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Experimental Study and Modeling of Three Classes of Collective Problem-Solving Methods

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Summary

People working together can be very successful problem-solvers. Many real-life examples, from Wikipedia to citizen science projects, show that, under the right conditions, crowds can find remarkable solutions to complex problems. Yet, joining the capabilities of many people can be challenging. What factors make some groups more successful than others? How does the nature of the problem and the structure of the environment influence the group's performance? To answer these questions, I consider problem-solving as a search process – a situation in which individuals are searching for a good solution. I describe and compare three different methods for structuring groups: (1) non-interacting groups, where individuals search independently without exchanging any information, (2) social groups, where individuals freely exchange information during their search, and (3) solution-influenced groups, where individuals repeatedly contribute to a shared collective solution.

First, I introduce the idea of transmission chains – a specific type of solution-influenced group where individuals tackle the problem one after another, each one starting from the solution of its predecessor. I apply this method to binary choice problems and compare it to majority voting rules in non-interacting groups. The results show that transmission chains are superior in environments where individual accuracy is low and confidence is a reliable indicator of performance. This type of environment, however, is rarely observed in two experimental datasets.

Then, I evaluate the performance of transmission chains for problems that have a complex structure, such as multidimensional optimization tasks. Again, I use non-interacting groups as a comparison, this time by selecting the best out of multiple independent solutions. Simulations and experimental data show that transmission chains outperform independent groups under two environmental conditions: either when problems are rather easy, or when group members are relatively unskilled.

Next, I focus on social groups, where individuals influence each other *during* the search. To understand the social dynamics that operate in such groups, I conduct two studies: I first examine how people search for a solution independently from others, and then study how this individual process is impacted by social influence. The first study presents experimental data to show that the individual search behavior can be described by a take-the-best heuristic, that is, a simple rule-of-thumb that ignores all but one cue at a time. This heuristic reproduces a variety of behavioral patterns observed in different environments. Then, I extend this heuristic to include social interactions where multiple individuals exchange information during their search. My results show that, in this case, individuals tend to converge towards similar solutions. This induces a collective search dilemma: compared to non-interacting groups, the quality of the average individual's solution is improved at the expense of the best solution of the group. Nevertheless, further analyses show that this dilemma disappears for more difficult problems.

Overall, this thesis shows that no collective problem-solving method is superior to the others in all environments and for all problems. Instead, the performance of each method depends on numerous factors, such as the nature of the task, the problem difficulty, the group composition, and the skill levels of the individuals. My work helps understanding the role of these different factors and their influence on collective problem-solving.

Zusammenfassung

Menschen, die zusammenarbeiten, sind in der Lage, Probleme erfolgreich zu lösen. Viele Beispiele aus der Praxis, von Wikipedia bis hin zu bürgerwissenschaftlichen Projekten, zeigen, dass Menschenmengen unter den richtigen Bedingungen bemerkenswerte Lösungen für komplexe Probleme finden können. Dennoch kann es eine Herausforderung sein, die Fähigkeiten vieler Menschen zu kombinieren. Welche Faktoren machen einige Gruppen erfolgreicher als andere? Wie beeinflusst die Art des Problems und die Struktur des Umfelds die Leistung der Gruppe? Um diese Fragen zu beantworten, betrachte ich die Problemlösung als einen Suchprozess - eine Situation, in der Einzelpersonen nach einer guten Lösung suchen. Ich beschreibe und vergleiche in dieser Doktorarbeit drei verschiedene Verfahren zur Strukturierung von Gruppen: (1) nicht interagierende Gruppen, in denen Einzelpersonen unabhängig voneinander suchen, ohne Informationen auszutauschen, (2) soziale Gruppen, in denen Einzelpersonen während ihrer Suche frei miteinander kommunizieren und Informationen austauschen und (3) lösungsbeeinflusste Gruppen, in denen Einzelpersonen mit ihrer Lösung zu einer gemeinsamen kollektiven Lösung beitragen.

In dieser Doktorarbeit stelle ich zunächst die Übertragungskette vor. Es handelt sich dabei um eine spezifische Art einer lösungsbeeinflussten Gruppe, in der Einzelpersonen das Problem nacheinander angehen, jede ausgehend von der Lösung ihres Vorgängers. Anschließend wende ich die Übertragungskette auf binäre Entscheidungsfragen an und vergleiche sie mit Mehrheitsregeln in nicht-interagierenden Gruppen. Die Ergebnisse zeigen, dass Übertragungsketten in Umgebungen mit geringer individueller Genauigkeit überlegen sind, wenn die Antwortsicherheit ein zuverlässiger Indikator für die Genauigkeit ist. Zwei experimentelle Datensätze zeigen, dass diese Art von Umgebungen selten gegeben ist.

Ferner bewerte ich die Leistung von Übertragungsketten für Probleme, die eine komplexe Struktur haben, wie z.B. mehrdimensionale Optimierungsaufgaben. Auch hier benutze ich nicht-interagierende Gruppen als Vergleich. In diesem Fall wähle ich die beste Lösung aus den allen, unabhängig voneinander, gefunden Lösungen der Einzelpersonen aus. Simulationen und experimentelle Daten zeigen, dass Übertragungsketten nicht-interagierende Gruppen in zwei Umgebungen übertreffen, zum einen, wenn die Probleme relativ einfach sind und zum anderen, wenn es den Gruppenmitgliedern an Fähigkeiten zur Lösung des Problems mangelt.

Anschließend konzentriere ich mich auf soziale Gruppen, das heißt Gruppen, in de-

nen sich Einzelpersonen bei der Suche gegenseitig beeinflussen können. Um die soziale Dynamik zu verstehen, die in solchen Gruppen entstehen, führe ich zwei Studien durch: Erstens untersuche ich, wie Menschen unabhängig von anderen nach einer Lösung suchen. Zweitens teste ich, wie diese individuelle Suche durch soziale Einflüsse verändert wird. Die erste Studie umfasst ein Experiment, welches aufzeigt, dass das individuelle Suchverhalten durch eine Take-the-best Heuristik beschrieben werden kann. Bei einer solchen Heuristik handelt es sich um eine einfache Faustregel, die jeweils alle bis auf einen Hinweis ignoriert. Diese Heuristik reproduziert die Art und Weise der Suche der Versuchspersonen in verschiedenen Umgebungen.

Zusätzlich erweitere ich diese Heuristik, um soziale Interaktionen abzubilden, bei denen Personen während ihrer Suche Informationen austauschen. Meine Ergebnisse zeigen, dass durch den Einfluss solcher sozialen Informationen die Lösungen der verschiedenen Personen ähnlicher werden. Dies führt zu einem kollektiven Suchdilemma: Im Vergleich zu nicht-interagierenden Gruppen wird die durchschnittliche Qualität der Lösung der Einzelpersonen verbessert, während sich die Qualität der besten Lösung der Gruppe verschlechtert. Meine weiteren Analysen zeigen, dass dieses Dilemma bei sehr schwierigen Problemen verschwindet.

Insgesamt verdeutlicht meine Arbeit, dass kein kollektiver Problemlösungsprozess allen anderen Prozessen in allen Umgebungen und für alle Probleme überlegen ist. Stattdessen hängt die Leistung jedes Prozesses von zahlreichen Faktoren ab wie beispielsweise von der Art der Aufgabe, der Schwierigkeit des Problems, der Gruppenzusammensetzung und den Fähigkeiten der einzelnen Personen. Meine Arbeit trägt zu einem besseren Verständnis über die Rolle dieser verschiedenen Faktoren sowie deren Auswirkungen auf das kollektive Lösen von Problemen bei.

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Contents

Chapter 1

General Introduction

All Life is Problem Solving

Karl Popper

In 1990, the then 21-year old student Linus Torvalds decided to develop his own computer operating system. Initially started as a hobby for himself, he soon made a momentous decision: He released the source code of the operating system – Linux – and asked people over the Internet to contribute to it (Torvalds, 1993). In 2017, over 15,000 programmers had participated in the development of the operating system, which is today used on countless computers, from small embedded devices to the largest supercomputers (The Linux Foundation, 2017).

Nine years later, Garry Kasparov, the then reigning Chess World Champion, played an unusual game against over 50,000 ordinary players located all over the world. These people, supported by five experienced players, decided each of their moves by majority vote. After a four-month long match with 62 moves, Kasparov eventually won the game. The champion later claimed that this was the most challenging game in his career and recognized the deep tactical skills of his many-headed opponent (Kasparov and King, 2000).

As these two prominent examples illustrate, groups of people working together have the potential to generate remarkable outcomes and solve problems that any single individual could not solve on its own (see figure 1.1). Yet, efficiently merging the capabilities of many people is not an easy task. Numerous examples have highlighted that a crowd can also make bad decisions, give wrong predictions, or produce flawed outcomes. On the last day before the 2016 US election, all polls and the majority of forecasters believed that Hillary Clinton was about to become the next president of the United States of America (Silver, 2016). Only a very small minority of the forecasters predicted otherwise (e.g. Lichtman, 2016). Surprisingly the minority was right and Clinton's challenger Donald Trump won the general election.

How do people solve problems together? Why are some groups more successful than others? How does the nature of the problem shapes the performance of a group? This thesis aims at providing answers to these questions.

The remainder of this chapter is structured as follows. First I provide a historical perspective on the broad concept of collective intelligence. Then, I focus on the more specific area of collective problem-solving, and express it as a search process (Newell et al., 1958; Newell and Simon, 1971; Newell and Simon, 1972). Subsequently, I suggest a classification of different collective problem-solving methods based on the nature of the interaction between individuals. Finally, I use this classification to identify important gaps in the scientific literature and conclude by outlining how this thesis aims at filling them.

1.1 A brief history of collective intelligence

Collective intelligence has been investigated in a variety of scientific disciplines, including biology, psychology, sociology, and economics (Malone and M. S. Bernstein, 2015; Surowiecki, 2004; Krause et al., 2010). However, perhaps unsurprisingly, one of the first concepts related to collective intelligence was described by a mathematician and philosopher: Nicolas de Condorcet. In his jury theorem formalized in 1785, the "Marquis" (the French word for marquess, nobleman) states that the accuracy of a majority vote increases with the number of voters, provided that the average individual accuracy is above 50% (Ladha, 1992; Boland, 1989). Hence, increasing the size of a jury usually increases the likelihood of correct verdict. Condorcet, a firm believer in the ideal of equal rights for everyone, built upon his theorem to argue in favor of a democratic system.

Yet, despite Condorcet's efforts, the crowd had a bad reputation in the 19th century: Charles McKay describes "the madness of crowds" in 1841 (McKay, 1841), and the French polymath Gustave Le Bon highlights the crowd's "incapacity to reason" in 1895 (Le Bon, 1895). The British statistician Francis Galton, founder of eugenics, shared similar ideas.

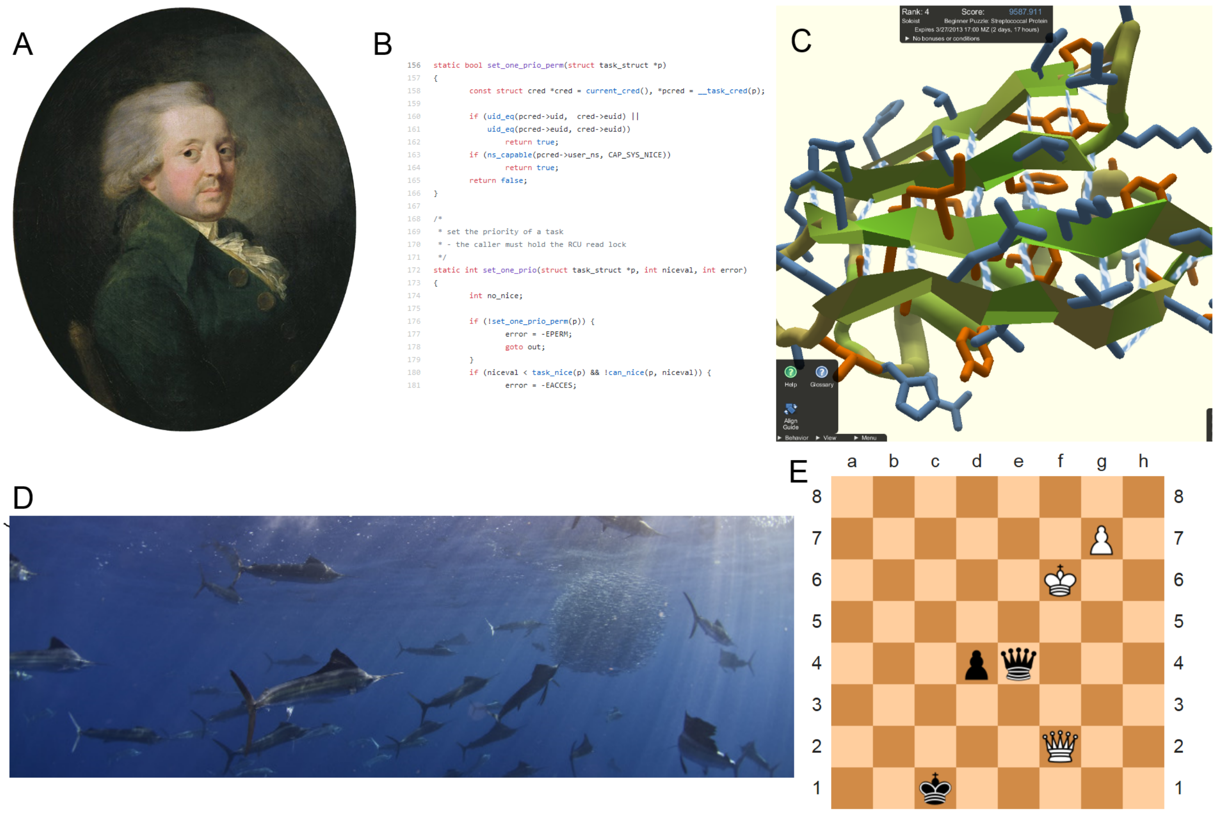

Figure 1.1. Illustrative examples of different instances of collective intelligence. (A) The French philosopher Nicolas de Condorcet, who first described the *jury theorem* stating that the quality of a majority judgment usually increases with the group size. From Portrait of Marquis de Condorcet, by Anonymous, circa 1789, https://commons.wikimedia.org/wiki/File:Nicolas_de_Condorcet.png, 20-08-2019. (B) Example of a program code used for the operating system Linux. It results from the cumulative efforts of myriads of programmers who improved it repeatedly. (C) Structure of a protein folding configuration discovered by anonymous citizen scientists using *Fold.it*. The scientific community has not been able to solve this specific protein folding problem after fifteen years of research. Retrieved from https://fold.it/portal/info/about, 20-08-2019. (D) Sailfish hunting a school of sardines organized in a defensive bait ball pattern. Photo from Krause and Seebacher (2018) by Rodrigo Friscione Wyssmann. (E) The final position of the chess game opposing Garry Kasparov (whites) to a crowd of 50,000 ordinary players (blacks). Retrieved from https://en.wikipedia.org/wiki/Kasparov_versus_the_World, 20-08-2019.

In an attempt to demonstrate the inaccuracy of collective judgments, Galton unintentionally discovered the so-called *wisdom of crowds* effect in 1907: When facing an estimation task, the average of all judgments given by many independent individuals falls close to the true value (Galton, 1907). For instance, Galton noticed that when estimating the weight of an ox, the average guess of many people was more accurate than the estimation of a randomly selected individual. In both the jury theorem and the wisdom of crowds, the collective achievement results from statistical properties and not from individual behavior. Hence, these kinds of groups are often called **statistical groups**.

