutions and the way this has happened is not considered within the model.

Then, our agents are bounded rational also in the sense that they can assess only two alternatives at a time. We restrict our analysis on what they chose among the two representations given the way they build them.

We have organized the remainder of the paper in Five Sections. In the next Section we review some models of teams of agents that address the issue of diversity and communication. In Section 2 we present our model and in Section 3 we display the structure of our simulations. Section 4 is devoted to the presentation of the results and we further discuss them in Section 5.

1. MODELING AGENTS' DIVERSITY, INFORMATION AVAILABILITY, AND COMMUNICATION

There is a rich and interdisciplinary debate on the role of diversity within teams of agents. A large share of contributions has focused into domain-specific models and empirical studies, targeted at better understanding the phenomenon within a particular field. In this section, we limit our analysis to a more general class of models of diversity in collective problem solving that have been developed at a more abstract level, without close reference to a specific field of application involved. Nevertheless, in many cases, the implications for the different domains of problem solving might be easily derived.

We consider in this Section four models of diversity in group problem solving. Recalling Newell and Simon (1972) distinction between problem solving and problem setting, these contributions are organized in Table 1 according to the source of diversity. Specifically, we distinguish diversity deriving from differences in problem solving, problem setting and in information availability among agents.

The first model of diversity that we review is the one developed by Hong and Page (2001, 2004), in which agents search in a landscape of solutions for the configuration displaying the maximum fitness value. The available searching strategies though, do not allow agents to easily find an optimal solution, but only to explore locally, and in a path-dependent way, the solution landscape on the basis of simple search heuristics. Diversity is introduced modeling agents as having heterogeneous problem solving abilities in a twofold way. (i) agent-specific knowledge embedded in framing the task problem, and (ii) different problem solving strategies, that is, knowledge represented by the cognitive tools used to solve the problem. The authors do not consider issues of asymmetric and imperfect information, as the available landscape for searching is the same to every agent. Rather, they conceive diversity as emerging from differences in knowledge at two distinct levels (i) and (ii). In Hong and Page (2004), diversity is modeled as difference in solution strategies ("heuristics"), while differences in both problem solving strategies and problem setting issues ("perspectives"), are the sources of diversity in Hong and Page (2001).

In their 2004 article, the authors claim that the more diverse – with respect to heuristics – agents are, the better the group performance, due to the larger landscape that is possible to explore. Results show that groups of diverse problem solvers outperform the group of the best performing agents. Note that in this model agents do not communicate with each other but they are rather considered as a set of independent problem solvers operating sequentially or simultaneously on the same problem. In fact, teams are defined with reference to each agent's performance: groups result from the evaluation of the average individual and totally autonomous performance of *n* best agents with regards to *n* randomly extracted agents, where diversity is assumed to derive from random selection.

In the 2001 article, instead, Hong and Page examine diversity in terms of pairs of perspectives and heuristics. In particular, diverse perspectives imply that agents translate their landscape into a problem space that is unique. As a result, the authors show that, *ceteris paribus*, diversity in perspectives enlarges the set of solutions considered during the search process. Even in this case, though, communication is not considered into the analysis.

Communication and information availability are at the center in Hutchins (1995) and in Marchiori and Warglien (2005); both contributions model teams of agents through a connectionist approach. Building on the distinction between problem setting and problem solving, Hutchins (1995) considers diversity in problem setting as externally generated by imperfect information – where poor information depends only on poor problem settings – or as internally generated from agents' misperception of correctly provided information – while information might even be complete in this case the agent's perception is faulty. Marchiori and Warglien (2005) explore these distinctions running a series of computational simulations. They conceive the inferential process, and more broadly problem setting, as deriving from the activity of comparing environmental stimuli with the knowledge agents have collected and stored under the form of memorized patterns. Once the pattern matching activity leads to the identification of a specific case that has been encountered before, choice derives almost automatically as a consequence of stored solutions attached to that setting.

As a matter of fact, in their models, agents search for a solution among a repertoire of previously encountered cases. They assess the similarity of the case at point with those which direct or indirect experience has provided, trying to match environmental signal they have received with organized inference-ready cases. Once they have identified the nearest solution, the stored associated solution is applied.

Marchiori and Warglien (2005) offer a first model in which the various agents receive different (noisy) signals from the environment, thus they identify different pattern cases to apply, misperceiving the correct true state of the world. As a result, diversity stems from the exposition to different aspects of the environment and the authors show to what extent communication can correct this kind of erroneous problem setting.

In a second and third series of simulation, the authors model diversity as an inner characteristic of the agents: knowledge regarding the possible patterns (also known as "schemata") is distorted or incomplete. Diversity here originates from incomplete knowledge or distorted understanding regarding the patterns of experienced cases. The authors show that communication corrects problems these cases, although the corrective power follows a non-monotonic trend.

All revised models explore diversity displaying the underlying assumption that communication among team members does not bear any dysfunctional facets (with the relevant exception of Marchiori and Warglien "credulous theorem", described earlier). However, the issue of diversity in teams opens the door to considerations on how much effective can be communication of ideas between diverse agents, especially when diversity is considerable and it is not only related to differences in information access but also to underlying knowledge differences. It is worth to mention that in most of these models the outcome considered is not a unique solution shared by all the team members, rather agents interact and exchange ideas while every individual maintains the autonomy of taking her own decision. Agents with identical knowledge basis should communicate with one another easily. Solvers having diverse perspectives on the problem though, may have troubles understanding each other's solutions. In order to balance potential benefits and mishaps related to the introduction of communication in diverse agents, it is worth addressing the issue of how much knowledge agents need to have in common in order to understand each other and conversely, how much diversity is best. In other words, how much background knowledge, including language and vocabulary, do they need to have in order to benefit most from each other's specialization without wasting time and energy in search of a common basis to refer to? We address these questions in the following Sections where we also provide our definition of diversity.

Table 1. Models of diversity in problem solving (part 1)

Contribu-tion	Operationalization of problem solving	Knowledge embedded in problem setting	Knowledge embedded in solution strategies	Imperfect information	Decision rule	Communication problems	Diversity
Hong and Page 2001	Solution Landscape is translated in encoded problem space (new landscape) which is different for every agent; Value function landscape: mappings of solutions into R	Perspectives	Heuristics as flipset heuristics(rules for generating neighboring strings) applied sequentially	No	Max value of the options searched by the group (same V function) = local optima deriving from the research by all the individuals	No communication; teams as sets of individual agents joining the team in different order	Diversity of two pairs perspective and heuristics = average of the objects that belong to only one person's neighborhood. (not directly by perspectives and heuristics because two different M and A can generate identical neighborhood structure)
Hong and Page 2004	Value function landscape: mappings of solutions into R (random values)	No	Heuristics defined by k and l: the agent searches l positions on the right of the status quo and within these l she checks k elements	No	Max value of the options searched by the group	No communication; teams as sets of individual agents searching sequentially or simultaneously. evaluation (as an average) of stopping points for a search that started at **any** initial point	Diverse group= randomly selected agents (independently from their performance) Diversity of two heuristics= defined by k and l
Hutchins 1995	Agents compare environmental stimuli with the knowledge agents have collected and stored under the form of patterns of situations	Different perception of environment		Different access to information		Communication intensity	

Table 1. Models of diversity in problem solving (part 2)

Contribu-tion	Operationalization of problem solving	Knowledge embedded in problem setting	Knowledge embedded in solution strategies	Imperfect information	Decision rule	Communication problems	Diversity
Marchiori and Warglien 2005 Sim 1	Agents compare environmental stimuli with the knowledge agents have collected and stored under the form of patterns of situations	Misperception of the environment		Noisy environment (same level, different features)	Similarity to stored patterns	Communication intensity as pressure to conform	different features of the environment (diversity coming from the environment)
Marchiori and Warglien 2005 Sim 2	Agents compare environmental stimuli with the knowledge agents have collected and stored under the form of patterns of situations	Erroneous knowledge as erroneous patterns stored in memories			Similarity to stored patterns		Heterogeneously wrong (diversity coming from the agents)
Marchiori and Warglien 2005 Sim 3	Agents compare environmental stimuli with the knowledge agents have collected and stored under the form of patterns of situations	Erroneous knowledge as erroneous patterns stored in memories			Similarity to stored patterns	Different communication structures (equal communication intensity)	Heterogeneously wrong (diversity coming from the agents)
This work	Agents build problem representations trying to give sense to evidence	Different causal inferences and explanations as problem setting: different causal elements in the schemata: expl. units		Evidence units in the schemata	Agents assess individually internal consistency of the arguments (a.k.a. “explanatory coherence”) and they chose the most coherent interpretation	Fixed level of communication intensity (on–off variable)	Diversity stems from differences in explanatory links and available information

2. THE MODEL

We model problem solving in teams using a constraint satisfaction approach stemming from the contribution of the PDP Group (Rumelhart et al. 1986) and we build on the ECHO model proposed by Thagard (1992b).