In 1932, Marjorie E. Shaw investigated another type of collective system: the **interacting groups**. She was one of the first to systematically compare the performance of single individuals and groups of interacting people (Shaw, 1932). Using six problems that required "real thinking", she found that groups were more likely than individuals to find the correct solution, but also needed more time in total. She assumed that this improvement was due to the groups being more effective in eliminating wrong solutions. Based on these experiments and Steiner's later classification of group tasks (Steiner, 1966), the study of **small group decision-making** developed rapidly, investigating when communication and social interactions can be beneficial in human groups (Kerr and Tindale, 2004). These examples showcase an important division in collective intelligence research: the distinction between interacting and non-interacting, statistical groups. In the wisdom of crowds and the jury theorem, individuals do not exchange any information. In fact, group members do not even need to be aware of each other. In contrast, in Shaw's experiment, individuals communicated and shared ideas and suggestions with each other – a necessary condition for the success of the group in her experiment (Laughlin, 2011).

Research on collective intelligence took a new dimension in the late 1980s, when biologists started to describe and understand the collective behavior of eusocial insects, such as ants and bees, and group-living vertebrates, such as fish and birds (Rogers, 1988; Couzin and Krause, 2003; Bonabeau et al., 1997). The field of **swarm intelligence** brought important insights to understand how animal groups, in the absence of any central organizer, perform complex cognitive tasks collectively, such as foraging for food, building a nest, and coordinating activities (Camazine et al., 2003). Biologists classified the underlying processes of swarm intelligence into two main classes (Moussaïd et al., 2009; Bonabeau et al., 1999; Theraulaz and Bonabeau, 1999): (1) those where individuals interact directly with one another by means of acoustic or visual cues, such as fish in a school or birds in a flock, and (2) those where coordination is achieved by indirect interactions, that is, when individuals leave traces in the environment, such as ants dropping pheromone trails behind them to indicate the route to a food source. Over time, research has revealed numerous common principles between the collective dynamics driving human groups and animal swarms, such that the term swarm intelligence is often broadened to include human groups as well (Moussaïd et al., 2009; Krause et al., 2010).

These insights from biology combined with the rise of new technologies in the early 21th century, opened several new lines of research. With the emergence of the Web 2.0, easy communication and coordination over the internet enabled collective projects that involved very large human crowds. The English version of Wikipedia, for instance, results from the joint effort of nearly 40 millions contributors, and has a quality level comparable to traditional encyclopedia written by experts (Giles, 2005). Likewise, **crowdsourcing**, a term introduced by Jeff Howe in 2006 (Howe, 2006), has been studied in business and organizational science and describes the act of outsourcing tasks to the public that were traditionally performed inside a company (Malone et al., 2010; Geiger et al., 2011). At the same time, **human computation** was introduced by the computer scientist Luis von Ahn in 2005 (Von Ahn, 2008; Von Ahn and Dabbish, 2008; von Ahn, 2005). Here, complex problems are divided into smaller sub-tasks that are distributed to a large number of people and later reassembled to form the full solution. For example, the language learning program *Duolingo* invites people to translate short sentences, which together form a completely translated document. The sub-tasks, such as translating one sentence, are often presented as simple entertaining games. This idea of *gamification* is also the root of another recent development of collective intelligence, called **citizen science** (Silvertown, 2009; Bonney et al., 2014). In citizen science, the public helps solving complex scientific problems presented in a simplified way. In a short time, this approach has achieved impressive results and long-standing problems in mathematics, biology, or physics were successfully solved by the public within a few weeks or months (Cooper et al., 2010; Sørensen et al., 2016; Gowers and Nielsen, 2009).

This overview reveals that collective intelligence research is composed of multiple coexisting concepts and terminologies that partly overlap. As a result, existing formal definitions of collective intelligence are usually very broad and rather unspecific. For example Francis Heylighen defines collective intelligence as a situation where a group "can find more or better solutions [. . .] than would be found by its members working individually" (Heylighen, 1999, p. 1). Anita Woolley and colleagues describe collective intelligence as "the general ability of the group to perform a wide variety of tasks" (Woolley et al., 2010, p. 2). Thomas Malone and colleagues propose to define collective intelligence as a "groups of individuals acting collectively in ways that seem intelligent" (Malone and M. S. Bernstein, 2015, p. 3). While these general definitions are useful for unifying the diverse aspects of collective intelligence, one may argue that they lack a meaningful boundary (for an attempt to define such boundaries, see Krause et al., 2010). That is, it becomes difficult to find (even very trivial) instances of collective behaviors that are not covered by these definitions.

To avoid these issues and to narrow down the subject of this thesis, I will focus on one particular well-defined domain of collective intelligence, namely **collective problem-solving** (Stasser and Dietz-Uhler, 2001). In contrast to the broader notion of collective intelligence, collective problem-solving is restricted to situations where groups of individuals are trying to find the best possible solution to a well-specified problem.

Using McGrath's terminology (1984), collective problem solving concentrates on rather cooperative tasks (i.e. high agreement between individuals goals), that are rather conceptual (i.e. more cognitive than physical), and that have an objectively evaluable solution. Therefore, collective problem-solving does not consider tasks (1) where individuals try to resolve a conflict (such as bargaining), (2) that are primarily physical (such as moving a heavy piece of furniture together), (3) where individuals are simply executing a sequence of predetermined instructions (such as when only following orders), or (4) where the quality of a solution cannot be measured objectively (such as rating a movie – a matter of taste).

In the next section, I first describe how people solve problems *individually*, and then how these individual processes can be combined to produce a collective solution.

1.2 Searching for solutions: alone and together

Individual-level processes

Research on individual problem-solving largely rests on the influential work of Allen Newell and Herbert Simon. In their book "Human Problem Solving", they describe individual problem-solvers as *information processing systems* that collect, store, and retrieve information related to a problem, and process that information by means of cognitive operators (Newell and Simon, 1972). Solving a problem is therefore described as a *search process*: The individual searches the problem space – the space of all possible states of the problem

– by means of operators that transform one state into another. Eventually, the individual reaches a *goal state*, corresponding to one solution of the problem. The search process can then be characterized by the path through the problem space connecting the initial state to the goal state.

Consider, for instance, the problem of solving a Rubik's Cube. The initial state is an arbitrary configuration of the small colored pieces, and the goal state is the configuration where the six faces of the cube are uniformly colored. In this problem, applying an operator comes down to moving one of the smaller pieces around the Rubik's Cube. Each application of the operator changes one state of the Rubik's Cube to another. The goal of the search is to find a sequence of operators that transforms the initial configuration into the goal state.

For most problems, the number of potential paths connecting the initial state to a solution can be enormous. Hence solving a problem requires the usage of search strategies. These strategies can be either specific to a particular problem (e.g. using the grid method for multiplication) or take the form of heuristic approaches that are applicable to a wide range of problems. Heuristics are simple rules-of-thumb that guide the search towards a reasonably good solution. For instance, one of the most common search heuristics is hill-climbing. It simply consists in repeatedly selecting and applying the operator that offers the highest immediate payoff. By doing so, an individual will eventually reach a local optimum of the problem space.

Another important aspect of search heuristics concerns the decision to stop the search. In fact, how to search and when to stop are two essential building blocks of search heuristics (Gigerenzer et al., 1999). The stopping rule can take the form of a simple aspiration level, as proposed in Simon's satisficing heuristic (Simon, 1955; Simon, 1956): The search ends as soon as the individual reaches a solution that exceeds a certain acceptability threshold.

Problem spaces have been described by means of so-called *solution landscapes* (Goldstone et al., 2008; Mason and Watts, 2012; Lazer and Friedman, 2007; Barkoczi and Galesic, 2016; Wu et al., 2018). A landscape is a conceptual representation of the solution space in which solutions are connected to one another based on their similarity (see figure 1.2). This description allows for a quantitative analysis of the individual's search pattern. Landscapes also reflect the structure of the problem. For instance, easier problems can be described by smooth landscapes: they have a single optimum that can often be reached by a hill-climbing strategy. In contrast, rugged landscapes tend to por-

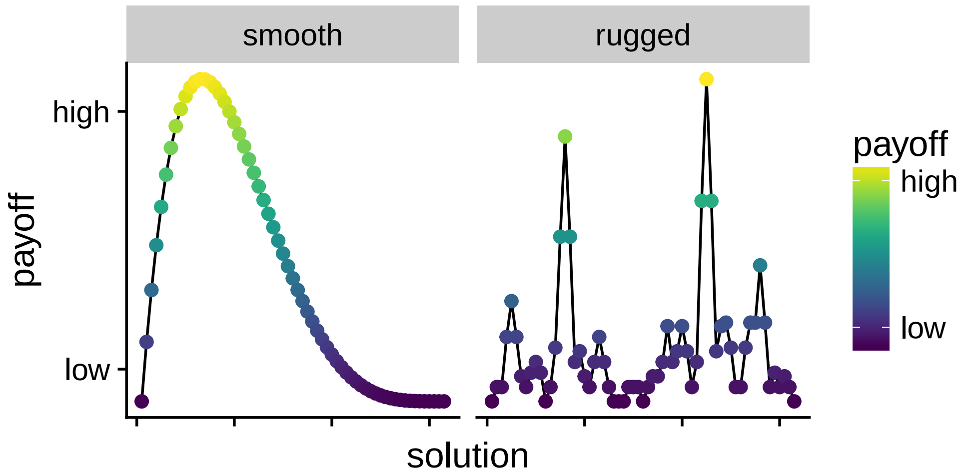

Figure 1.2. Two examples of landscapes. Each dot represents one solution and the links between the dots connect neighboring solutions. The color-coding indicates the payoff associated with each solution. The landscape on the left is smooth and has one single local (and hence global) optima. The landscape to the right is rugged. It has numerous local optima.

tray more difficult problems in which the presence of many local optima necessitate more sophisticated search strategies.

Anticipating on *collective* problem-solving, it is important to note that different individuals might use different search strategies and can picture the problem space differently (e.g., due to different interpretation of the problem, of the operators, when missing a solution, or using a different heuristic) (Mayer, 1992; Neisser, 2014). For these reasons, two problem solvers often find different solutions to the same problem. Garry Kasparov, for instance, certainly searched the problem space of next moves more efficiently than any of the regular players composing the crowd he was playing against. Similarly, the minority of forecasters who predicted the electoral success of Donald Trump had probably a different perspective on the problem space or a different search strategy than the majority of other forecasters. One central question is therefore: How to combine these multiple perspectives on the same problem to produce a collective benefit?

Collective-level methods

A very diverse set of methods can be involved in collective problem-solving. Here I classify them according to the nature of the interaction between the individuals. More specifically, I look at when, during the search process, information is exchanged between the group members. For this, three categories are defined: (1) **non-interacting groups**, where no information is exchanged, (2) **social groups**, where individuals freely exchange information during the search, and (3) **solution-influenced groups**, where individuals only share their solution at the end of their individual search process.

Non-interacting groups

The first category includes all situations where the group members do not exchange any information. In these **non-interacting groups**, individuals solve problems independently from one another. Their individual search processes are thus not impacted by the search of the others. This is typically achieved by collecting the individual solutions first, and then combining them or selecting one of them. The latter step is commonly performed by an external entity that is not part of the group (e.g., a person, a statistical method, or an algorithm).

The most famous example of non-interacting groups is the aforementioned wisdom of crowds (Herzog et al., 2019). In its most basic form, individuals are first asked to provide an independent solution to an estimation task and these individual estimations are averaged to form the collective solution. Since its first description by Francis Galton, this idea gave rise to a variety of more sophisticated aggregation techniques. For instance, one may take the previous performance of individuals into account to only consider high performing individuals (Mannes et al., 2014) or incorporate the confidence level as a possible proxy for accuracy (Hertwig et al., 2004). In choice tasks, Condorcet's majority rule has been expanded in similar ways. In recent research, Dražen Prelec and colleagues proposed a variation of the majority rule that can be successful even when most of the individuals are wrong (Prelec et al., 2017). It consists in asking individuals what they think others will answer, and measuring how much the actual answers deviate from the crowd's prediction. A "surprisingly popular" solution is indicative of a correct answer, even if only a minority of individuals have chosen it. The wisdom of crowds has numerous applied perspectives such as helping doctors to make better medical decisions (Kurvers et al., 2016) or economists to predict market fluctuations (Chen et al., 2014).

As the above examples illustrate, the wisdom of crowds has been mostly applied to problems that have a simple solution structure, such as estimation or choice tasks. How about problems with a complex and multidimensional solution structure? One way consists in dividing the problem into a multitude of sub-tasks, distributing them to different individuals, and eventually recombining them to form the collective solution. For example, a large audio transcription task could be split into a multitude of small parts. The collective solution would then be the complete transcription resulting from the union of all individual's sub-solutions. Problems on crowdsourcing marketplaces like Amazon Mechanical Turk are typically presented in this way (Mason and Suri, 2012).

However, not all problems with a complex solution structure are easily divisible. For example, when searching for a protein folding configuration (Cooper et al., 2010; Romero et al., 2013), or when improving quantum transport (Sørensen et al., 2016), individual solutions can neither easily be aggregated nor combined. In this case, the most common practice simply consists in collecting a large number of independent solutions and choosing the best one at the end (Cooper et al., 2010; Sørensen et al., 2016).

Social groups

The second category concerns methods for which individuals are structured in directly interacting social groups. Here, group members can exchange any kind of information during their search process, including final and intermediate solutions, or ideas and strategies to reach a solution. The collective solution is then obtained either when a consensus solution is reached or when an external decision-maker applies one of the approaches introduced for non-interacting groups (e.g., by averaging the judgment of the group members at the end of the discussion). This category of methods has been extensively studied in the literature (see the above historical overview and Steiner, 1972; McGrath, 1984; Woolley et al., 2015a; Woolley et al., 2015b) and is often considered as the most elementary form of collective problem solving, as it allows for beneficial synergistic effects between group members (Laughlin, 2011).

Social groups are often small in size, enabling everyone to communicate with everyone else, such as in group discussions (Stasser and Stewart, 1992; Stasser, 1985). Group discussions constitute a powerful tool for solving problems together, allowing group members to consider different perspectives on a problem, learn from each other and pool different skills (Laughlin, 2011; Woolley et al., 2015b). A group of students trying to solve an algebra problem together or a team of physicians discussing a medical diagnostic in an examination are examples falling in this category. In 2010, Woolley and colleagues found evidence for a collective intelligence factor that predicts the performances of social groups across a wide variety of tasks (Woolley et al., 2010). This factor is uncorrelated with the average intelligence of the group members. Instead, it is partly determined by the individuals' social sensitivity – a measure of how much people listen and integrate the judgment of others. This major discovery shows that the collective performance of a social group lies less in the intelligence of its group members than in the way they interact with one another.

As the size of the group increases, it becomes increasingly more difficult for the individuals to communicate efficiently in a group discussion setting (Fay et al., 2000). Larger social groups are thus best described as networks, where each individual interacts only with a subset of the group members. Depending on how the individuals are connected to each other (i.e. the network topology), information can spread rapidly or inefficiently through the group, which in turn has major implications for the collective performance (Mason and Watts, 2012; Lazer and Friedman, 2007; Barkoczi and Galesic, 2016).