Agents' perspective on a problem is made of a schemata of causality in which agents draw explanations of why some evidence appeared in order to figure our how to intervene. Explanations are built on the basis of agents' knowledge, and they connect evidence to knowledge. Information is meant to report about collected evidence. Formally, in the model, knowledge and evidence are represented by units, causal explanations by links among knowledge and evidence units. For every problem, each agent builds two alternative explanations that compete one against the other. Agents assess these perspectives of the problem on the internal consistency of the argument. The more internally consistent, the more convincing, thus the preferred is the alternative. Subsequently, they implement the choice/action which is associated with the preferred alternative.

Let us specify how, formally and substantially, our model differs to more popular CS models assuming pattern matching activities. According to the latter models, a series of patterns X_i (for i=1, …, n) are stored into the network through a careful selection of the weights and the aim of the relaxation process is to assess the ability of the model to recognize the correct pattern X_i when the signal coming from the environment is noisy (the initial activation is $X_i + E$). Conversely, in our model, each weight is assigned on the basis of the existence of an explanatory relationship that links two different unit of the network according to a rule that will be explained in the next Subsection, and, similarly to other constraint satisfaction models, such as Axelrod (1997), the aim of the relaxation process is to observe what solution the model displays.

2.1 Structure of the Model

Agents.

Agents are represented by their schemata, which denote how they make sense of the world on the basis of their available data and knowledge.

Agents are modeled as a causal map of two theories or alternatives each composed by a series of hypotheses causally explaining bits of evidence. It is assumed that these competing theories have been elaborated on the basis of the agent's logical reasoning, knowledge and access to evidence.

Formally, an agent is modeled as a constraint satisfaction network of *n* units representing either scraps of available evidence (a.k.a. *evidence units*) or hypotheses giving causal explanations for one or several evidences (a.k.a. *units of hypothesis*, *explanatory units* or *explainers*); moreover, *special evidence units* (units that are only connected with evidence units) are introduced in the model in order to clamp evidence units to positive activation values (see below for the details).

Explanatory units are grouped into two competing sets (theories, say A and B), representing alternative interpretations of the problem setting. Thus, the network can be imagined as a three-layer graph, in which the top layer represents explanatory units belonging to theory A, the middle layer represents evidence units, while the bottom layer collects the explanatory units belonging to theory B.

Units' Activation.

Units' initial activation represents the agent's original beliefs regarding the units, that is, the agent's preliminary confidence on the environmental evidence and on the various theories' constituents.

Units' activations, that may take values in the [-1, 1] interval, are updated overtime according to the relaxation rule (see below); the fixed point that is reached at the end of this process represents the final belief of the agent regarding the units of the model.

This steady state may highlight that the agent favors one theory over the other if all explanatory units from one theory – say A – are positive while vice versa occurs for the units of the other theory – say B. If such a configuration does not occur, the model does not give a clear indication in terms of choice of one theory over the other, suggesting a case in which the agent does not judge the collected evidence and/or the supporting hypotheses conclusive.

Connections.

Connections or weights in each agent's network w_{ij} are set in order to reflect the competitive or cooperative relationship that exists between two units of the network (see Thagard 1992b for the full rationale). This procedure follows the rationale according to which agents' try to build theories as series of arguments that support one with each other. For sake of simplicity, we restrict our analysis to simple direct causality, thus explanatory links might only be set between units of evidence and explanatory units, while longer causal chains are not considered.

Positive connections between units of evidence and explanatory units represent direct causal relations (e.g., event x is causally explained by hypothesis y) and their intensity is coded through positive weights, such that higher weights correspond to higher causal relationships. In order to introduce positive feedback between co-hypotheses, positive connections are also introduced between explanatory units (from the same theory) that jointly explain the same set of evidence units.

Finally, competitive relationships are modeled by introducing negative connections between explanatory units, belonging to opposing theories, which jointly explain the same units of evidence.

Formal Procedure for Connections' Initialization.

Let $\mathbf{s} = (s_1,...,s_i,...,s_n) = (a_1,...,a_k,b_1,...,b_l,e_1,...,e_m) \in \mathbb{R}^n$ be the vector of the activations of all the units of the network, where k and l represent the number of explanatory units belonging, respectively, to theory A and B, m is the number of units of evidence (note that $n = k + l + m$). Let also $\mathbf{f} = (f_1,...,f_i,...,f_n) \in \mathbb{R}^n$ (with $f_i = 0$ for $i = 1,...,k + l$) be the vector of the activations of the special evidence units.

Let W be a n x n null matrix. Define α as the excitatory default value for assigning positive connections among units and β as the inhibition default value for assigning negative connections among units. Then, the weights w_{ij} (for $i = 1,...,n$, $j = 1,...,n$) are assigned according to the following steps:

Step 1. *Positive connection between an explanatory unit and a unit of evidence*: for each unit of type e that is causally explained by one or more explanatory units of type a:

i. let i corresponds to the position of the unit e in $\mathbf{s}$;

ii. compute the number r of explanatory units of type a that explain s_i;

iii. for each one of the r explanatory units of type a that explain s_i:

   a. let j correspond to the position of the unit a in $\mathbf{s}$;

   b. set $w_{ij} = w_{ji} = \alpha / r$;

iv. repeat step 1. for theory B.

Step 2. *Positive connections between explanatory units that belong to the same theory*: for each couple of units of type a that are co-hypotheses (they jointly explain one or more units of evidence:

i. let i correspond to the position of one unit of type a in $\mathbf{s}$ and j correspond to the position of the other unit in $\mathbf{s}$;

ii. set $w_{ij} = w_{ji} = \sum_{e=k+l+1}^{n} w_{ie} \cdot \mathrm{I}$;

where $\mathrm{I} = \begin{cases} 1 \text{ if } w_{ie} = w_{je} \\ 0 \text{ otherwise} \end{cases}$;

iii. repeat step 2. for theory B.

Step 3. *Negative connections between explanatory units belonging to different theories*: for each couple of units, one belonging to theory A and the other one belonging to theory B, that competitively explain one or more units of evidence:

i. let i correspond to the position of the unit of type a in $\mathbf{s}$ and j correspond to the position of the unit of type b *in* $\mathbf{s}$;

ii. set p as the number of units of evidence that are jointly explained by s_i and s_j;

iii. set q as the overall number of co-hypotheses (of type a and b) that jointly explain the units of evidence at step *ii*;

iv. set $w_{ij} = w_{ji} = \beta p/(q/2)$.

Note that W is symmetric, $w_{ii} = 0$ for $i = 1,...,n$ and $w_{ij} = 0$ for $i = 1 + k + l,...,n$ and $j = 1 + k + l,...,n$.

Relaxation rule.

Units' activation values are updated through a connectionist algorithm that is meant to increase the degree of coherence of the network in the sense that it performs a gradient-descent path towards levels of activation of the units that better satisfy constraints (see Rumelhart et al. 1986 for a formal treatment of analogous formalizations).

At each iteration, units' activation levels are synchronously updated according to the following rule (Thagard 1992b, 2000; Rumelhart et al. 1986):

$$s_j(t+1) = (1-d)s_j(t) + \begin{cases} \mathrm{net}_j(\max - s_j(t)) & \text{if } \mathrm{net}_j > 0, \\ \mathrm{net}_j(s_j(t) - \min) & \text{otherwise} \end{cases} \tag{1}$$

where $s_j(t)$ is the activation of unit j at time t, d is a decay parameter that, at each iteration, weakens the activation value of every unit. Min and max represent, the lower and upper boundaries of the units' activation and are generally set, respectively, at -1 and 1.

Finally,

$$\text{net}_j = \sum_i w_{ij} s_i(t) + f_j \tag{2}$$

is the net input to unit j, computed as the sum of the activation of all the units weighted by the connections w_{ij} linking each of these units with unit j. Note also that, in the case of evidence units, their net input also includes the value of the corresponding special evidence unit.
It is worth to mention that the formal treatment of this model is still incomplete. In particular, there is no proof of convergence of the system to a stationary state, nor of coherence maximization, since through relaxation the system might settle on a local maximum. However, there is a considerable body of literature (Thagard 1989, 1991, 1992a, 199b, Nowak and Thagard 1992a, 1992b, Eliasmith and Thagard 1997) that has shown convergence towards fixed points in finite time. In the simulations reported in the next Section, we will employ a choice of parameters consistent with previous literature and we will study the issues of convergence and of multiplicity of local maxima (fixed points).

Communication.
A group is a set of p agents modeled as a "network of agents' networks" (Hutchins 1995; Marchiori and Warglien 2005). Communication between two agents is modeled by linking each unit s_j of one agent with the corresponding unit s_j of the other agent. In this respect, communication is here intended as a parsimonious activity of beliefs exchange, in which only the activation of the units, and not the whole schemata is shared. This means that in our model agents exchange beliefs on how important or how credible a hypothesis or a scrap of evidence is, without sharing how they constructed their causal relations or how their entire causal map looks like.
It is worth to note that our approach is far to be the only way to introduce communication between agents: Hutchins (1995) and Marchiori and Warglien (2005) experiment various settings varying symmetry and introducing hierarchic structures. Other possible ways of modeling communication among agents have been explored in other domains for instance Thagard (2000) studied how scientific consensus is reached modeling agents that exchange verbal inputs and Thagard and Kroon (forthcoming) introduced emotional connections between agents.

In this group model, the vector of units is represented by the union of the p agents' vectors of units (**s**), while the weight matrix contains both the individual weight matrices (that are arranged as $n \times n$ blocks along the main diagonal) and the communication matrices (that are arranged as $n \times n$ blocks outside the main diagonal). The strength of communication is modeled through the communication intensity parameter $\delta \geq 0$; note that for $\delta = 0$ no communication occurs and the model reduces to a mere collection of independent agents. Also, as mentioned above, we assume the simplest form of communication: each agent communicates with everyone else with the same strength (each communication matrix has $\alpha\delta$ over the main diagonal and 0 elsewhere). This model is still a constraint satisfaction network and we apply the same relaxation rule for modeling the individual case.

Diversity.

The first source of diversity that we model is represented by differences in the number of causal explanations that agents might possess. The larger the set of explanatory links available to one agent, the larger his *knowledge amplitude*.

By limiting the available explanatory links we can model two different types of restrictions in agents' cognitive capabilities related to problem solving. If one causal link is missing, it might be the case that, the agent, albeit exposed to an evidence unit (that is already explained by one or more other explanatory units) and despite having already expressed a hypothetical unit (that already explains one or more evidence units) is not able to formulate correctly the existence of a causal explanation which links the two units together. On the whole, this suggests that agents have fragmented knowledge that only allows them to poorly interpret and understand the problem setting. This case can properly be understood as a problem of bounded rationality of the agents or of high specialization.

According to an alternative interpretation, the lack of explanatory links may point out that agents are diverse in the way they select scraps of information from the broader set of environmental stimuli, or in the way they are exposed to this information or are able to capture it. In this case, if an (evidence/exploratory) unit is not available to the agent, all explanatory links departing from this unit are unavailable as well. This case might be considered as a problem of information scarcity. In what follows, we do not distinguish properly between these two different class of cognitive restrictions: we will focus explicitly on restrictions of the first kind (decrease in the number of available links), albeit in some cases they would also imply the introduction of information scarcity (e.g.: if we remove a link that is the last one connecting a unit to the schemata, the unit is not considered in the agent's problem solving process).

As a second dimension of diversity, we model agents that are different because they might vary in the explanatory links they own. We will refer to this dimension as *knowledge variety*. For instance, two agents might be identical in terms of knowledge amplitude, but still diverse in the sense that the explanatory links belonging to each agent might be only partially overlapped. In our simulations, *knowledge variety* is been defined in relation to a given level of *knowledge amplitude* in order to simplify cases to be investigated. In this way, we focus on the contribution that knowledge variety offers to a group of peers (agents displaying the same level of knowledge amplitude).

Formally, in order to define a setting in which diversity can vary in a controlled way, we will model these two dimensions of diversity by introducing restrictions in the set of the available knowledge constituents (explanatory links) from a complete scenario defined as the reference point:. The specifications included in the next Section will clarify our modeling choices.

3. THE SIMULATION MODEL

For the purpose of providing a common basis for the analysis of agents' performance under various communication and diversity settings, we model a simplified problem which allows two alternative representations (theory A and B) each giving access to different actions, or highlighting a specific solution strategy. We define this baseline problem in terms of the sets of environmental evidence (e_i), explanatory units (a_i and b_i), and causal connections (w_{ij}) which are displayed in Table 2 and Figure 2. The number of units is $n = 12$, with $k = l = m = 4$ and the number of explanatory links is g=15. Note that, in Figure 2, solid lines represent positive connections between evidence and explanatory units while dashed lines represent competitive links between alternative theories. Note also that special evidence units (and their links to evidence units), cooperative links between explainers and actual weights values are omitted for clarity.

An agent having this complete representation of the problem – named "fully endowed" agent in the following – will always select theory A over theory B as the result of the relaxation process.

Table 2: List of Explainers in the Full Endowment Setting.

unit of evidence	**explainers in theory A**	**explainers in theory B**
e_1	a_1, a_2, a_3	b_1
e_2	a_3	b_2, b_3
e_3	a_2, a_3, a_4	b_3, b_4
e_4	a_3, a_4	b_4
tot. nr.	9	6

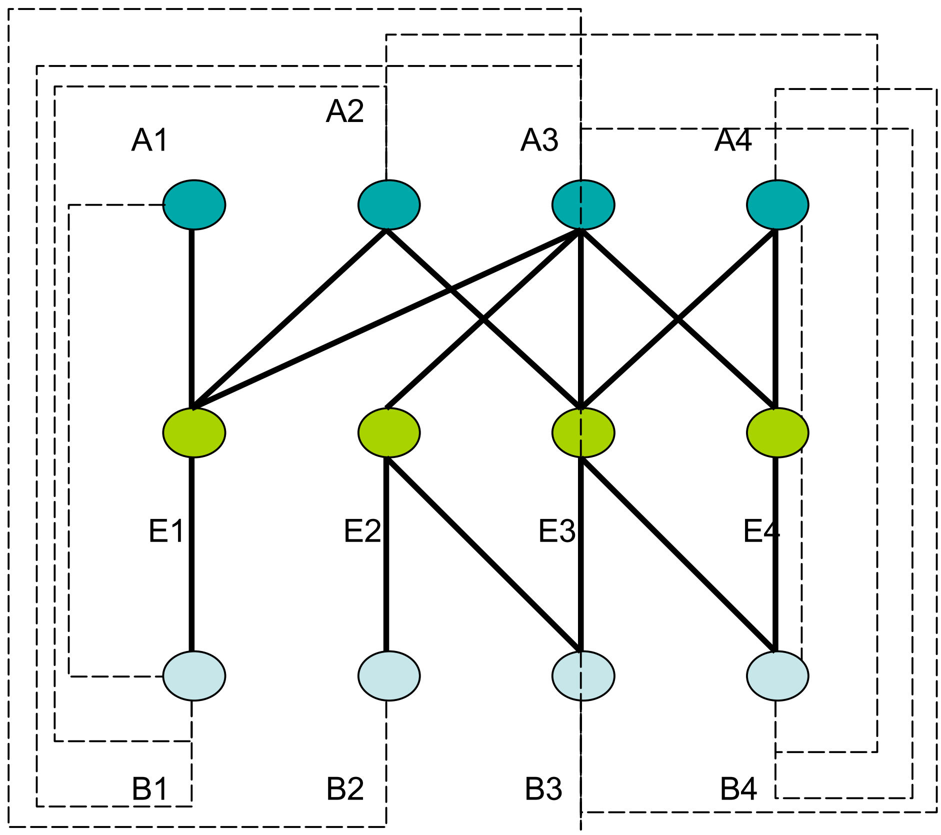


Figure 2: Representation of the Schemata in the Full Endowment Setting.