Despite its benefits, the direct influence in social groups can also cause numerous detrimental dynamics. Examples include the hidden profile effect (i.e. when group members fail to share important information with others) (Stasser, 1985; Stasser and Stewart, 1992), groupthink (i.e. when group members ignore important facts to reach a non-contentious consensus) (Janis, 1972), or opinion herding (i.e., when solutions become more alike due to conformity) (Moussaïd et al., 2013). To overcome some of these limitations, techniques have been developed to mitigate the loss of diversity in social groups without impairing the synergistic effects. The Delphi method, for instance, interweaves phases of independent thinking with phases of controlled social influence (Ven and Delbecq, 1974). Likewise, imposing momentary breaks of social interactions in networked groups can have a similar beneficial effect (E. Bernstein et al., 2018).

Solution-influenced groups

The third category concerns what I coin solution-influenced groups. In these groups, individuals are not directly in contact with one another, but influence each other by contributing to a shared collective solution. Information is therefore exchanged indirectly, via the collective solution, with no need for direct communication between individuals. Over time, a collective solution that aggregates the contributions of all individuals emerges.

This type of methods is typically at play in eusocial insects like ants or termites (Heylighen, 2016; Theraulaz and Bonabeau, 1999). When ants engage in the construction of a nest, individuals work separately on a common structure. Individuals do not exchange information directly, but the current state of the collective construction guides the construction process. At any moment of time, the collective solution reflects the cumulative actions of all the group members (Khuong et al., 2016).

As highlighted by Francis Heylighen (2016) the principles of solution-influenced groups can be applied human problem-solving as well. Many long-lasting collaborative endeavors lie in this category. A Wikipedia article, for example, emerges mostly as the result of indirect interactions between multiple contributors (Malone et al., 2010): an individual's solution (i.e. the article that is being written) serves as a starting point of another person's work, who will in turn provide an updated version for a third person, and so forth. Likewise, numerous open-source projects for developing software – such as Linux – involve solution-influenced groups. An individual proposes a first solution to the problem (taking the form of a programming code) and transfers it to another individual who can improve on it in turn, and so forth. Despite its applicability to a wide range of different domains, this methods has gathered relatively little attention in the human collective problem-solving literature. Implementations of solution-influenced groups in large-scale collaborative project like Wikipedia can be rather sophisticated. In their simplest structure, however, solution-influenced groups take the form of transmission chains (see figure 1.3C and Mesoudi, 2007). Here individuals solve problems strictly sequentially, one after another, and one's initial state corresponds to the goal state of the predecessor. The collective solution is then the last individual's solution.

In recent years, transmission chains have received a lot of attention in a specific subdomain of anthropology, namely, cumulative cultural evolution. This field was originally developed by Boyd & Richerson (1996), and Tomasello (1999) to describe the development of human culture and technologies. The process leading to cultural innovations, as described by Michael Tomasello, clearly matches our definition of solution-influenced groups:

> some individual [. . .] invented a primitive version of [an] artifact or practice, and then some later user [. . .] made a modification, an 'improvement', [. . .] at which point some other individual [. . .] made another modification, [. . .] and so on over historical time.
> (Tomasello, 1999a, p. 5)

Recent research has elaborated specific experimental designs to show that transmission

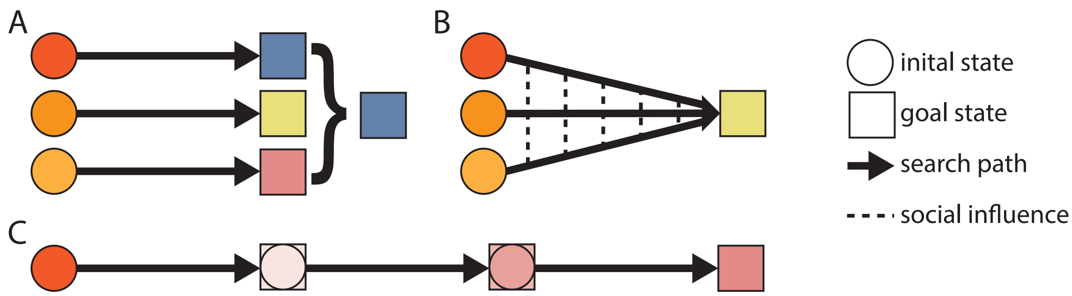

Figure 1.3. Schematic illustrations of the three categories of collective problem-solving methods transforming initial to goal states. (A) In this non-interacting group, each of the three individuals searches independently and one of their solutions is later chosen as the collective solution. No information is exchanged during the search process. (B) In social groups, individuals exchange information during the search process. In this example, the three individuals gradually converge to a consensual solution. (C) In this transmission chain (an instance of solution-influenced groups), three individuals search one after the other, each one taking the goal state of its predecessor as an initial state. The last individual's solution serves as a collective solution.

chains can indeed promote the emergence of sophisticated cultural artifacts, which can be seen as collective solutions to a given problem (Kempe and Mesoudi, 2014; Caldwell et al., 2016; Caldwell and Millen, 2008; Mesoudi and Whiten, 2008).

Thesis overview

This thesis takes the form of a cumulative dissertation. Each chapter consists of an independent publication – either accepted, submitted, or in preparation – that can stand on its own.

The aim of the thesis is twofold: (1) establish the less-known solution-influenced groups as a useful method of collective problem-solving, and (2) compare different methods and identify environmental factors that impact their relative performances. In chapters 2 and 3, I will compare the performance of transmission chains with those of non-interacting groups for problems of different complexity levels (that is, comparing the structures presented in figures 1.3A and 1.3C). In chapter 4 and 5, I will focus on the comparison between social groups and non-interacting groups (i.e, the structure presented in figures 1.3A and 1.3B).

More specifically, chapter 2 evaluates the efficiency of transmission chains for *binary* *choice problems*. By means of numerical simulations, we explored the impact of various factors on the performance of the transmission chain, such as the group size and the structure of the population. We then compared this approach to two common wisdom of crowd techniques, namely the majority rule and the confidence-weighted majority. The chapter finally relies on two experimental datasets (namely, physicians evaluating whether a skin lesion is cancerous, and participants assessing which of two cities has a larger population) to compare the performances of the three techniques empirically. The results indicate that the parameter space where transmission chains have the best performance rarely appears in the real datasets.

After showing that transmission chains are, most of the time, not suited for binary decision tasks, the chapter 3 raises the question of whether it could be relevant for more complex problems. For that, we model problem-solving as a search in a landscape. We first introduce NK-landscapes – multidimensional tunably-rugged problem spaces – and study two problem-solving methods: transmission chains and groups of independent solvers. The latter is commonly used for addressing complex problems (e.g., in citizen science projects) and consists in collecting a large number of independent solutions and choosing the best one at the end. We compare the performance of these methods in numerical simulations and in a behavioral experiment, while manipulating the problem difficulty and the skill of the individuals. Our results indicate that that transmission chains outperform independent groups either when problems are rather easy or when the group members are rather unskilled.

Next, chapters 4 and chapter 5 focus on the collective dynamics that take place in social groups. For this, I divided my research in two distinct steps: (1) understanding how people solve problems alone (chapter 4), and (2) understanding how this individual process is impacted by the presence of others (chapter 5).

In chapter 4, we investigate how individuals search in landscapes, independently from one another. By means of a dedicated experiment, we show that the search behavior can be described by a simple heuristic model. Both in rich and poor landscapes, a take-the-best procedure that ignores all but one cue at a time is capable of reproducing a diversity of observed behavioral patterns. Chapter 5 then extends the take-the-best model to include the social influence of other simultaneous problem-solvers. Our results highlight the existence of a *collective search dilemma*: When people are influenced by others, they tend to improve the quality of their own individual solution, but this comes at the expense of the collective performance. We show that this dilemma is affected by the structure of the landscape, as its negative effects are mitigated in more difficult environments.

Lastly, chapter 6 provides a concluding discussion about my work and proposes possible lines of future research.

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Chapter 2

Can Simple Transmission Chains Foster Collective Intelligence in Binary-Choice Tasks?

Moussaïd, Mehdi, and Yahosseini, Kyanoush S. (2016). *PloS One*, 11.11, e0167223.

Abstract

In many social systems, groups of individuals can find remarkably efficient solutions to complex cognitive problems, sometimes even outperforming a single expert. The success of the group, however, crucially depends on how the judgments of the group members are aggregated to produce the collective answer. A large variety of such aggregation methods have been described in the literature, such as averaging the independent judgments, relying on the majority or setting up a group discussion. In the present work, we introduce a novel approach for aggregating judgments – the transmission chain – which has not yet been consistently evaluated in the context of collective intelligence. In a transmission chain, all group members have access to a unique collective solution and can improve it sequentially. Over repeated improvements, the collective solution that emerges reflects the judgments of every group member. We address the question of whether such a transmission chain can foster collective intelligence for binary-choice problems. In a series of

numerical simulations, we explore the impact of various factors on the performance of the transmission chain, such as the group size, the model parameters, and the structure of the population. The performance of this method is compared to those of the majority rule and the confidence-weighted majority. Finally, we rely on two existing datasets of individuals performing a series of binary decisions to evaluate the expected performance of the three methods empirically. We find the parameter space where the transmission chain has the best performance rarely appears in real datasets. We conclude that the transmission chain is best-suited for other types of problems, such as those that have cumulative properties.

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2.1 Introduction

Collective intelligence refers to the ability of groups of individuals to find solutions to complex problems. The term "collective intelligence" – also referred to as "swarm intelligence" or "collective problem-solving" – is used in a surprisingly large diversity of interdisciplinary domains. These include the collective behaviour of animal swarms (Camazine et al., 2003; Sumpter, 2010; Couzin, 2007), the processes underlying group discussions and brainstorming in business and industry (Woolley et al., 2010; Kerr and Tindale, 2004), the wisdom-of-the-crowds and other methods for combining judgments (Galton, 1907; Lorenz et al., 2011; Koriat, 2012; Soll and Larrick, 2009; Moussaïd et al., 2013), the design of artificial multi-agents systems in robotics and biomimetics (Garnier et al., 2007; Bonabeau et al., 1999), the behaviour of pedestrian crowds (Moussaïd et al., 2009; Moussaïd et al., 2011), networked experiments in social computing (Kearns et al., 2006; Kearns et al., 2009; Mason et al., 2008), citizen science (Gowers and Nielsen, 2009; Sørensen et al., 2016), and numerous online collaborative projects such as Wikipedia and Threadless (Malone et al., 2010). All these seemingly disparate domains share the same overarching principle: The collective solution that is produced by the group results from the *aggregation* of every individual's judgment. The central question is therefore: What is the best way to aggregate a multitude of individual solutions? A very large number of such aggregation methods exist in the literature. These can be classified into three major families, depending on the nature of the interactions between the group members.

The first family of aggregation methods concerns situations where group members *do not interact* with each other. In this case, a third-party decision-maker collects the independent solutions of each individual and aggregates them to produce the collective solution (Koriat, 2012; Kurvers et al., 2016; Bahrami et al., 2010). Various aggregation methods have been proposed, such as a simple average, a majority rule, a quorum-based decision, or aggregation rules taking into account the confidence level of the individuals, such as the maximum-confidence slating or the confidence-weighted majority (Koriat, 2012; Kurvers et al., 2016; Bahrami et al., 2010; Boland, 1989). For instance, the wisdom-of-the-crowds is a prominent method that consists in computing the mean or the median value of all individuals' judgments (Galton, 1907). More sophisticated aggregation methods can successfully combine individual solutions even for complex, multi-dimensional problems, such as the traveling salesman problem (Yi et al., 2012), or ranking problems (Steyvers et al., 2009). In any case, all individual solutions must be independent from one another, since direct or indirect sources of social influence often tend to undermine the power of aggregation (Lorenz et al., 2011).

The above family of aggregation methods has been studied for more than a century (Galton, 1907). More recently, the understanding of self-organized social systems has demonstrated that groups of people and swarms of animals are also capable to solve complex problems collectively without the intervention of a third-party decision-maker. In this case, the aggregation of the information is supported by the interactions among the individuals (Moussaïd et al., 2009). In the 90s, biologists studying animal swarms have classified these interactions in two types: direct and indirect interactions (Garnier et al., 2007; Bonabeau et al., 1999; Heylighen, 2016; Theraulaz and Bonabeau, 1999), which turned out to be applicable to human groups as well. Formally, direct interaction refers to situation where individuals collect information directly from other individuals. In contrast, indirect interaction describes situations where individuals collect information from the collective solution that is emerging, which indirectly reflects what other individuals have done. In the following paragraphs, we describe and illustrate these two processes.

Direct interactions constitute the second family of aggregation methods, and refer to groups in which the individuals collect information directly from other individuals, through visual, acoustic, or electronic signals. Over repeated interactions, the information that each group member possesses flows from individual to individual, and eventually gives rise to an adaptive collective response. In biological systems, fish schools and bird flocks are typical examples of systems that address complex problems through direct interactions. Animals perceive visual and acoustic cues from their neighbors and adapt their behavior accordingly. The propagation of information from individual to individual gives rise to collective patterns, for instance, when detecting and avoiding predators (Ward et al., 2008; Couzin et al., 2005; Couzin, 2009).

In humans, situations where people directly interact with each other are typically group discussions. During group discussions, all members can freely exchange ideas, suggestions and information, and try to come up with a joint solution to a given problem. Depending on the structure and the composition of the group, the discussion can constitutes a powerful mean to aggregate judgments (Woolley et al., 2010; Clément et al., 2013), but this method is also subject to various undesirable effects such as opinion herding, groupthink, and the hidden profile effect (Kerr and Tindale, 2004; Stasser and Stewart, 1992; Stasser, 1985). Direct interactions can also take place in social networks. In networked experiments, for instance, all group members can observe the behavior and solution of their neighbours and adapt to it. Over successive rounds of interactions, the group often converges to a collective solution (Kearns et al., 2006; Kearns et al., 2009). This method has been successfully applied to the graph-colouring problem (Kearns et al., 2006), and other collective exploration problems (Mason et al., 2008; Mason and Watts, 2012).

Finally, the third family of aggregation methods contains situations where the group members *indirectly interact* with one another. That is, individuals do not directly collect information from each other, but from the current state of the collective solution. In these situations, individuals typically work simultaneously or sequentially on a common collective solution. At any moment, the current state of the collective solution drives the subsequent actions of the individuals.

In biological systems, this type of interaction is best illustrated by the nest construction in social insects (Khuong et al., 2016; Theraulaz et al., 2003; Tschinkel, 2004): Each piece of construction material that an insect deposits on the collective construction motivates the other insects to add another piece to the structure. Each individual collects information from the current state of the structure, which reflects the cumulative actions of previous workers. Over time, this process gives rise to small heaps, which become columns and eventually form the complex structure of the nest. In human groups, Wikipedia is one of the most studied examples of such indirect interactions structure. Each article in Wikipedia constitutes a collective solution that results from the repeated updates of different individuals.