Given this case as the reference point, we introduce agents' diversity in the model by introducing diverse partial representations of the problem. Each agent is represented by one of these partial representations that display a differently bounded perspective for understanding the problem. Formally, each agent is a represented by a subset of the g explanatory links which jointly characterize the full problem setting.

In our simulations, subsets, and thus diversity, differ along two dimensions that we have called knowledge amplitude and knowledge variety. First, subsets vary according to the number of explanatory links (shown by the h parameter). We treat the h parameter as a proxy of agent's knowledge amplitude, so we will refer to "fully endowed agents" (for h=g) or "partially endowed agents" (for h<g).
Second, subsets of explanatory links for different partially endowed agents vary in terms of knowledge variety, by distinguishing between agents' shared *vs.* personal explanatory links. Here we restrict our analysis to the case of 2-person teams with peers (agents having the same knowledge amplitude – the same value for h). We introduce knowledge variety through the parameter v (with $0 \le v \le h$), that measures, for a couple of h-partial agents, the number of explanatory links, belonging to one agent, which differ from the explanatory links belonging to the other agent. Note that v=0 if the two h-partial agents are identical (they have exactly the same explanatory links), and v=h if all explanatory links of one agent are different from all the explanatory links of the other agent (to improve readability, the figures collected in the Section "Results" will show knowledge variety through the complement to h of v, that is the number of explanatory links that are shared in common by the couple of agents – the lower this value, the higher knowledge variety).
Formally, let us define the fully endowed agent as the agent having a complete representation of the problem (g=15) in terms of environmental evidence (e_i), explanatory units (a_i and b_i), and causal connections (w_{ij}). We refer to this case also as the *full endowment* treatment.
The fully endowed treatment will function as benchmark for comparing the performance of partially endowed agents acting individually or in teams. Partially endowed agents are agents having a partial representation of the schemata represented in Figure 2 and are modeled using a table of explainers that is a subset of the corresponding table in the baseline treatment. Given that the number of causal links available to the fully endowed agent is g=15, and a h-partial agent (for $h = 1,...,g-1$) is a bounded agent having only h causal links (over the g links of the full endowment treatment). There are C_g^h possible different h-partial agents.
We measure performance in terms of the frequency with which partially endowed agents' choices coincide with the fully endowed agent's ones. Given that the numerousness of partially endowed agents becomes quickly very large for the presence of the binomial coefficient, we will be able to offer statistics for the whole population only in extreme cases, that is for h close to g or to zero, while in all other cases we will derive our results via Monte

Carlo simulations with randomly generated h-partial agents, as will be explained better in the next Section.

A final remark regarding the parameterization of the model: we run all the instances of the model according to a choice of parameters (d=0.05, α=0.04, β=-0.06, s_j=0.01 for j=1, …, n, f_j=0.1 for j=k+l+1, …, n) that has been commonly employed in the previous literature on ECHO, and it has shown a remarkable capability of fitting data from various empirical domains. While some sensitivity analysis on these parameters showed that qualitative results do not change over a considerable parametric space, results from robustness analysis are not reported in this paper. Also, in the following Section, in order to pursue computational tractability of the problem, we restrict to the case of the smallest possible team (p=2). Finally, we treat communication as an on-off variable ($\delta = 0$ or $\delta = 0.5$) for all the simulations but the last one, where we focus on the effects of different communication strengths, increasing δ to 1 and to 1.5.

4. RESULTS

We organize our results into five Subsections. In the first one we show the performance of partially endowed agents as individual problem solvers (no communication occurs), and we explore the impact on performance of different levels of endowment. These results are used as a benchmark in the subsequent Subsections, in which we study how performance is affected by the introduction of team communication.

In the second Subsection we introduce 2-person teams made by one fully endowed agent and one partially endowed agent as a way to study the impact of increasing differences in knowledge amplitude within a team.

In the third Subsection we study 2-person teams made by two partially endowed agents having the same degree of knowledge amplitude. Here results are compared with the individual benchmark (Subsection 1) in order to assess to what extent communication can make up for partiality. In all these three treatments we measure performance by varying agents' endowment within the whole domain of the h parameter. Treatment three is investigated also in the two remaining Subsections.

Subsection four inquires the interplay between different sources of diversity in 2-person teams: we study to what extent performance is jointly affected by bounds in agents' explanatory ability (that is h<g) and by agents' knowledge variety (different elements in the h

causal links). Finally, the last Subsection deepens the previous analysis providing a simple sensitivity analysis over the communication strength parameter.

4.1 Agents as individual problem solvers: partial representations of the problem and performance

Figure 3(a) shows the outcome on individual performance resulting from introducing limits in knowledge amplitude. Note that, since agents do not communicate in this case, we are not investigating issues of diversity among interacting agents: here we are interested in varying knowledge amplitude only as a means to understand how much, at the individual basis, performance is affected by the deterioration of knowledge regarding a problem. Data are organized in order to distinguish poorly endowed agents (low values of the h parameter) from "almost fully" endowed agents (high values); frequencies are computed over the whole populations of possible h-partial agents, whose sizes are shown in Figure 3(b).

Recalling that a fully endowed agent always solves the problem in terms of theory A, the decline in the capability of correctly interpreting the problem is clearly visible if one moves from the right to the left side of the plot: agents that are more and more bounded in the representation of the problem display a decreasing rate of selecting theory A. Interestingly enough, the selection of theory B does not increase correspondingly. On the contrary, the decrease in performance is almost entirely due to the emergence of confusion as the result of the agents' efforts to interpret the problem: agents select outcomes which are inconclusive as they do not highlight any winner between the two available theories. Formally, the system converges to fixed points in which the values of the s_j units do not allow to clearly separate a winning theory (the theory whose units are all positive) from a losing one (the theory whose units are all negative).

Note that in the case of very poor problem settings (for $h \leq 5$), agents tend to get less stuck into inconclusive outcomes, as it becomes more and more probable that the few remaining links provide an unambiguous and strong support for one theory over the other one.