Indirect interaction methods are usually applied to more complex problems, where the individual contributions *accumulate* over time to give rise to the collective solution. For instance, in the crisis-mapping task, a group of participants is instructed to annotate a map to indicate the zones of emergency in a particular area after a natural disaster has occurred (Mao et al., 2016). Every group member is facing the same map, can see every modification made by the other group members, and is free to update it at any moment. Over time, the map converges to an accurate collective solution that aggregates every group member's knowledge about the situation. Group members may also work on the collective solution *sequentially* rather than simultaneously. In a transmission chain (also called diffusion chain), each group member updates the collective solution only once before passing it to the next individual who can update it in turn, and so forth until the last individual of the group (e.g. Moussaïd et al., 2015). Transmission chains have been widely used in the domain of cultural evolution (Caldwell and Millen, 2008; Kempe and Mesoudi, 2014b; Kempe and Mesoudi, 2014a), in which evolutionary anthropologists study human's ability to produce increasingly complex cultural artifacts by improving them sequentially, generation after generation. In fact, cultural evolution can be seen as a process relying, at least in part, on the principles of indirect interactions.

To illustrate these three families of aggregation methods, imagine a group of ten individuals trying to solve a jigsaw puzzle, such as the one studied by Kempe and Mesoudi (2014b). The task consists in assembling together a large number of small pieces to produce a complete picture. In the *no-interaction* case, each group member proposes an independent, possibly-incomplete solution to the problem. The individual solutions are later combined by a decision-maker to produce the collective solution. The decision-maker could, for example, follow a majority rule and fill each position of the puzzle with the piece that has been used by the majority of the group members. In the *direct interaction* case, all ten group members would sit around the puzzle and try to solve it together by exchanging ideas and suggestions about where to put each piece and what the final picture could look like. Finally, in the *indirect interaction* case, every group member could sequentially look at the current state of the puzzle, try to improve it by adding new pieces or moving those that are already positioned, and transmit the updated version of the puzzle to the next group member who can update it in turn. This process repeats until the tenth individual.

To date, most of the research on human collective intelligence focuses on aggregation methods that are based on direct interactions (e.g., group discussion and networked experiments), and on those where interaction is absent (e.g. the wisdom-of-the-crowd). In comparison, the mechanisms of indirect interaction methods are much less understood. Such methods are usually studied in very sophisticated forms and applied to very complex problems, which renders the basic processes of indirect interactions difficult to understand. Here, we address the question of whether indirect interactions could constitute an efficient approach for solving elementary problems. For this, we present a series of numerical simulations describing the expected performance of a transmission chain in the case of binary-choice tasks. We deliberately chose a simple aggregation method (i.e. the transmission chain, for which individuals sequentially update a collective solution) and a simple class of problems (i.e., binary-choice tasks, for which any solution is a uni-dimensional, binary object). We compared the performance of the transmission chain to two other aggregation methods: the majority rule and the confidence-weighted majority rule — two methods assuming the absence of interactions. By varying systematically the structure of the environment and the size of the group, we show that the best method depends on the structure of the environment. Furthermore, the analysis of two real datasets reveals which environmental structure is more likely to be found in the real world.

2.2 Methods

In the present work, we will examine the expected performance of the transmission chain as an aggregation method, and compare it to two other methods: The majority rule, which is commonly used for aggregating judgments in discrete choice problems, and confidence-weighted majority (hereafter, weighted-majority) that extends the majority rule by taking the confidence of the individuals into account. For this, we restrain our investigations to binary-choice tasks, where only two options are possible: a correct one and a wrong one.

Sample population

As a starting point, we assume a large sample population in which a proportion q_1 of individuals would independently choose the correct solution to the problem in the absence of any interaction or social influence. Reversely, a proportion $q_0 = 1 - q_1$ of individuals in the sample population would independently choose the wrong solution. In addition, every individual's answer is associated with a confidence level c describing how confident the individual is about his or her answer. We define the confidence level as a continuous value ranging from 0 to 1, where $c = 0$ refers to individuals who are very uncertain about their answer, and $c = 1$ refers to individuals who are very certain about their answer. In the simulations, we describe the confidence levels of the individuals who give the correct answer with a beta distribution Ω_1 that has shape parameters α_1 and β_1, and the confidence levels of the individuals who give a wrong answer with a beta distribution Ω_0 that has shape parameters α_0 and β_0. That is, the confidence levels follow different distributions depending on whether the associated answer is correct or wrong. For many problems, confidence can be a good proxy for accuracy, but this tendency is not systematic and often non-linear (Koriat, 2012; Moussaïd et al., 2013). In fact, the shape of these two distributions depends on the nature and the statement of the problem. To begin with, we assume the two distributions Ω_1 and Ω_0 represented in 2.1, for which correct answers are on average associated with higher confidence levels than wrong answers, but a

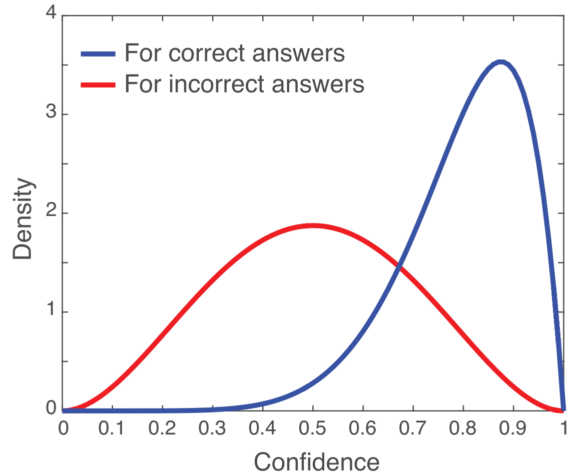

Figure 2.1. Description of the environment. Assumed distributions of confidence among the individuals who provide the correct answer to the problem (in blue), and among those who provide a wrong answer to the problem (in red). The interval of confidence values ranges from $c = 0$ (very uncertain) to $c = 1$ (very certain). The blue and red distributions are beta distributions with shape parameters $\alpha_1 = 8$ and $\beta_1 = 2$ (mean value: 0.8), and $\alpha_0 = 3$ and $\beta_0 = 3$ (mean value: 0.5), respectively. In the simulations, a proportion q_1 of the sample population gives the correct answer and have confidence levels drawn from the blue distribution, and a proportion $q_0 = 1 - q_1$ of the sample population gives a wrong answer and have confidence levels drawn from the red distribution. In empirical data, the shape parameters of the blue and red distributions depend on the nature of the task.

considerable overlap exists between the two distributions (i.e. an individual with a wrong answer can possibly be more confident than an individual with the correct answer).

Constitution of the group

In this environment, we compare the performances of the three aggregation methods for groups of N individuals randomly selected from the sample population. Therefore, each of the N individuals of one group g has a probability q_1 to give the correct answer and a probability q_0 to give the wrong answer. We call x_p the independent solution of one specific individual p in the group, and c_p the confidence level of that specific individual. We have $x_p = 1$ if the individual p independently provides a correct answer, and $x_p = 0$ if that individual independently provides a wrong answer. The confidence c_p of that individual is then randomly drawn from the distribution Ω_1 if $x_p = 1$ (i.e. the blue distribution in figure 2.1), and from the distribution Ω_2 if $x_p = 0$ (i.e. the red distribution in figure 2.1).

Aggregation methods

The outcome of each aggregation method can be computed for any given group g composed of N individuals. We call M_g, W_g, and C_g the outcomes (0 or 1) of the majority rule, the weighted-majority rule, and the transmission chain for that particular group g, respectively. Furthermore, we call M, W, and C the success chance of the three methods for any group g of size N.

For a given group g, the outcome of the majority is $M_g = 1$ if $n_1 > n_0$ and $M_g = 0$ if $n_0 > n_1$, where n_1 and n_0 correspond to the number of group members independently choosing the correct answer (i.e. those with $x_p = 1$) and the wrong answer (i.e. those with $x_p = 0$), respectively. If $n_1 = n_0$ we choose randomly. For computing the outcome of the weighted-majority, we first measure m_1 corresponding to the sum of the confidence levels c_p of all the group members who chose the correct answer, and m_0 corresponding to the sum of the confidence levels c_p of all the group members who chose the wrong answer. We then have $W_g = 1$ if $m_1 > m_0$ and $W_g = 0$ if $m_0 > m_1$. If $m_1 = m_0$ we choose randomly. For the transmission chain, we first assign each group member to the chain position p. We call X_p the current collective solution in the chain at position p. The first individual located at position 1 initiates the collective solution with his or her independent solution, leading to $X_1 = x_1$. For all subsequent chain positions, we assume that the individuals whose confidence level is too low are not confident enough and do not modify the collective solution. In contrary, the individuals whose confidence is sufficiently high replace the collective solution by their own independent solution if they disagree with it. Formally, we define a contribution threshold τ, and have $X_p = x_p$, if $c_p \leq \tau$ (i.e. the collective solution is replaced by the individual solution if the confidence is high enough) and $X_p = X_p - 1$, if $c_p < \tau$ (i.e. the collective solution remains unchanged if the confidence is not high enough). The outcome of the transmission chain for that particular group is then $C_g = X_N$, corresponding to the collective solution that is present in the chain after the update of the last individual.

Unlike the majority and the weighted-majority rules, the definition of the chain method requires a parameter τ. This parameter represents the confidence threshold above which individuals are sufficiently confident to contribute to the collective solution rather than solely forwarding it to the next person. For that reason, we call τ the contribution threshold. The individual p is considered to be a contributor when $c_p \leq \tau$. More specifically, we call positive contributors the group members who bring in the correct answer (i.e., those with $c_p \leq \tau$ and $x_p = 1$), and negative contributors those who bring in the wrong answer (i.e., $c_p \leq \tau$ and $x_p = 0$).

Example

We illustrate the outcome of each aggregation method in a simple example where $q_1 = 0.6$ and $N = 10$. That is, we constitute a group g with 10 individuals randomly drawn from a sample population that contains 60% of correct answers. The confidence levels are drawn from the distributions shown in figure 2.1. In this example, we assume a contribution threshold $\tau = 0.6$. The independent answers of each group member and their confidence are represented in figure 2.2A. In that particular group, five individuals independently provide a correct answer, and five others provide a wrong answer. The majority rule results in a tie and has, therefore, 50% chance to yield a correct answer $M_g = 1$ and 50% chance to yield a wrong one $M_g = 0$. In that particular group, the sum of confidence levels among all individuals who provide a correct answer is $m_1 = 2.39$ and the sum of confidence levels among those who provide a wrong answer is $m_0 = 2.19$. The weighted majority rule, therefore, yields a correct answer $W_g = 1$. In the transmission chain, the first individual initializes the collective solution X_1 with a correct answer. At chain position 2, the individual has a wrong answer but is not confident enough ($cp < \tau$) and thus leaves the collective solution unchanged. The first contributor with a confidence level higher than τ appears at the chain position 4. That individual replaces the collective solution by a wrong answer. The individual at position 6 is also a contributor and replaces the collective solution by the correct answer. All subsequent individuals have confidence levels lower than the contribution threshold τ and thus do not impact the collective solution. The correct answer set by the individual at position 6 remains unchanged until the end of the chain, leading to $C_g = 1$ for this particular example.

2.3 Results

Order effect

As compared to the two majority rules, one specificity of the transmission chain is the spatial structure of the group, that is, the fact that group members are organized in a

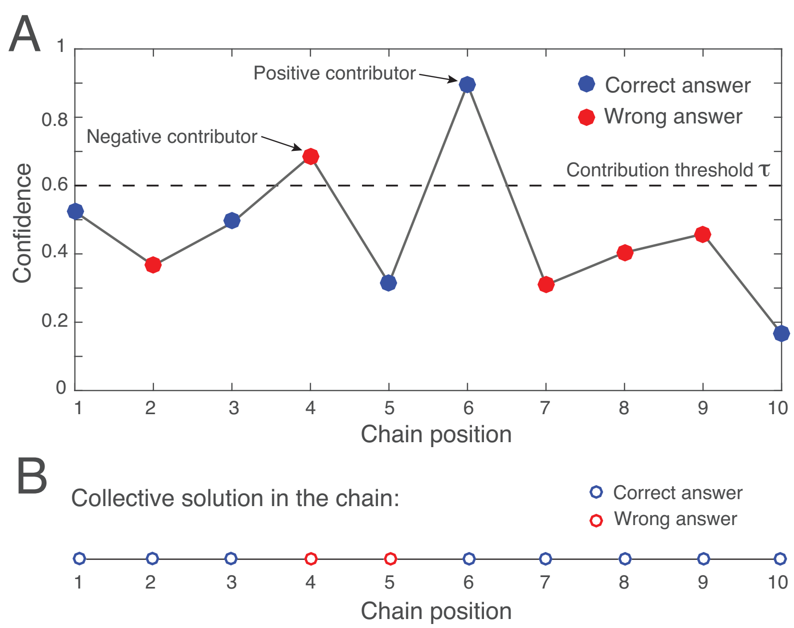

Figure 2.2. Illustration of a transmission chain. For this case study, we assume a group size of $N = 10$, and a proportion of correct answers $q_1 = 0.6$. (A) The N individuals are randomly drawn from the sample population and assigned to a random position in the chain (the red and blue dots). Among them, five individuals have the correct answer (i.e., the blue dots at chain positions 1, 3, 5, 6, and 10), and five individuals have a wrong answer (i.e., the red dots at chain position 2, 4, 7, 8, and 9). The black dashed line represents the activity threshold $\tau = 0.6$ indicating the confidence level above which individuals contribute to the collective solution. The contributors replace the current collective solution by their own solution. Individuals who do not contribute (i.e., those with a confidence level lower than) leave the collective solution unchanged. (B) The resulting collective solution in the chain at each position. The blue open circles indicate a correct answer, and the red open circles indicate a wrong one. In this example, the individual at chain position 1 initializes the collective solution with a correct answer. The collective solution remains unchanged until the contributor at chain position 4 replaces it by a wrong answer. The individual at position 6 is also a contributor and restores the correct answer. All other individuals have no impact on the collective solution. In this example, the chain generates a correct solution.

linear chain. Yet, a large number of different chains can be produced from a unique group of N individuals (precisely, $N!$ different chains), depending on how the group members are ordered. What is the impact of the order in which the group members are positioned? In the example shown in figure 2.2, only two group members are contributors (those located at chain position 4 and 6). One of them is a positive contributor whereas the other one is a negative contributor. If the positive contributor is positioned *after* the negative contributor, the chain yields a correct answer (because all subsequent individuals are neutral). Reversely, if the positive contributor is positioned *before* the negative contributor, the chain yields a wrong answer because the wrong answer overrides the correct one. In the end, this particular group of individuals has a 50% chance to produce a correct answer and 50% chance to produce a wrong one, depending on the ordering of the two contributors, and irrespective of the position of the eight other group members. The ordering, therefore, has a strong impact on the expected outcome of the chain in this example. More generally, for a given group of individuals, the probability that the chain produces a correct answer is the probability that at least one positive contributor appears after the last negative contributor. This probability equals to $N_1/(N_1 + N_0)$, where N_1 is the number of positive contributors and N_0 is the number of negative contributors. The smaller the difference between N_1 and N_0 the more the outcome of the chain is sensitive to the ordering of the group members. Therefore, a given group of N individuals does not always produce a unique outcome with the transmission chain. Instead, the outcome of the chain depends, to some extent, on the order in which the group members are positioned.