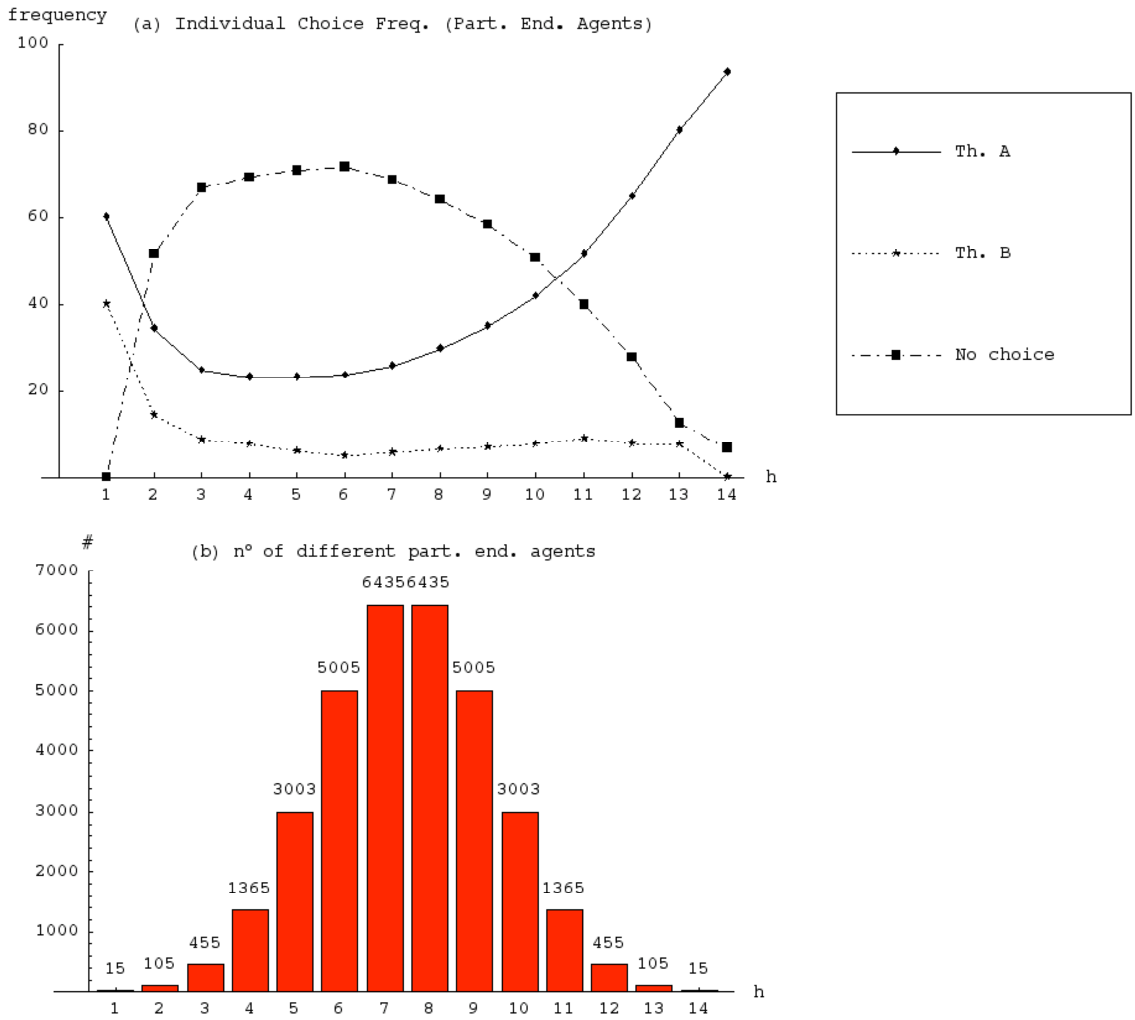


Figure 3. (a) Frequencies of the correct interpretation ("theory A"), wrong one ("theory B") and of reaching an inconclusive outcome (inability of selecting between the two theories), computed for *h*-partial agents (according to the various values of *h*) and (b) frequencies of the possible *h*-partial agents, computed according to the binomial coefficient C_{15}^{h}, for h=1,…,14.

4.2 Performance in Diverse Teams: the Role of Knowledge Amplitude

We address the topic of diversity at first by studying the impact of increasing differences in knowledge amplitude in teams. For the sake of simplicity we restrict our analysis to the case of 2-person teams composed by one fully endowed agent and one partially endowed agent, and we model increases in diversity by decreasing the number of links available to the latter agent. A diffused practice in organizations is to group workers having a vast knowledge with novices. Through this simulation we evaluate if novices benefit from experienced buddies or if through interaction, they are able to confound even the most experienced colleagues with their poor knowledge.

Figure 4 collects the observed frequencies of performance, respectively for (a) the partially endowed agent and (b) the fully endowed agent. As it is evident from Figure 4(b), the effect of communicating with a bounded agent has no effect at all on the fully endowed agent performance. On the other hand, communication helps the partially endowed agent to avoid the trap represented by the wrong theory (B), which is never selected. Nevertheless, partially endowed agent's performance is still far from the levels of the fully endowed one. In fact, similarly to the baseline treatment, when his knowledge is very poor, the frequency of inconclusive outcomes is still higher than the frequency of the correct interpretation (theory A). Despite this, an overall look at the results allows to claim that communication has a positive effect on teams composed by an experienced worker and a novice at any level of *h*, as summarized in Figure 5.

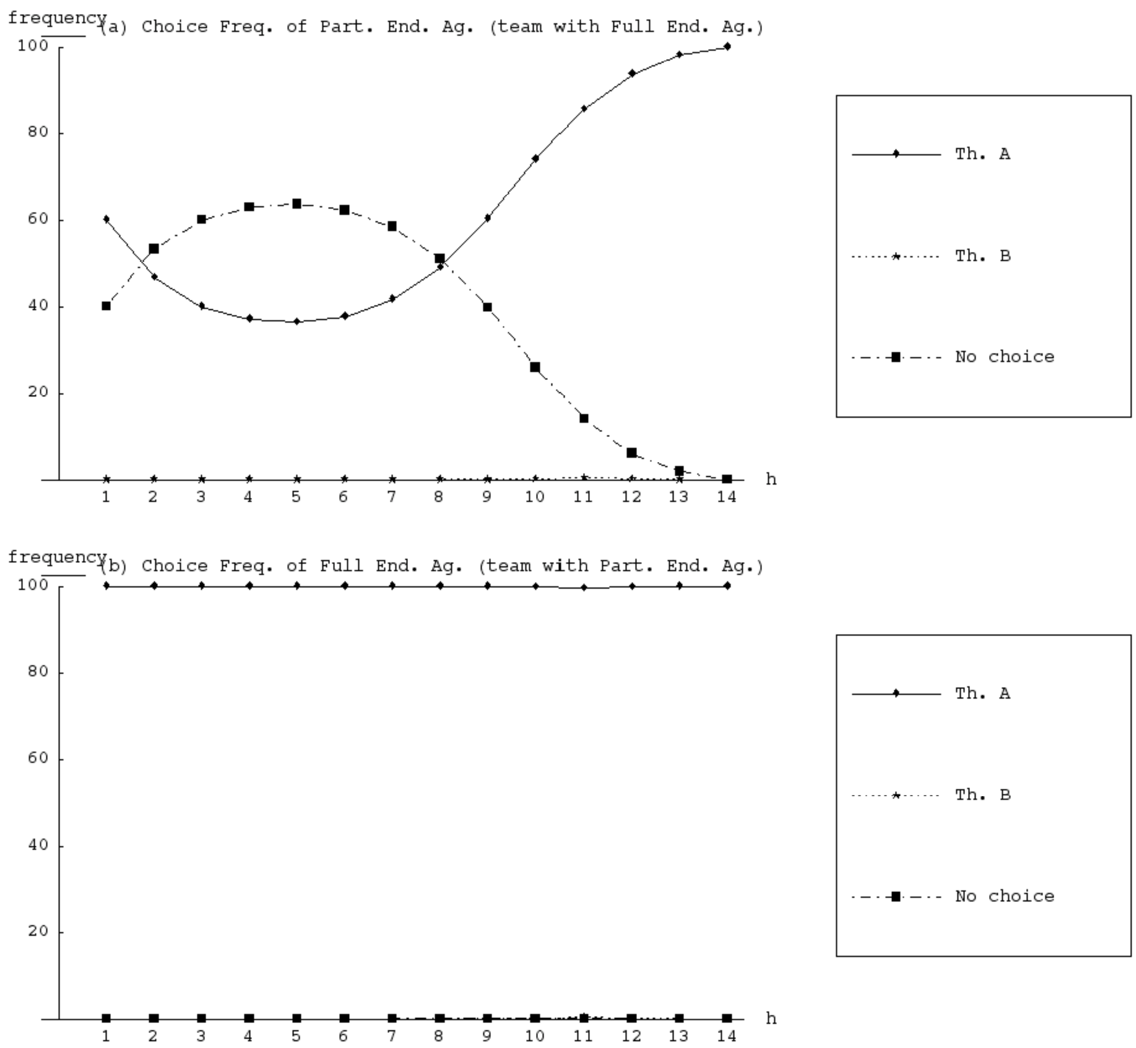


Figure 4. Frequencies of the correct interpretation ("theory A"), of the wrong one ("theory B") and of reaching an inconclusive outcome, respectively, for (a) a partially endowed agent and (b) a fully endowed agent, communicating in a 2-person team.

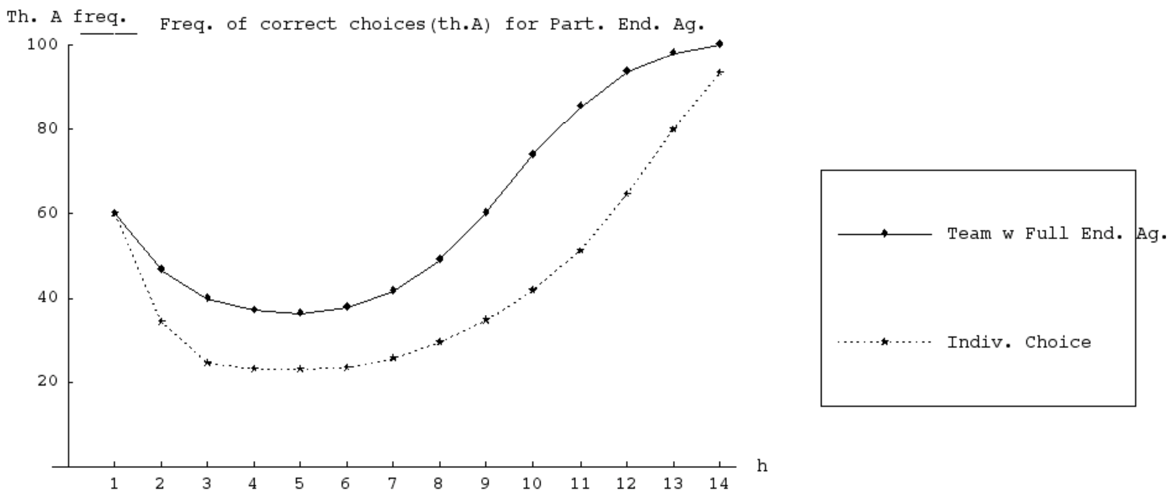
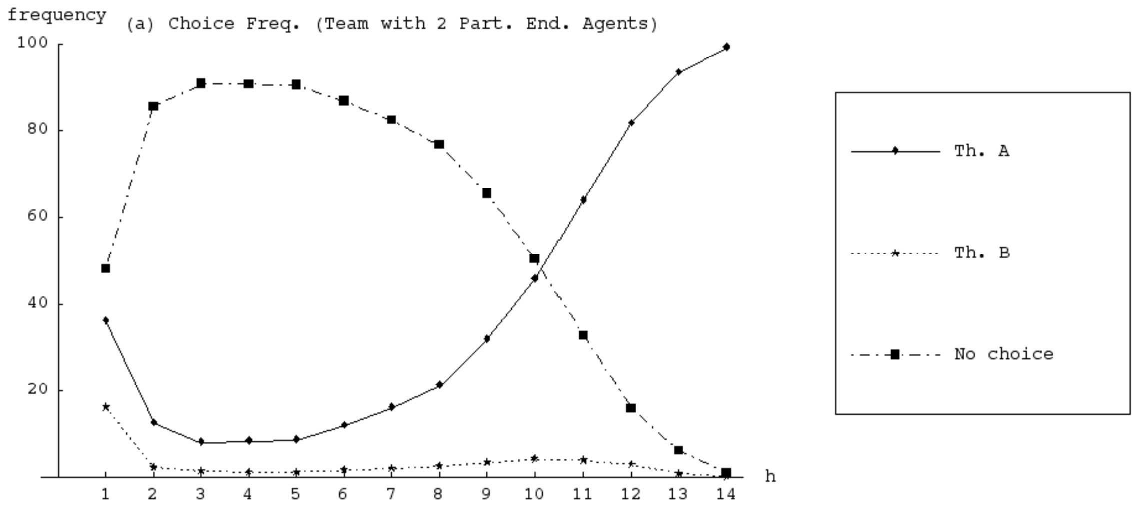


Figure 5. Frequencies of the correct interpretation ("theory A") for a partially endowed agent with and without team communication with a fully endowed partner.

4.3 Teams with Two Partially Endowed Agents

In Figure 6 we introduce team communication between couples of partially endowed agents. We restrict the analysis to the symmetric case and we assume that a *h*-partial team is composed by two *h*-partial agents (note that here we do not control for knowledge variety, that is investigated in the next Subsection). Since the sizes of the populations of the possible *h*-partial teams, as shown in Figure 6(b), are large, frequencies depicted in Figure 6(a) are collected through random sampling of 20.000 *h*-partial agents randomly grouped in 10.000 teams (data for the two agents are pooled in the analysis). From Figure 6(a), and Figure 7, that compares the observed frequency of the correct interpretation over the three treatments (partial agent alone, partial agent matched with a full agent, partial agent matched with another similarly partial agent), it is possible to derive the following considerations: (i) communicating in a team with a fully endowed agent betters the performance of the partially endowed agent for all the levels of *h*. On this respect, the partially endowed agent should always prefer to team with the fully endowed agent than with similarly partially endowed fellows; (ii) when two partially endowed teammates form a group, performance deploys a less straightforward trend. When peers' problem representation, albeit limited, still gives a rough picture of the situation (intermediate levels of *h*), team interaction can improve agent's performance. On the contrary, as their limits in representing the problem increase, they might reach a point after which performance as individuals seems more effective, since in the communication treatment the frequency of inconclusive outcomes becomes larger.



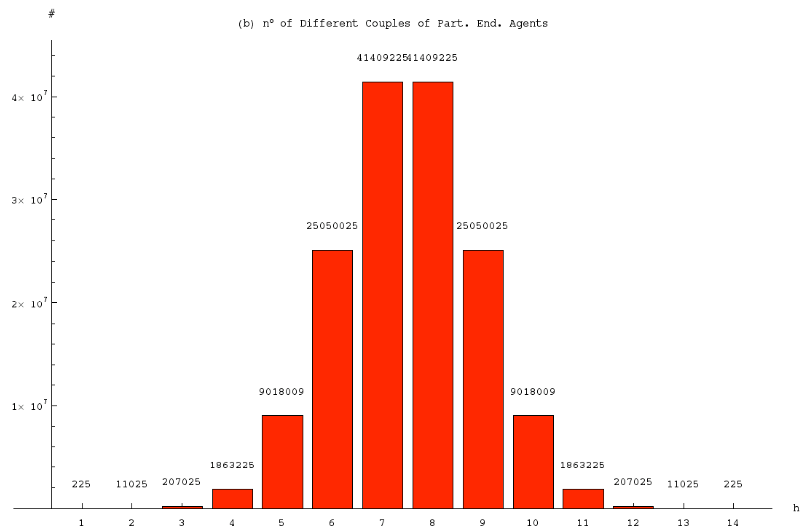


Figure 6. (a) Frequencies of the correct interpretation ("theory A"), wrong interpretation ("theory B") and of reaching an inconclusive outcome (inability of discriminating between the two alternative interpretations), computed for a h-partial agent communicating in a 2-person team with another h-partial agent (b) frequencies of the possible couples of h-partial agents, computed according to the formula $\left(C_{15}^{h}\right)^{2}$, for h=1,…,14. Frequencies in (a) are computed with respect to random samples of 10.000 couples of h-partial agents.

An intuitive interpretation for these results is that, when agents can only represent poorly the problem they are facing, communication might drive them into a decision trap, making them incapable to reconcile messy suggestions coming from their teammate with their own, already fragmented representation. One possible explanation for the poor performance of communication might lie in the observation that, the more limited agents' problem representations, the higher the probability that their schemata would have very few element in common, something that we would expect to increase confusion. In order to investigate better this issue, we integrate another dimension of diversity into the analysis: knowledge variety.

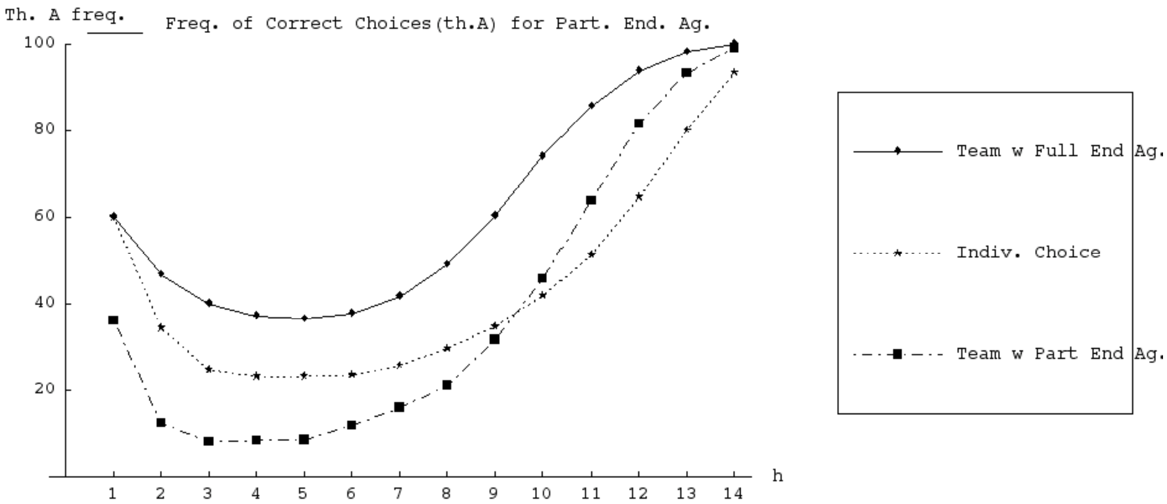


Figure 7. Frequencies of the correct interpretation ("theory A") for a partially endowed agent under three different treatments: individual behavior, communication with a fully endowed partner, communication with a partially endowed partner.