Contribution threshold

The second specificity of the chain is the presence of social influence. Unlike the two other methods, the chain does not aggregate the independent answers of every group member. Instead, it filters out the answers of those who are confident enough to change the collective solution (Johnson and Goldstein, 2003). The contribution threshold τ is thus an important parameter that determines which individuals are confident enough to contribute to the final solution. What is the impact of the contribution threshold τ? To address this question, we explored the performances of the transmission chain while varying the contribution threshold from $\tau = 0$ to $\tau = 1$. For each value of τ, we generated 1000 groups of size $N = 10$ with $q_1 = 0.6$ and the confidence distributions shown in figure 2.1, and measured the success chance C of the chain (i.e., how often it produced a correct answer). The result is shown in 2.3. When the contribution threshold is small and approaches $\tau = 0$, every group member is confident enough to contribute. In this case, everyone overrides the previous person's solution and the outcome of the chain is simply the answer of the last individual of the chain. Because every individual has a probability $q_1 = 0.6$ of being correct, the success chance of the chain is also $C = 0.6$. Likewise, when the activity threshold approaches $\tau = 1$, none of the group members are confident enough to contribute. In this case, the answer of the first individual of the chain remains unchanged until the end of the chain. Because the first individual has a probability $q_1 = 0.6$ of providing a correct answer, success chance of the chain is also $C = 0.6$. Between these two extreme values, the performance of the chain reaches a peak for $\tau = 0.83$. At this point, the success chance of the chain is $C = 0.93$ (i.e. the chain yields a correct answer 93% of the time). In fact, the optimal threshold value maximizes the probability to pick a positive contributor, while at the same time minimizes the probability to pick a negative contributor. Note that this performance measure takes into account the order effect because groups are randomly ordered in each replication. For comparison, the success chance of the majority rule is $M = 0.73$ under these conditions, and the success chance of the weighted-majority is $W = 0.90$.

Group size

The weakness of the majority rule in the previous case study was the relatively small group size ($N = 10$). In fact, the majority of the individuals in the entire sample population do actually provide the correct answer. Yet, the majority of the $N = 10$ group members has only 73% chance to produce a correct answer because the majority within the group often points toward the wrong answer (Boland, 1989). Hence, group size matters for the majority rule. How does it impact the outcome of the transmission chain? To address this question, we run an additional series of simulations, this time varying the contribution threshold τ as well as the group size N. We generate again 1000 groups of size N with $q_1 = 0.6$ and the confidence distributions shown in figure 2.1, and measure the frequency of correct answers produced by the chain for different values of τ and N. As figure 2.4A shows, group size has relatively little influence on the chain performances, which increase rapidly until $N = 10$ and plateaus for larger group sizes. This result is consistent with the previous result showing that the ratio between positive and negative contributors is more important than the total number of contributors. In addition, the optimal contribution

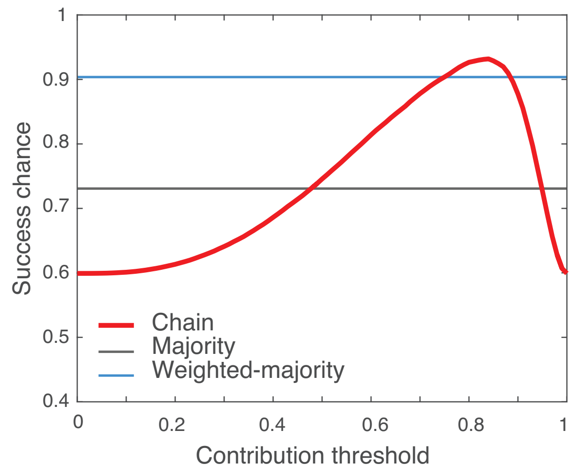

Figure 2.3. Impact of the contribution threshold τ. The red line indicates the probability that the chain generates a correct solution for different values of the contribution threshold τ, assuming a group size of $N = 10$, a proportion of correct answers $q_1 = 0.6$ and the confidence distributions shown in figure 2.1. In these conditions, the optimal value for the contribution threshold is $\tau = 0.83$, for which the chain produces the correct solution 93% of the time. The grey and blue lines indicate the success chances of the majority and the weighted-majority rules, respectively.

threshold only marginally varies between $\tau = 0.8$ and $\tau = 0.9$ with increasing group size. Figure 2.4B compares the evolution of the majority, the weighted-majority and the chain with $\tau = 0.85$ for increasing values of N. While the performance of the majority increases slowly with N, the weighted majority and the transmission chain reach higher performances for smaller group size. This weak dependency on N for these two methods results from the fact that they also rely on the individuals' confidence and can thus extract the correct answer from a smaller number of individuals. The weighted-majority and the transmission chain have relatively similar performances in this environment, with the chain converging slightly faster to its best performance, and the weighted majority converging slower but reaching a slightly higher performance level.

Structure of the environment

In order to generalize our findings, we explored the performances of the three methods for different proportions of correct answers q_1 in the sample population, and different confidence distributions. It is difficult, however, to vary systematically the confidence distributions, because these distributions depend on a total of four parameters (i.e., the

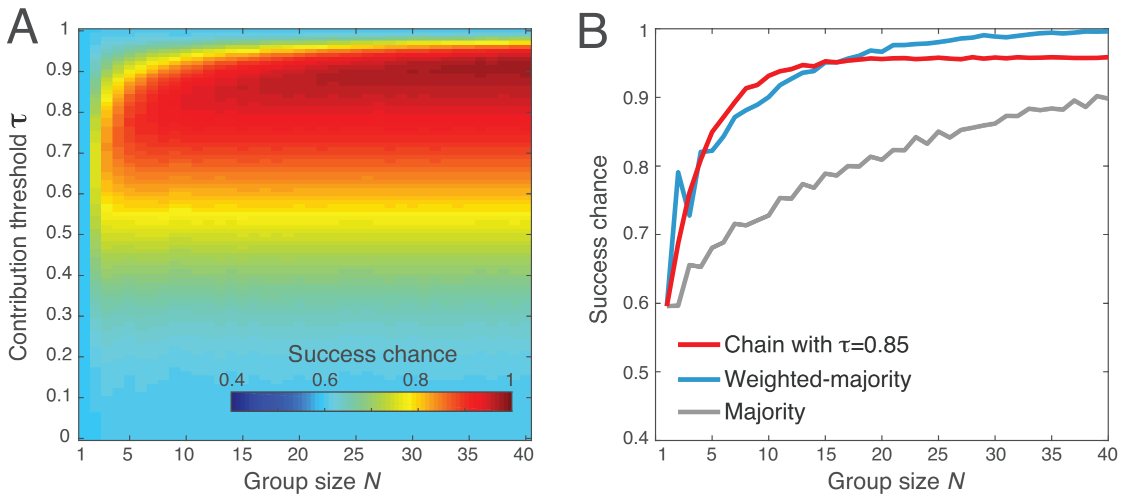

Figure 2.4. Impact of the group size N. (A) The color-coding indicates the probability of success of the chain method as a function of the group size N and the contribution threshold τ. The column of values at $N = 10$ corresponds to the red curve shown in figure 2.3. (B) Comparison of the performance of the chain method with the contribution threshold set to $\tau = 0.85$ (in red), the majority rule (in grey), and the weighted-majority rule (in blue). These results are computed assuming a proportion of correct answer $q_1 = 0.6$ and the confidence distributions shown in figure 2.1

shape parameters α_1, β_1 and α_0, β_0). Therefore, we computed a single confidence indicator from the two distributions Ω_1 and Ω_0, that we called the *confidence utility* u. The confidence utility measures the probability that an individual with the correct answer has a higher confidence level than an individual with the wrong answer. In other words, u is the probability that a value drawn from Ω_1 (the confidence associated to correct answers) is higher than another value drawn from Ω_0 (the confidence associated to wrong answers). For the simulations, we systematically varied the mean values of Ω_1 and Ω_0 from 0.1 to 0.9 and computed each time the corresponding confidence utility u. In addition, we also varied the proportion of correct answers q_1 from 0 to 1. For each combination of u and q_1, we generated 1000 groups of size $N = 10$ and measured the performance of the three aggregation methods. For the sake of simplicity, we chose the contribution threshold τ that maximises the success chance of the chain for each combination of u and q_1, such that our results represent the best-case scenario for the chain. The results are shown in figure 2.5. Clearly, the majority rule does not depend on u and has success chances that approach $M = 1$ when $q_1 > 0.5$ and $M = 0$ when $q_1 < 0.5$. The majority rule amplifies the dominant view in the population. The weighted-majority has a similar pattern but also relies on the group members' confidence. Therefore, the weighted-majority can yield a correct answer even when the population accuracy q_1 is slightly lower than 0.5, but only when the confidence is a useful cue (i.e., when u approaches 1). Reversely, if the confidence is misleading (i.e. when u approaches 0), even a population accuracy higher than 0.5 is not always sufficient to yield a correct collective answer. The performance of the transmission chain exhibits a similar tendency: When confidence is a useful cue ($u > 0.5$), the chain performs well, even for extremely low values of q_1. When confidence is less reliable ($u < 0.5$), the chain performance equals the population accuracy. This is due to the fact that, when confidence is misleading, the best contribution threshold is such that nobody contributes to the collective solution (i.e. very high value of τ), and the final solution is simply the first individual's solution. Hence the chain performs relatively well where the majority performs very good, and relatively bad where the majority performs very bad. The best aggregation method, therefore, depends on the values of q_1 and u. Roughly speaking, the majority is a better method in the upper-left quarter of the parameter spaces ($q_1 > 0.5$ and $u < 0.5$), the weighted-majority is better in the upper-right quarter ($q_1 > 0.5$ and $u > 0.5$), and the chain is better in the lower-right quarter ($q_1 < 0.5$ and $u > 0.5$). The lower-left quarter ($q_1 < 0.5$ and $u < 0.5$) is the most difficult environment because the population accuracy and the confidence both point to the wrong answer. In this case, the chain is the least bad method because it preserves a small chance of success where the majority and the weighted-majority tend to be systematically wrong.

Empirical data

An important question that arises from these simulations is what do real environments look like? Knowing the values of $q1$ and u for a given class of problems would help finding out what is the most efficient aggregation method to use. To address this question, we reanalyzed two datasets of previously published experiments in which people were facing a series of binary-choice tasks. In the first dataset (Yu et al., 2015), 109 participants were instructed to indicate which of two cities has a larger population, across 1000 pairs of cities. For each pair of cities, the participants indicated their answer and their confidence level on a continuous scale between 0.5 and 1. In the second dataset (Argenziano et al., 2003; Kurvers et al., 2016) a total of 40 physicians evaluated 108 cases of skin lesions

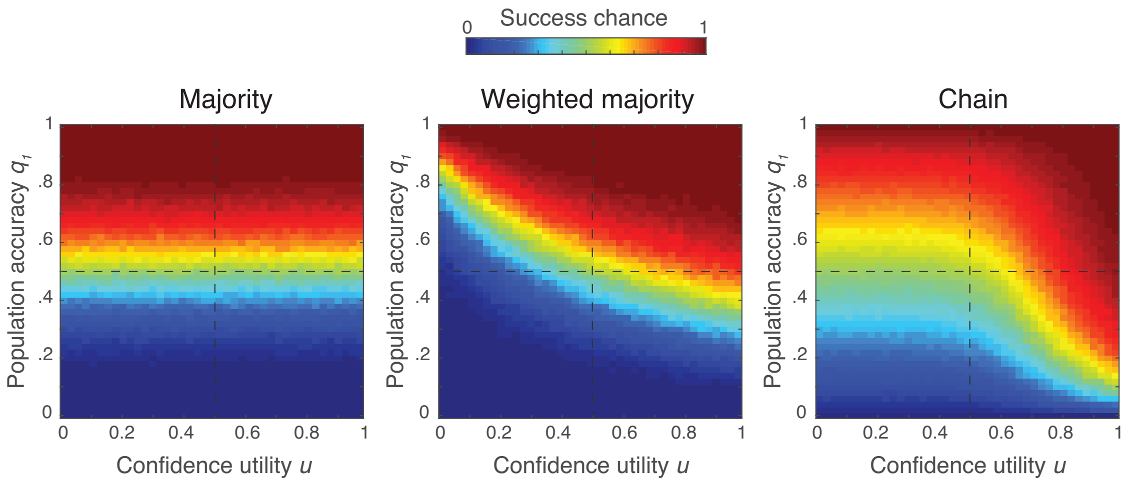

Figure 2.5. Impact of population structure. Expected performance of the majority, the weighted-majority, and the transmission chain as a function of the proportion of correct answers q_1 in the sample population and the confidence utility u. The confidence utility is the probability that an individual with a correct answer reports a higher confidence level than another individual with a wrong answer. The group size is $N = 10$.

and were instructed to evaluate whether the lesion is cancerous or not-cancerous, and to indicate their confidence level on a Likert scale from 1 to 4. For each of the 1000 instances of the cities dataset and for each of the 108 instances of the doctors dataset, we estimated the population accuracy q_1 by measuring the proportion of correct answers among the respondents, and the confidence utility u by measuring the probability that an individual who gave a correct answer reported a higher confidence than an individual who gave a wrong answer. For this, we randomly sampled (1000 times, with replacement) one individual among those who gave a correct answer and one among those who gave a wrong answer, and looked at the frequency at which the first has a higher confidence than the second. In addition, we computed the success chance of the three aggregation method, with groups of size $N = 10$. The results are presented in figure 2.6. The first interesting element is the striking diversity of environmental structures. Within each domain, the observed values of u and q_1 vary almost uniformly between 0 and 1. Nevertheless, a correlation is visible between these two variables: confidence is a relevant cue when most people give the correct answer, and a misleading cue when most people give the wrong answer. In other words, confidence tends to be indicative of consensuality rather than accuracy – an important result that has been already suggested in previous research (Koriat, 2012; Pleskac and Busemeyer, 2010). Consequently, confidence adds little information to what is already available by just looking at the individuals' answers. Most cases, therefore, lie in the upper-right and lower-left quarter of the parameter space. As expected from our previous simulations, the majority and weighted-majority perform best in the upper-right quarter, because both the number of individuals and the confidence levels indicate the correct answer. The chain also performs relatively well in this area of the parameter space (see figure 2.5 and in the supplementary material figure A1 and figure A2), but not as good as the two majority rules. In the lower-left quarter, however, all methods exhibit poor performances, because all available information is misleading. In this area, the chain does not amplify the misleading information as the two majority rules do and, thus, preserves a small chance to yield the correct answer.

When using a single method for all the instances of a task, very little difference of performance exist between the three methods. The strengths and weaknesses of each method compensate each other at the aggregate scale, leading to similar overall performances (For the "cities dataset": M = 74%, W = 75%, and C = 75%; for the "doctors dataset": M = 65%, W = 65%, and C = 67%). Ideally, one would adaptively choose the most efficient aggregation method for each new instance of the task, depending on the expected values of q_1 and u for that instance, but the diversity of observed structures makes it difficult, if not impossible, to anticipate the nature of an upcoming instance of the problem.

2.4 Discussion

We have defined and studied the performance of a new aggregation method – the transmission chain – as a tool to improve collective decision-making in binary choice tasks. The transmission chain relies on processes of indirect interactions, for which group members sequentially try to improve a common collective solution without directly interacting with one another. The chain exploits the default heuristic – a common bias in people's decision-making: When given a decision to make and a default option, people tend to choose the default option unless they have good reasons not to do so (Johnson and Goldstein, 2003; Gigerenzer et al., 1999). In the chain, the "default option" is the current state of the collective solution that has been produced by the preceding group members. Thus, most people choose the default option unless they strongly disagree with it. In the end, the chain functions as a confidence-based filter: the group members who are the most

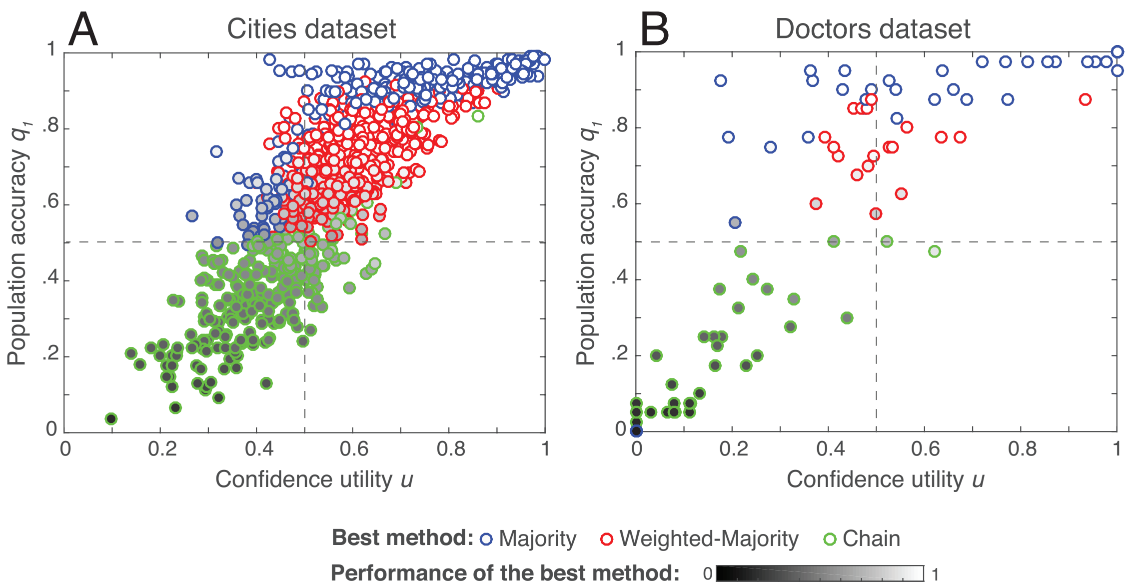

Figure 2.6. Population structure and corresponding best method for two binary-choice task studies. Experimental participants evaluating which of two cities has a larger population. The task is repeated across 1000 different pairs of cities. Each point in the graph corresponds to one instance of the task (i.e., one pair of cities). (B) Dermoscopists evaluating 108 cases of skin lesions and evaluating whether the lesion is cancerous or not-cancerous. Each point in the graph corresponds to one medical case. In (A) and (B) the position of each point indicates the proportion of respondents (i.e., participants or doctors) who provided the correct answer (y-axis), and the confidence utility (x-axis) for that case. The border colour of each point indicates the aggregation method that performs best in this particular case (the majority in blue, the weighted-majority in red, and the chain in green). Cases for which several methods perform equally good are represented in blue if the majority rule is one of them and in red if the weighted-majority is one of them. In addition, the grey-scale colour inside each point indicates the success chance of the best performing method, ranging from 0 (in black) to 1 (in white). These results are calculated assuming 1000 groups of N = 10 individuals randomly sampled from the pool of available respondents.

confident contribute to the collective solution whereas those who are unsure have no impact on the collective outcome. When comparing the transmission chain to the majority and the weighted-majority rules, we have found that the chain only outperforms the two other methods for problems of a specific nature, namely, when confidence is a reliable indicator and when the most people give a wrong answer. In the two datasets that we have analyzed, however, instances of such nature are rare.

It is important to note that many behavioural components of our simulations remain uncertain. For instance, we have always studied the best-case scenario in our simulations, where the contribution threshold τ is set to the optimal value for each instance of the problem. However, the contribution threshold is not a parameter but a behavioural variable, for which the experimenter has little control. The exact value of the threshold and whether it is well calibrate is an issue that needs to be addressed experimentally. In the supplementary materials figure A1 and figure A2, we compared the chain performances when is adjusted for every instance of the problem and when τ is fixed for all instances of the problem. Overall, the difference is minor.

A multitude of implementations can be imagined for the transmission chain. Group members can act simultaneously rather than sequentially (i.e., all group members can see the current state of the collective solution at the same time and update it at any moment), which should mitigate the order effect. Beside, the collective solution can take various forms. Instead of considering only the solution of the predecessor, group members could be exposed to the k previous solutions, or an aggregated form of the k previous solutions. This variation should create a "memory" in the chain. This memory could allow the collective solution to resist to the detrimental influence of a few outliers, but at the same time, increase the risk of opinion herding and groupthink (Kerr and Tindale, 2004; Stasser, 1985; Yasseri et al., 2012). Finally, participants could be informed about their position in the chain and about the number of other group members who have previously contributed to the collective solution. This would strengthen the weight of the collective solution at the end of the chain, equivalent to gradually increasing the contribution threshold with chain position in simulations.

With regard to the existing literature and to the present results, the transmission chain seems to be more suited to cumulative, multidimensional problems than simple binary choice tasks. In fact, in complex tasks like writing a Wikipedia article, the group members' contributions can take various forms and apply to many different components of the collective solution. The contributions to a Wikipedia article, for example, can range from correcting a minor typographical error to changing the entire structure of the article or adding new content to an existing article. As such, the contributions of the group members accumulate over time but rarely override each other (except, e.g. in the case of "edit wars" (Yasseri et al., 2012)). The same applies to problems addressed in cultural evolution (Kempe and Mesoudi, 2014a). In contrast, binary choice tasks are limited to a single possible action of the group members: switch the collective solution to the other answer or not. Thus, every new contribution necessarily overrides the previous ones. The cumulative property is therefore absent. Furthermore, the uncertainty surrounding the contribution threshold is important. If the contribution threshold is well calibrated, the chain is a good candidate for certain types of binary choice tasks. Otherwise, the chain will arguably not outperform a simple majority. The next step, therefore, is to examine the value of the threshold experimentally, explore more sophisticated implementations of the design, and extend the methodology to more complex problems.

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Chapter 3

Transmission Chains or Independent Solvers? A Comparative Study of Two Collective Problem-Solving Methods

Yahosseini, Kyanoush S. and Moussaïd, Mehdi. In Prep.

Abstract

Groups can be very successful problem-solvers. This collective achievement crucially depends on how the group is structured, that is, how information flows between members and how individual contributions are merged. Numerous methods have been proposed, which can be divided into two major categories: those that involve an exchange of information between the group members, and those that do not. Here we compare two instances of such methods for solving complex problems: (1) transmission chains, where individuals tackle the problem one after the other, each one building on the solution of the predecessor and (2) groups of independent solvers, where individuals tackle the problem independently, and the best solution found in the group is selected afterwards.

By means of numerical simulations and experimental observations, we show that the best performing method is determined by the interplay between two key factors: the skills of the individuals and the difficulty of the problem. We find that transmission chains are superior either when the problem is rather easy, or when the group is composed of rather unskilled individuals. On the contrary, groups of independent solvers are preferable for harder problems or for groups of rather skillful individuals. Finally, we deepen the comparison by studying the impact of the group size and diversity. Our research stresses that efficient collective problem-solving requires a good matching between the nature of the problem and the structure of the group.

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3.1 Introduction

Collective problem-solving and the related concepts of swarm intelligence and collective intelligence have been studied in a wide variety of domains. In biological systems, examples include the nest construction in eusocial insects (Seeley and Visscher, 2004; Khuong et al., 2016) or collective foraging in group-living species (Couzin, 2009). In robotics and artificial intelligence, swarms of relatively simple agents can explore and solve optimization problems efficiently (Garnier et al., 2007; Rendell et al., 2010). Likewise, humans can solve problems in groups during discussions (Kerr and Tindale, 2004), by means of wisdom of crowds procedures (Herzog et al., 2019), or when creating Wikipedia articles (Yasseri et al., 2012; Malone et al., 2010). Despite this considerable diversity of examples and application domains, all instances of collective problem-solving come down to one central challenge: How should the group be structured to produce the best possible collective output?

Numerous procedures have been proposed to that end. These can be divided into two major categories (Koriat, 2015; Moussaïd et al., 2009): (1) those that involve an exchange of information between the group members, and (2) those that do not. In the first category, direct or indirect interactions among individuals can lead to the emergence of a collective solution (Woolley et al., 2010; Malone and M. S. Bernstein, 2015; Heylighen, 2016). With direct interactions group members exchange information directly via physical signals. Group-living animals, for example, communicate by means of acoustic and visual cues to detect and avoid predators (Domenici et al., 2014; Couzin et al., 2005; Ward et al., 2008). In human groups, the most common case of direct interaction for solving problems takes the form of group discussions (Stasser and Stewart, 1992; Stasser, 1985), where all group members can freely share ideas and strategies to tackle a problem. This approach can produce good results (Toyokawa et al., 2019; Woolley et al., 2015; Trouche et al., 2014; Baron, 2005), but is also subject to numerous detrimental effects such as opinion herding, groupthink, and the hidden profile effect (Janis, 1972; Stasser, 1985; Stasser and Stewart, 1992). Also, direct interaction in humans becomes difficult to apply when groups are too large, when members do not work at the same time, or when they have no easy means of communication (e.g., interactions between algorithms and humans (Crandall et al., 2018)).

Some of these limitations can be overcome by *indirect* interaction (Moussaïd and Yahosseini, 2016). In this case, individuals are not directly in contact with one another, but work separately on a common shared group solution. This type of interaction (also known as stigmergy in biological systems) has been heavily investigated in social insects (Heylighen, 2016; Theraulaz and Bonabeau, 1999). For example, when ants engage in the construction of a nest, individuals adapt their behaviour to the current state of the collective construction, which reflects the cumulative actions of all other ants (Khuong et al., 2016). Information is therefore exchanged indirectly, via the collective solution, with no need for direct communication between individuals. This principle can also be applied human groups; a Wikipedia article, for example, emerges mostly as the result of indirect interactions between multiple contributors (Malone et al., 2010; Heylighen, 2016). In the simplest case, indirect interaction takes the form of a transmission chain, where group members work on a problem sequentially, one after another (Mesoudi and Whiten, 2008). Each individual starts from the final solution of her predecessor and try to improve it, hence gradually giving rise to a collective solution that accumulates the contributions of all group members. Transmission chains have traditionally been investigated in the context of cultural evolution (Mesoudi and Whiten, 2008; Henrich and Boyd, 1998; Kirby et al., 2008; Tomasello et al., 1993) and have more recently been applied to other domains (Moussaïd et al., 2015; Moussaïd and Yahosseini, 2016; Derex and Boyd, 2015).

Beside all these methods, there exists a second class of approaches that do not involve any form of information transfer between individuals. In these cases, individuals first solve the same problem independently and in isolation, and their solutions are eventually combined by an external entity to produce the collective outcome (Koriat, 2015). The most prominent example of such procedures is the *wisdom of crowds*, in which individual solutions are merged by means of statistical aggregation function, such as the mean or the median of all solutions (Herzog et al., 2019). Wisdom of crowds methods are easily scalable as they allow for arbitrarily large group sizes and can yield to accurate solutions (Mannes et al., 2014; Herzog et al., 2019; Surowiecki, 2004). One drawback, however, is that most statistical aggregation techniques cannot be easily applied to complex, multi-dimensional solutions, such as when optimizing a protein folding configuration (Cooper et al., 2010; Romero et al., 2013), improving quantum transport techniques (Sørensen et al., 2016), or trying to solve a jigsaw puzzle (Kempe and Mesoudi, 2014). Thus for problems that have a complex solution structure, the most common practice consists in collecting a large number of independent and hence diverse solutions and choosing the best one at the end (Cooper et al., 2010; Sørensen et al., 2016).

In this work, we specifically focus on problems that have such a multidimensional solution structures. How should a group be structured in this case? In particular, we compare two types of methods: groups that work on the collective solution sequentially, such as transmission chains, or groups that work on independent solutions in parallel? Consider, for instance, the traveling salesman problem – an optimisation task where one has to find the shortest path connecting all cities on a map exactly once (Ochoa and Veerapen, 2018). In a transmission chain, the first individual proposes her solution and transfers it to the next person, who will try to optimize it and pass it in turn to the third one, and so forth. This process continues until all individuals of the group have worked on the collective solution. Would the emerging collective solution be better or worse than when letting all group members search independently and choosing the best one at the end?

In the present paper, we compare the performances of these two methods by means of a behavioural model and a dedicated experiment. In particular, we study how the performances of both methods are influenced by (1) the difficulty of the problem, (2) the skills of the individuals, (3) the group size, and (4) the group's diversity.

To address these questions, we model problem-solving as a search task (Newell and Simon, 1972; Lazer and Friedman, 2007). We assume that individuals are searching for the best possible solution in a multi-dimensional NK-landscape representing the solution space (see figure 3.1 and Kauffman and Levin, 1987). For the transmission chains, individuals search sequentially, one after another, each one starting from the last position of her predecessor. The collective solution is then given by the last person's final position in the landscape. For independent solvers, all individuals start at the same initial position and search in parallel without interactions. The collective solution is then given by the best final solution of all individuals.

Furthermore, we manipulate two variables: the individual skill S and the ruggedness of the landscape K. We define S as the number of dimensions a given individual is able to manipulate (with $S \leq N$, N being the total number of dimensions of the NK-landscape), assuming that more skilled individuals are capable of manipulating more dimensions during their search. For instance, an individual with $S = 2$ searching in a NK-landscape with $N = 10$ can only manipulate two out of the ten dimensions in the landscape. The value of S can thus be interpreted as the individual's ability to solve that specific problem.

The parameter K represents the ruggedness of the landscape, i.e. the number of local optima, and is used as a measure of the problem difficulty (see the methods section for

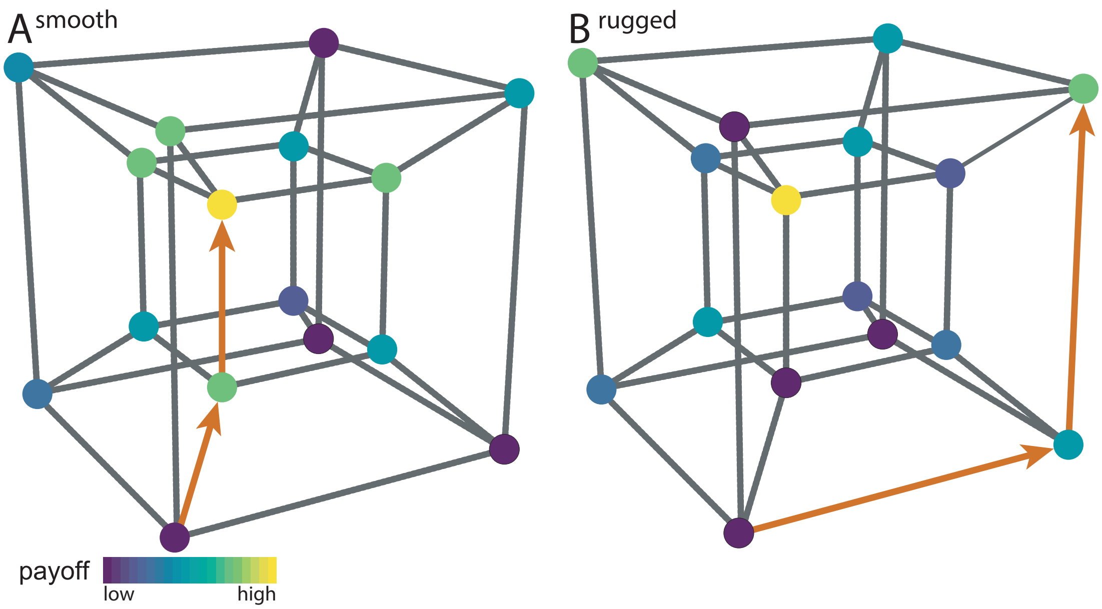

Figure 3.1. Two examples of four-dimensional NK-landscapes ($N = 4$). Each dot represents one solution and the links between the dots indicate a change along one dimension, illustrating that one can directly move from one solution to another. The color-coding indicates the payoff associated with each solution. In (A), the landscape is smooth ($K = 1$) and has one single locally and globally optimal solution (in yellow). The search trajectory (in red) illustrates how a searcher could reach the optimal solution by gradually moving to the highest neighboring solution. In (B), the landscape is rugged ($K = 3$). It has numerous local optima (i.e. solutions where all neighboring solutions give a worse payoff) and a simple exploration strategy based on gradual improvements is likely gets stuck on a sub-optimal solution.

more details). Smooth landscapes (with low values of K) are reminiscent of problems that are well understood and as such can be easily solved with gradual optimization. In contrast, rugged landscapes (with high values of K) have a noisier structure, and can be interpreted as unstructured problems where gradual optimization is usually not an efficient strategy.