4.4 The Interplay between Diversity dimensions: Knowledge Amplitude and Knowledge Variety in Teams of Two Agents

We measure knowledge variety for a given couple of *h*-partial agents as the complement to *h* of the number of common causal links shared by the couple. In Table 3, which counts the possible *h*-partial teams with respect to *h* and to the number of shared causal links, the level of variety increases if we move from the right to the left side of the table.

Table 3. Frequencies of the possible couples of h-partial agents, computed distinguishing for the level of endowment (h) and for the variety among the h features available to each of the two agents (that can be measured in terms of the complement to h of the number of causal links that they share). Note that the elements a_{ii} (for i=1,…, 14) correspond to the frequencies of the populations of h-partial agents shown in Figure 3(a), and horizontal sums corresponds to the frequencies of the population of h-partial teams shown in Figure 6(b). Also note that from the lower to the upper bound of the Table we move towards agents more bounded in their knowledge, and that from right to left we move, *ceteris paribus*, toward agents with less shared links, thus displaying more variety in their knowledge.

	shared links														
h	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
1	210	15	-	-	-	-	-	-	-	-	-	-	-	-	-
2	8190	2730	105	-	-	-	-	-	-	-	-	-	-	-	-
3	100100	90090	16380	455	-	-	-	-	-	-	-	-	-	-	-
4	450450	900900	450450	60060	1365	-	-	-	-	-	-	-	-	-	-
5	756756	3153150	3603600	1351350	150150	3003	-	-	-	-	-	-	-	-	-
6	420420	3783780	9459450	8408400	2702700	270270	5005	-	-	-	-	-	-	-	-
7	51480	1261260	7567560	15765750	12612600	3783780	360360	6435	-	-	-	-	-	-	-
8	-	51480	1261260	7567560	15765750	12612600	3783780	360360	6435	-	-	-	-	-	-
9	-	-	-	420420	3783780	9459450	8408400	2702700	270270	5005	-	-	-	-	-
10	-	-	-	-	-	756756	3153150	3603600	1351350	150150	3003	-	-	-	-
11	-	-	-	-	-	-	-	450450	900900	450450	60060	1365	-	-	-
12	-	-	-	-	-	-	-	-	-	100100	90090	16380	455	-	-
13	-	-	-	-	-	-	-	-	-	-	-	8190	2730	105	-
14	-	-	-	-	-	-	-	-	-	-	-	-	-	210	15

Figure 8 shows the frequencies of selecting the correct interpretation (theory A) in a h-partial team for various levels of knowledge amplitude (h) and variety (measured in the horizontal axis). Frequencies are computed over the whole corresponding team population if, according to Table 3, its size is less than 10.000, otherwise frequencies refer to 10.000 random couples. The points displayed in the plot refer to the case in which the number of shared links is equal to h, thus representing teams between 2 identical agents. Note that in this case outcomes correspond exactly to the performance of individual agents that have been previously collected in Figure 3. Starting from every point, two different lines depart towards the left side of the plot: solid lines represent the frequency of the correct interpretation under team communication for increasing levels of variety in the couple of agents (data are pooled for the two agents); dashed lines represent how these agents would perform without communication (these frequencies are slightly different from the values at each corresponding right-end point because they are computed over different random samples).

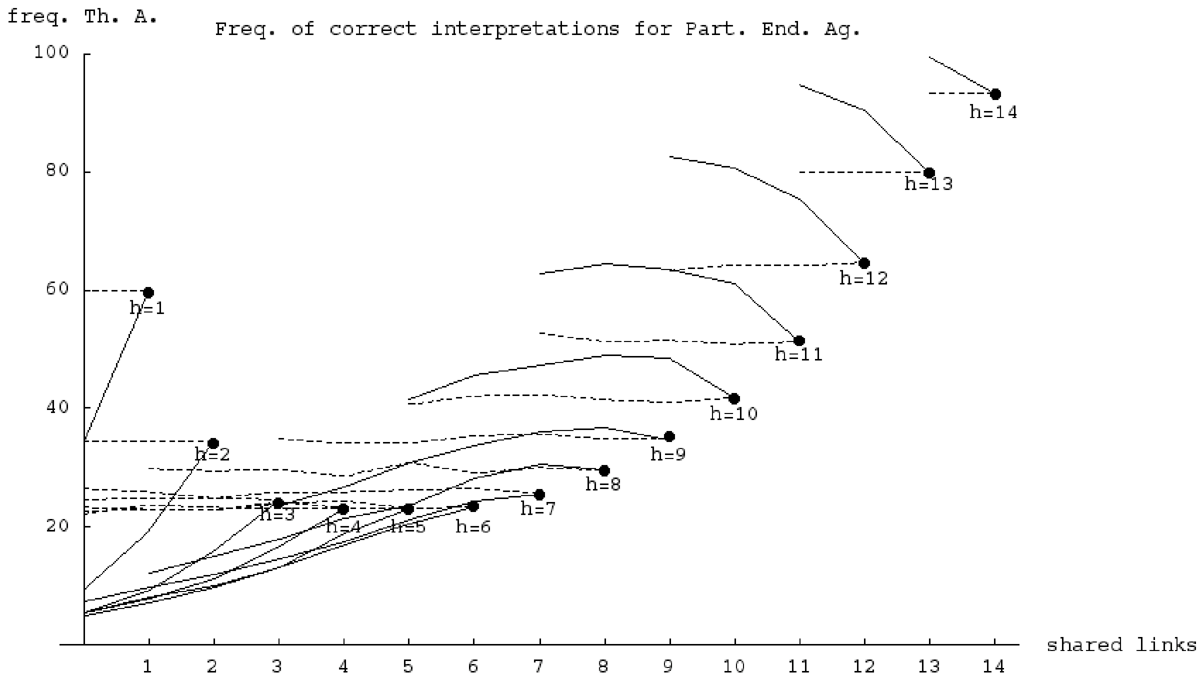


Figure 8. Frequencies of the correct interpretation (theory A) measured for *h*-partial teams under various level of endowment (*h*) and variety (measured on the horizontal axis, fewer shared links corresponds to a higher variety in the team).

Overall, results shown in Figure 8 allow to shed some light on the interplay between three intertwined elements: team communication, agents' knowledge amplitude in the problem representation and knowledge variety. For high levels of knowledge endowment (right side of Figure 8), communication always betters individual outcomes and the more various knowledge agents have, the better the probability of inferring the correct interpretation. This trend shows that when agents have an almost complete representation of the problem, they can benefit most from interaction, because they are able to enrich their view of the problem with aspects that they ignored or were not able to explain. In short, communication helps them closing the puzzle. The circulation of missing links of the problems representation is positive if the vision that is already available to the agents is complete enough so that these missing links can be added to a set of problem explanations which is relatively stable within the group. As a matter of fact, we observe that for intermediate levels of knowledge endowment (center), agent's performance still benefits from communication, while there is an optimal amount of variety granting the highest performance levels, after which performance declines (up to a point in which extreme levels of variety might result in worse performance than in the case of independent individual problem solving). In fact, for lower levels of knowledge endowment (left side) team communication always provides worse conclusions than the individual case.

This evidence shows that groups can benefit most from being composed by diverse members – in terms of variability of knowledge – when all of them have a very good representation of the problem. Conversely, when they understand little of the situation, diversity gives rise to disorientation rather than improvements in problem solving.

4.5 The Role of Communication Strength

Results from the previous Subsections were obtained with a degree of communication strength that supposes a moderate interaction among agents. In this Subsection, we perform a discrete sensitivity test by doubling and tripling the value of the communication strength parameter. Recalling how the schemata is initialized, these three values correspond, respectively, to the case in which communication has a lower, similar or higher impact on the weights of the communication matrices in comparison with the default intensity of the causal relationships of the individual weight matrices. We restrict the analysis to these values, arguing that this choice is consistent with the aim of preserving enough intelligibility in the graphical presentation of the results, without losing depth in the analysis, since outcomes for lower or higher communication strengths can easily be derived from the analysis carried out at the levels that we focus on in the following. Results are collected in Figure 9, in which solid lines are arranged so that thicker lines correspond to higher communication strengths. Due to the multiple series of data, in order to improve readability, we show the results only for selected h values.