3.2 Results

Numerical simulation

We first propose a heuristic model to describe how individuals search in multidimensional landscapes. For this, we assume that individuals randomly manipulate one dimension of

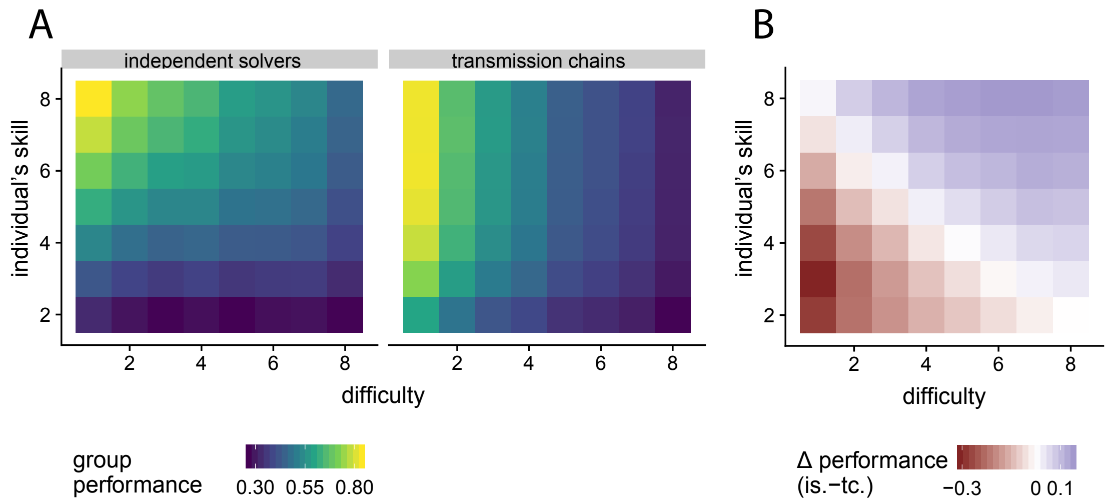

Figure 3.2. Performance for transmission chains and independent solvers as obtained by numerical simulation, for a group size of 8 individuals and $N = 10$ dimensions. (A) Average collective performance of the two methods for varying degrees of difficulty K and individual skill S. (B) Difference in performance between the two methods. Positive values, in blue, indicate that independent solvers outperform the transmission chains and vice versa, in red.

their current solution and switch to that new solution if it produces a better payoff than the current one (Gigerenzer et al., 1999; Barkoczi and Galesic, 2016). We use this model to simulate transmission chains and independent solvers, while systematically varying the difficulty of the problem K, and the individuals' skill S. As shown in Figure 3.1A, both methods are influenced by K and S. As intuitively expected, performances decrease with increasing problem difficulty, and increase with increasing individual skill. However, the transmission chains are less sensitive to the individual skill than the independent solvers, giving rise to two zones of interest as shown in figure 3.2B: (1) In the lower left corner – for rather easy problems and unskilled individuals – transmission chains outperform independent solvers, (2) in the upper right corner – for rather difficult problems and skilled individuals – groups of independent solvers perform better. Between these two zones, the performances of both methods become increasingly similar.

Experimental data

Our simulations suggest that the difficulty of the problem and the individual skills determine which of the two methods performs better. We verify this prediction by means of a controlled experiment. In the experiment, participants searched for the best possible solution either in smooth or rugged landscapes ($K = 1$ or $K = 8$, respectively), and with low or high individual's skill ($S = 3$ or $S = 6$, respectively). Participants were either part of a transmission chains or in a group of independent solvers (see the Methods section for the detailed procedure). As shown in figure 3.3, our experimental data confirms the model predictions. In smooth environments, transmission chains outperform independent solvers ($t(338) = -6.56$, $p \leq 0.005$, 95ci: $-258.17 - 139.09$, BF > 100), and this difference is larger for low skills ($t(166) = -7.07$, $p \leq 0.005$, 95ci: $-361.92 - 203.90$, BF > 100) than for high skills ($t(172) = -2.89$, $p \leq 0.005$, 95ci: $-191.24 - -36.11$, BF$=$ 15.03). In rugged environments, the opposite is true: Independent solvers outperform transmission chains ($t(336) = 4.02$, $p \leq 0.005$, 95ci: $51.00 - 148.43$, BF > 100). However, contrary to the predictions, the difference of performance is not larger for high skills ($t(168) = 2.86$, $p \leq 0.005$, 95ci: $32.44 - 176.53$, BF $=$ 13.98) than for low skills ($t(168) = 2.93$, $p \leq 0.005$, 95ci: $30.56 - 156.87$, BF $=$ 16.48). In other words, our simulations predicted that the transmission chains would perform better for difficult problems than they actually do. Why is that so?

In transmission chains, performances are considerably affected by the decisions of the last individuals (Moussaïd and Yahosseini, 2016). For instance, the last person of the chain could make the risky decision to leave the good solution found by her predecessors and search for a better one. A failure to do so would impair the collective performance of the entire group.

This behavior is not captured by our search model, in which individuals only leave a solution for a better one (see figure 3.4). To account for such risky decisions, we extend our model with a parameter r reflecting the probability that an individual would not immediately return to the previous solution after sampling a worse one. A positive value of r confers some flexibility to the behavior of the agents, preventing them to get stuck at only locally optimal solution, but at the same time increases the risk to lose track of the previous solution. We fit r to our experimental data by measuring the frequency of risky decisions in the experimental data ($r = 0.11$). The new simulations match the observed performance very closely (see figure 3.3, and 3.4). That is, $r > 0$ decreases

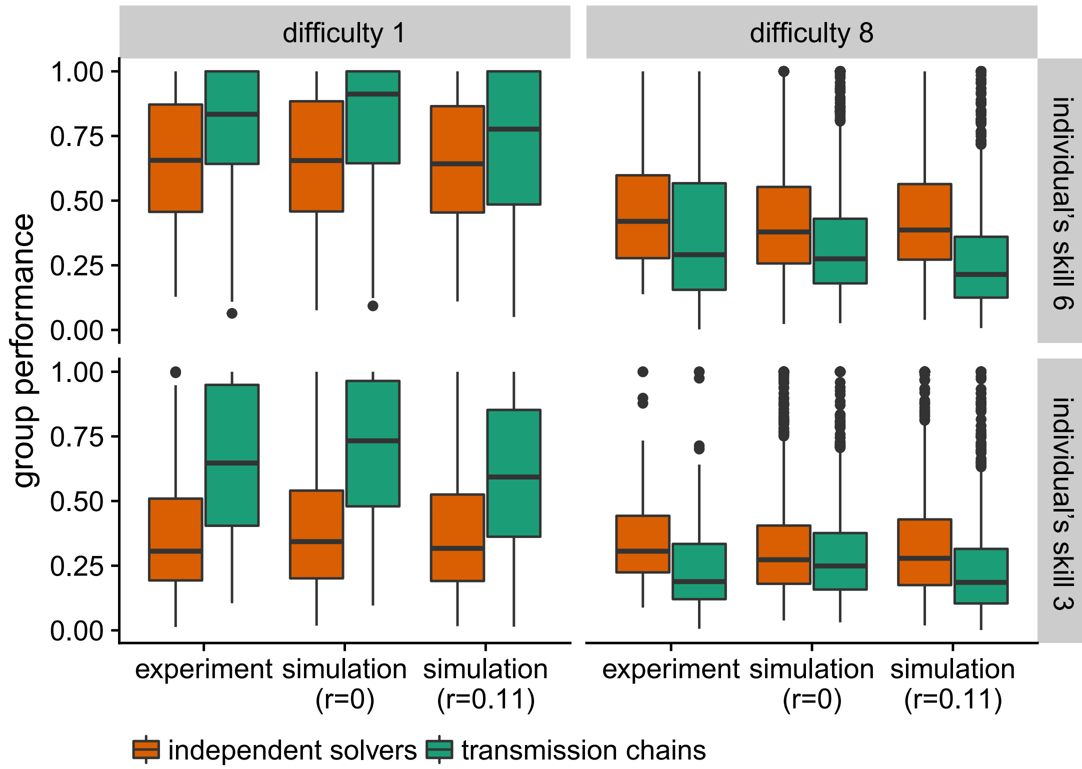

Figure 3.3. Observed and simulated performances for the transmission chains (in green) and the independent solvers (in orange), for smooth and rugged landscapes (as columns, $K = 1$ and $K = 8$) and for low and high individual skill (as rows, $S = 3$ and $S = 6$). The box plots indicate the interquartile range (box), the median (horizontal line) and 1.5-times interquartile range (whiskers). Outliers are shown as a single dot. For the simulations, the parameter r indicates the probability of risky decisions (i.e. the probability to leave a solution for a worse one). The group size is limited to eight individuals.

the performance of transmission chains for high difficulty and low skills, while slightly improving the performance of groups of independent solvers.

Group size and diversity

Finally, we investigate the influence of the group size for the two methods. To account for smaller groups in the experimental data, we simply excluded later individuals to match the desired size and recalculated the group's performances. Overall, simulations and experimental data exhibit very similar tendencies (see figure 3.5). In either case, our

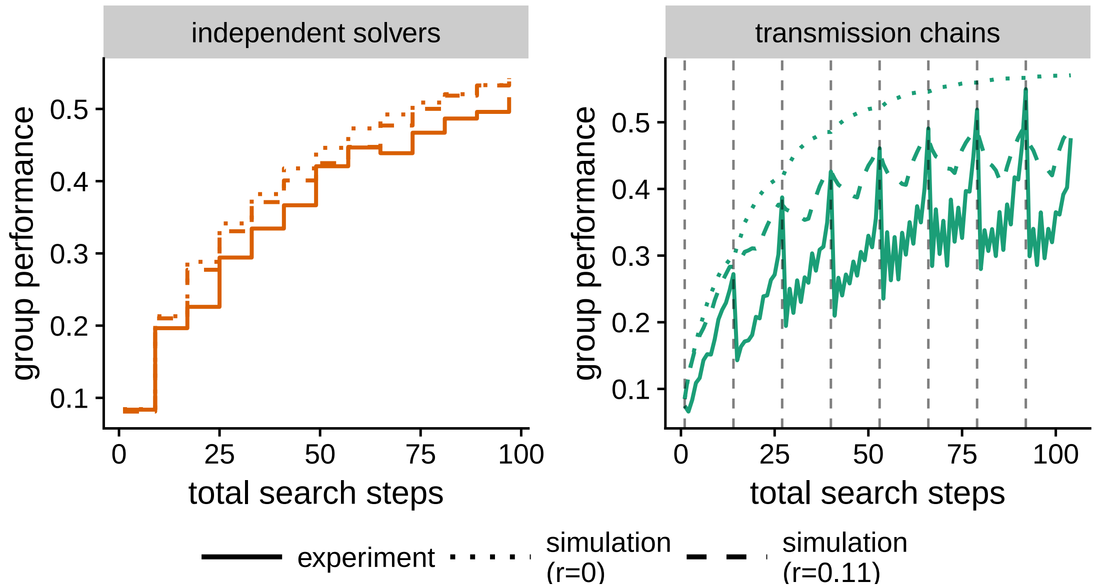

Figure 3.4. Group performance as a function of total search steps for $S = 6$ and $K = 1$ or 8. Total search steps are the sum of all search steps at the disposal of the entire group. For the transmission chain, a dashed vertical lines indicates that a new individual has started.

previous findings are robust to group size variations: with at least three group members, transmission chains outperform independent solvers in smooth environments and are outperformed in rugged ones. In general, group performance increases with group size while the difference between the two procedures remains about the same. The only exception concerns smooth landscapes with high skilled individuals, where both strategies lead a nearly optimal performance.

Overall, we find a diminishing returns for larger groups. In other words, performance does not improve linearly with group size, but eventually plateaus. For example, over all conditions an increase in group size from two to five members improves performance by an average of 0.1 in the experimental data, whereas the same change from five to eight members only improves performance by 0.07. In transmission chains, too many members can even decrease the collective performance, because longer chains increase the risk of losing a good solution due to a risky decision (as described by the parameter r).

Finally, we study how the collective performance is impacted by the group diversity – a factor that is known to be critical for collective intelligence (Derex et al., 2018; Jönsson et al., 2015; Tump et al., 2018; Surowiecki, 2004). For this, we define a group's diversity

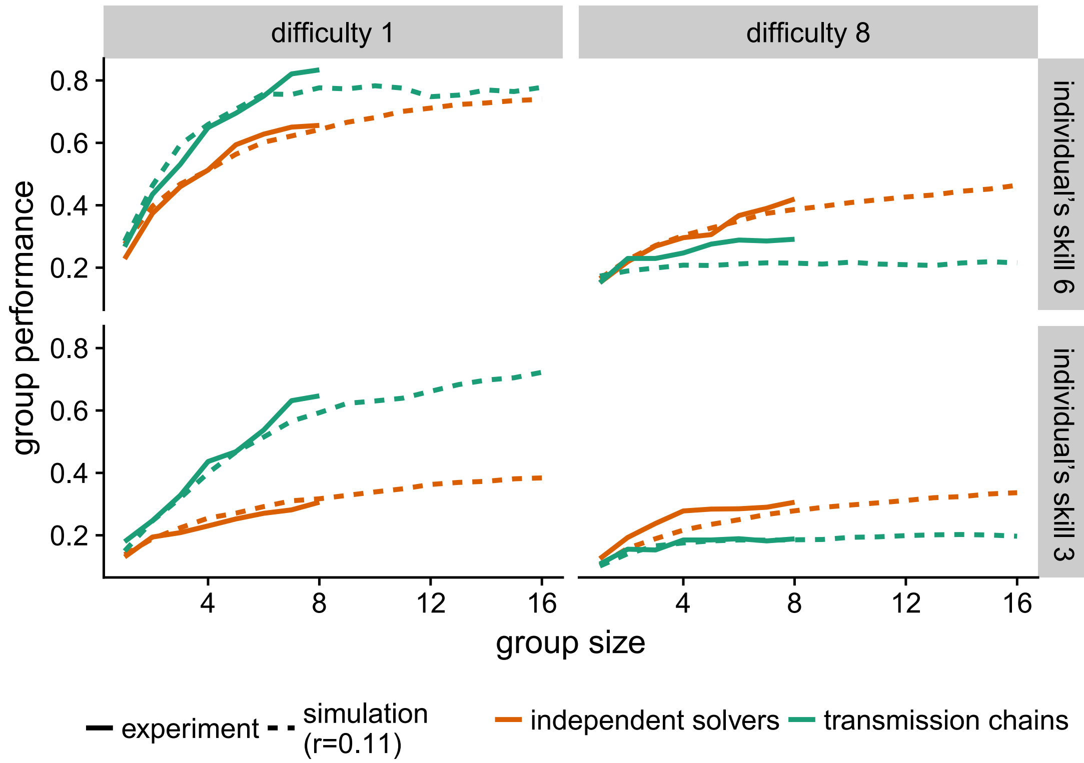

Figure 3.5. Influence of group size on performance for the two procedures (color-coded), as observed in the experiment data and obtained in simulations.

as the dissimilarity between the dimensions that the group members can manipulate. Put differently, a diverse group is made of individuals that have different perspectives on the same problem. Formally, diversity is measured as the average number of dimensions that only one individual can manipulate in all possible pairs of individuals in the group.