We arrange our results distinguishing between low/high levels of endowment. For low levels (left side of Figure 9, for $h \leq 8$), sensitivity analysis clearly confirms the negative contribution of communication: all communication levels produce a performance worse than individual outcomes. Communicating more does not help agents that have a poor understanding of the problem setting: there is a clear-cut and monotonic negative relationship linking performance and communication strength, resulting in communication mishaps that are particularly evident for the highest δ value. This means that teams of agents having very poor representations and over-discussing the details of the problem are more likely to distort even those few elements they understand and to get stuck at a point in which they cannot see which choice should be made.

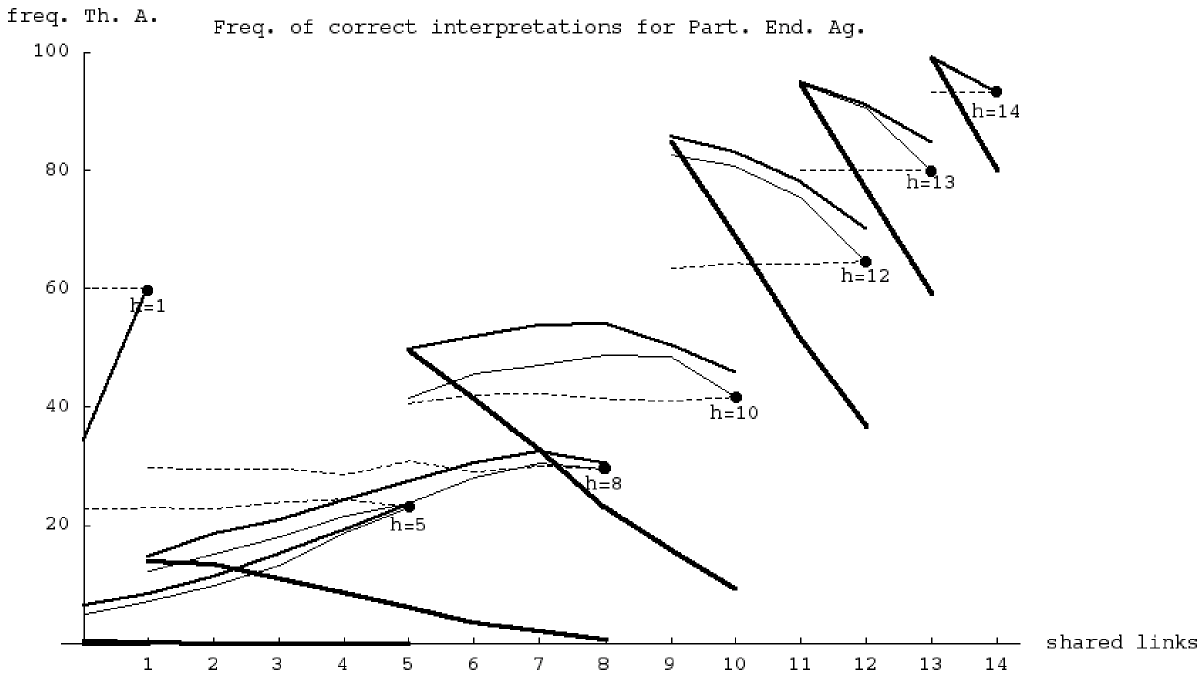


Figure 9. Frequencies of the correct interpretation (theory A) measured for h-partial teams under various level of endowment (h) and variety (measured on the horizontal axis, fewer shared links corresponds to a higher variety in the team), for different degrees of communication strengths: the thinnest (solid) line corresponds to the initial treatment displayed in Figure 8 (the lowest, with $\delta = 0.5$), the thickest one to a highest communication level ($\delta = 1.5$), while the intermediate thickness corresponds to an intermediate strength level ($\delta = 1$).

For higher levels of endowment ($h \geq 10$) findings are less straightforward and can be summarized as follows. First, there is a clear non-monotonic relationship between communication strengths and performance: while we did not perform a complete exploration of the strength space in order to find an optimal value, it is clear that performance corresponding to the intermediate communication value is always better than both the lower and higher strength levels. Second, as endowment increases, sensitivity to changes in communication strength decreases, since differences in performance improvements get smaller. Third, the interplay between communication and variety in agents' knowledge seems to be particularly unanticipated. In fact, while performance differentials for various communication strengths are negligible in the case of very diverse agents, they are considerably large as agents become more and more similar. In particular, the non-linearity of the phenomenon is startling: while doubling the communication strength results in relatively limited performance improvements, moving from $\delta = 1$ to $\delta = 1.5$, we observe a severe performance breakdown. Finally, higher communication strengths might affect the behavior even in teams of identical agents: while for $\delta = 0.5$ communication did not result in any

observable difference with respect to individual behavior, as the strength of communication increases identical agents change their behavior when interacting in a team.
More precisely, this results in improvements at the intermediate communication level, while for the highest level it corresponds to a considerable deterioration in agents' problem solving abilities.

5. DISCUSSION

In this paper we investigated the impact of communication in teams of diverse problem solvers. We modeled diversity as differences in problem representation. Extant literature addresses the relation between team diversity and performance through models that do not allow to control for various determinants and sources of diversity in teams of heterogeneous agents. Our model, instead, defines diversity along two different dimensions: knowledge amplitude and knowledge variety, thus opening the door to explorations of the effects of distinct features and levels of diversity on the performance of problem solving teams.
We studied interactions among diverse peers, which are agents having the same knowledge amplitude, but that might display diversity in terms of knowledge variety. Likewise, we provided results regarding agents' interactions in teams composed by novices and more experienced problem solvers as a way for investigating the role of diverse levels of knowledge amplitude in problem solving performance.
Our results allow to derive some implications on groups composition and interaction in firms and organizations. Our main findings show that teams are not always effective means for tackling problem solving in organizations.
This is certainly not the case of teams pairing more experienced workers with partners having a poor understanding of the problem. In fact, the first are not diverted by their teammate's doubts or partial understanding, since they prove to be able to lead the less experienced to solutions that are better off, without registering significant losses in their performance.
Conversely, if we address the topic of communication effectiveness in teams of peers, results may vary. In particular, communication might have a negative impact when the understanding of the situation is very fragmented. We showed that when peers display a very limited understanding of the problem, their propensity for failure increases. In fact, when agents don't share a considerable overlap in their problem representation, their perspectives on the world diverge and languages do not find a common basis for beneficial interaction. In this scenario, communication might eventually result in being more troublesome than helpful.

Moreover, adding variety into these poor interpretations makes the situation even worse: agents confound more and more each other as they become more diverse.

Communication helps when peers have a vast knowledge domain that allows them to identify the majority of the relevant information and to define consistent and coherent explanations of the evidence. As a matter of fact, interaction allows them to complement each other's knowledge in an effective way, and increases in knowledge variety allow to further improve the team performance, too.

These results notwithstanding, we also showed that interacting too much might change the overall impact of communication. This is not the case of teams unfolding high variety in knowledge meaning that talking more or more intensely with people that are well-read in domains that are different from our own is enriching and eventually increases performance. Very similar agents though are extremely sensitive to higher than optimal communication strengths, as their performance declines considerably. This points out that discussing too much the same ideas does not make them clearer nor more effective. On the contrary, too many repetitive arguments make agents less sharp and incline to fail more often. Interesting enough, the opposite case of interacting too little is less disruptive as lower than optimal communication strengths have a less significant impact on performance.

Our results are limited in various ways. First of all, they rely on a specific, albeit common in the literature, choice of the model parameters and run over a specific instance of a problem setting displaying an abstract and acceptable despite arbitrary structure. The reasons for starting from this unique and *ad hoc* instance can be justified if one takes into account that: (i) we needed to start from a full representation of the problem setting which relaxed towards one theory, something that is not granted by generating at random lists of explainers (as the one collected in Figure 2), since the corresponding fixed point might be inconclusive; (ii) computational parsimony suggested to restrict the analysis to one structure (as opposed to averaging results for a series of different instances) and to a limit the amount of units involved (n=12). Similar reasons suggested to limit our analysis to the case of 2-agent teams and of two competing theories. Finally, we explored knowledge variety only in the case of similarly endowed agents (peers) while more complex cases in which amplitude and variety still need to be addressed.

The current model does not pretend to be complete, and several extensions could be made. We offer it with a twofold attempt: first, of investigating the contribution of diversity to team problem solving thus providing a deeper understanding of dynamics of collective problem solving; second, for exploring models of decision making that detach from pattern matching basis or from bounded evaluations of consequences.

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