As shown in figure 3.6, our results reveal very strong evidence for a positive influence of diversity on the performance of independent solvers ($F(1, 346) = 39.15$, BF > 100, $adj.\ r^2 = .10$) and a moderate one for transmission chains ($F(1, 343) = 5.47$, $BF = 3.14$, $adj.\ r^2 = .01$). In short, diversity is indeed a positive factor, and more diverse groups outperform less diverse ones, irrespective of the chosen method.

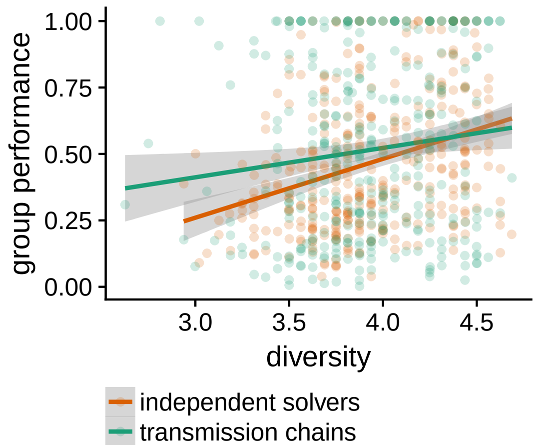

Figure 3.6. Influence of diversity on the collective performance, as observed in our experimental data. Diversity is defined as the dissimilarity between the dimensions that the group members can manipulate. Each point corresponds to one landscape in one condition. The straight lines indicate the best fitted linear models and the standard error to the two methods (color-coded).

3.3 Discussion

How should a group be structured for solving multidimensional problems? Here we compared two approaches: (1) transmission chains, where individuals tackle the problem sequentially, one after the other, each one building on the solution of its predecessor, and (2) groups of independent solvers, where individuals tackle the problem in parallel without influence and the best solution found in the group is selected afterwards. Our results suggest that the performances of the two methods depend on the interplay between two factors: the problem difficulty (i.e., the ruggedness of the landscape) and the skills of the individuals. Transmission chains outperform groups of independent solvers for easier problems or when the individuals are rather unskilled. In opposition, independent solvers have better performances for difficult problems or when the group members are rather skilled. To put it differently, when trying to continuously improve a solution to a well understood problem or when dealing with rather unskilled individuals, reliance on previous solutions is beneficial. When trying to come up with solutions to an unstructured or ill defined problem in a group of experts one should rather select amongst multiple independent suggestions.

The intuition underlying these results is the following. In smooth landscapes (i.e., easier problems), the global maximum can be found by means of a simple hill-climbing strategy that operates on all the problem's dimensions. However, low-skilled individuals have only access to a subset of these dimensions. For that reason, independent solvers performs poorly in this case (corresponding to the lower-left corner of the map, figure 3.2B). Transmission chains, in contrary, combine the skills of the group members. The different dimensions of the problem can therefore be optimized sequentially, explaining the better performance of this method here. As the group members become more skilled (i.e., moving towards the upper-left corner of the map, figure 3.2B), the difference between the two methods decreases. The collective outcome becomes naturally less sensitive to the chosen method when easy problems are addressed by skillful individuals.

As the problem becomes more difficult, the performances of both methods decline, but the decrease is less pronounced for groups of independent solvers. The challenge of such rugged environments, is that the hill-climbing strategy gets easily stuck at a local optimum. To overcome this issue, individuals need to temporarily reduce their payoff in order to leave the local optimum and explore another region of the landscape. Participants, however, are reluctant to do so (as indicated by the relatively low rate of risky decisions $r = 0.11$). In this situation, independent searchers exhibit better performances because individuals in such groups try different trajectories and arrive at different solutions – thus maximizing the likelihood that at least one of them reaches a good solution. Along these lines, citizen science projects, where people try to solve extremely complex optimization problems, have shown that high-performing participants are less efficient when first exposed to example solutions than when they work independently (Sørensen et al., 2016; Cooper et al., 2010).

Two behavioral factors are driving our results. The first one is the reluctance of individuals to temporarily decrease their payoff, although this is often the only way to find the global optimum. This behavior can be interpreted as risk aversion (Frey et al., 2017), because abandoning a reasonably good solution to search for a better one has considerable chances to fail (Boyd and Richerson, 1996; Miu et al., 2018). Furthermore, research has shown that the willingness to take risks tends to decreases when the problem space becomes vaster and more complex (Yahosseini and Moussaïd, 2019; Mehlhorn et al., 2015), which prevents individuals from "getting lost" in very large problem spaces. In situations where the individuals search is not predominantly guided by payoff (e.g., when individuals are more likely to take risky decisions and move away from a local optimum, or when the payoff information is not immediately available), additional simulations indicate that transmission chains would outperform independent searchers (as shown in figure B2 in the appendix).

The second important behavioural factor is related to the payoff structure. In our setup, individuals are only rewarded for their personal payoff, but not for the group's performance. This incites individuals to follow rather conservative search strategies and avoid the risk of losing a good solution. Adding a "safety net" – for instance by rewarding the collective performance – could possibly increase the frequency of riskier search behaviors, favoring the discovery of *leaps* – truly novel and substantially improved solutions (Miu et al., 2018).

In our simple implementation of transmission chains, the collective performance depends substantially on the last individuals of the chain. In other words, the system has no memory of the past solutions, which can result in losing track of a very good solution (Moussaïd and Yahosseini, 2016). This leads to very volatile collective performances over time, as observed in our experimental data and when introducing risky decisions in the simulations (see figure 3.4). This is along the lines of previous research showing that less inclusive strategies, i.e. strategies that depend on a smaller number of individuals, are more prone to wrong judgments, outliers and noise (Herzog et al., 2019; Mannes et al., 2014). Nevertheless, research in cultural evolution – studying how an innovation can emerge as solutions are passed from person to person, across generations – has shown that more sophisticated forms of transmission chains can retain memory of past events and yield more stable collective results.

Future research will consider mixtures and variations of these collective problem-solving methods, such as alternating phases of influenced and independent search (E. Bernstein et al., 2018), or mixing direct and indirect interactions in more elaborated chain structures (Mesoudi and Thornton, 2018).

3.4 Methods

Search environment

The search environments used in our simulations and the experiment were produced by means of the NK-model, which generates multi-dimensional tunably rugged landscapes (Barkoczi and Galesic, 2016; Lazer and Friedman, 2007). The structure of these landscapes is determined by the two eponymous parameters: N is the number of binary dimensions and K controls the ruggedness by varying the number of interdependencies between each dimension. Low values of K generate smooth landscapes with few or no local maxima, which are easy to solve by means of a local optimization procedure (i.e. hill climbing). In contrast, high values of K create rugged landscapes with many local maxima, where local optimization is not an efficient search strategy (see figure 3.1 for a visualization of two NK-landscapes and (Kauffman and Levin, 1987) for a more detailed description of the underlying model).

The NK-landscapes used in our study were generated by fixing $N = 10$ (i.e. our landscapes have 10 binary dimensions, corresponding to $2^{10} = 1024$ different solutions) and with various values of K. Following several authors, we normalized the payoffs in each landscape by dividing them by the maximal achievable payoff and using a monotonic transformation to raise each payoff to the power of eight (Lazer and Friedman, 2007; Barkoczi and Galesic, 2016). This process causes most solutions to be mediocre and only few to be very good.

Simulation procedure

Following Barkoczi and Galesic (2016), we use a minimalistic heuristic model of individual search (which nevertheless captures experimental data surprisingly well). The model assumes that each agent manipulates one randomly selected dimension at a time, and moves to the new solution if it offers a better payoff than the current one. The agent repeats this search behaviour until the end of the search time. We vary the individual's skill S by allowing only S randomly selected dimensions to be manipulated by the agent. That is for $S = 2$ the agent can only manipulate two dimensions of the search environment.

The duration of the search is set to 16 consecutive decisions (but our results seem robust to variations of this number) and all results are averaged over 1000 repetitions.

Experimental treatment

Participants were instructed to search for the best possible solution in a NK-landscape. To facilitate the visual representation, all payoffs were multiplied by 1000, and the 10 dimensions of the landscape were represented as 10 light bulbs that could be either on or off (representing the binary values '0' or '1', see the supplementary figure B1). Not all light bulbs could be manipulated, due to the restrictions imposed by S (those were visually marked by a cross). In each round participant could change the state of one light bulb. After their decision, they were informed about their new payoff and where allowed to return to their previous solution before a new round started.

The eight experimental conditions where selected based on preliminary simulation results, and where matched to the four corners of the figure 3.2B. The eight conditions consisted of smooth and rugged landscapes ($K = 1$ or $K = 8$, respectively), low or high individuals skill ($S = 3$ or $S = 6$, respectively) and transmission chain or independent group. The order of the experimental conditions was randomized. Each participant played a total of 128 levels, that is, 16 landscapes per experimental condition. To prevent participants from searching all possible solutions, the duration of the search was limited to $2 \times S$ rounds for all experimental conditions. Groups of eight individuals were formed searching the same landscape in the same condition.

Experimental procedure and participants

Participants were recruited from the Max Planck Institute for Human Development's pool and gave informed consent to the experiment. The experimental procedure was approved by the Ethics Committee of the Max Planck Institute for Human Development. Participants were first familiarized with the experiment and informed about their goal, the incentives, and the rules of search in the experiment. Figure B1 in the appendix shows the experimental interface.

We invited 50 participants to the behavioural laboratory of the Max Planck Institute for Human Development. Data of two participants had to be excluded due to technical issues. There were 25 females among the remaining 48 participants (mean age = 27.9, $SD = 5.13$). Participants received a flat fee of 8€ plus a monetary bonus based on their total performance (0.16€ per 1000 points, mean bonus = 6.65€, $SD = 1.11$€). The average completion time was 33.64 minutes ($SD = 10.67$ minutes).

Statistical tests

All reported t-tests are one sided. We also report Bayes factors (BF), quantifying the likelihood of the data under H_1 relative to the likelihood of the data under H_0. For parametric tests, the data distribution was assumed to be normal, but this was not formally tested (Wu et al., 2018). Our hypotheses also hold for non-parametric wilcoxon ranked sum tests.

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Chapter 4

Search as a Simple Take-the-Best Heuristic

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Abstract

Humans commonly engage in a variety of search behaviours, for example when looking for an object, a partner, information, or a solution to a complex problem. The success or failure of a search strategy crucially depends on the structure of the environment and the constraints it imposes on the individuals. Here we focus on environments in which individuals have to explore the solution space gradually and where their reward is determined by one unique solution they choose to exploit. This type of environment has been relatively overlooked in the past despite being relevant to numerous real-life situations, such as spatial search and various problem-solving tasks.

By means of a dedicated experimental design, we show that the search behaviour of experimental participants can be well described by a simple heuristic model. Both in rich and poor solution spaces, a take-the-best procedure that ignores all but one cue at a time is capable of reproducing a diversity of observed behavioural patterns. Our approach, therefore, sheds lights on the possible cognitive mechanisms involved in human search.

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Data access: Anonymous participant data, model simulation, and experimental code are available at https://github.com/cuehs/search_heuristic

4.1 Introduction

Many aspects of life can be seen as search for rewarding outcomes (Hills et al., 2015; Mehlhorn et al., 2015). Animals forage for food or mates (Cook et al., 2013; Todd, 1997), people search for information in the Internet or for a smart move during a chess game (Fu and Pirolli, 2007), and organisations search for new market opportunities (March, 1991). Search involves at least two main components: 1) sampling solutions by *exploring* the environment, and 2) collecting rewards by *exploiting* the discovered solutions (Hills et al., 2015; Mehlhorn et al., 2015; March, 1991). For example, a hungry tourist searching for a place to eat in a foreign city will first examine the surrounding streets and evaluate the quality of several restaurants (exploration), before eventually deciding which one to have dinner at (exploitation).

Exploration and exploitation are not always mutually exclusive (Hills and Dukas, 2012; Mehlhorn et al., 2015). In fact, numerous search problems exhibit a structure where the payoff of every explored solution is immediately earned and accumulates over time. This situation typically induces a dilemma between exploring new solutions and exploiting known ones (Bubeck and Cesa-Bianchi, 2012). For example, in multi-armed bandit problems (MAB) a gambler needs to decide which of many slot machines to play next, while simultaneously collecting the reward of each decision (Gittins, 1979; Bubeck and Cesa-Bianchi, 2012). Similarly, foraging hummingbirds combine feeding on nectar with the pursuit of finding new flowers (Mehlhorn et al., 2015). In other types of search problems, however, exploration and exploitation are *temporally separated*. In these cases, as in the hungry tourist example, the reward is based on one single solution that the individual chooses by stopping the exploration process and transitioning from exploration to exploitation. This type of search problems has been studied for example in the sampling paradigm (Hertwig et al., 2004) or in the secretary problem (Ferguson, 1989).

Another dimension along which search problems differ is how the environment can be explored (Srivastava et al., 2013). In some situations, individuals can directly move between two distant solutions, irrespective of their location. That is, they can *jump* between remote regions of the solution space, without the necessity to move through all the intermediate solutions. Examples include search for information in the Internet, where individuals are free to switch from one website to any other, or Mason and Watts' network experiment where participants harvest resources in a virtual landscape (Mason et al., 2008). In other search problems, however, jumps between distant solutions are not possible. In such problems, the exploration is *gradual*, that is, it is constrained to the neighbourhood of the current solution. Our hungry tourist, for example, can only evaluate the quality of the adjacent restaurants. Likewise, people searching for a good solution to the travelling salesman problem in the experiment performed by Dry and colleagues can only add or remove one connection at a time, exploring the solution space gradually (Dry et al., 2006).

These two features of the search problem (i.e. the separation of exploration and exploitation and the gradual exploration) can have a strong impact on the way individuals deal with search problems. Yet, research has mostly focused on search problems where exploration and exploitation happen simultaneously (e.g. MAB: Lee et al. (2011); abstract search: Goldstone et al. (2008); Lévy processes: Namboodiri et al. (2016); comparison of different paradigms: von Helversen et al. (2018)) and/or where jumps in the solution space are allowed (e.g., correlated MAB: Wu et al. (2018); sampling paradigm: Hertwig et al. (2004); secretary problem: Seale and Rapoport (1997); random sampling: Yahosseini et al. (2018)). Nevertheless, many search problems are characterised by separated exploration and exploitation phases and gradual exploration; examples include animals deciding where to hunt prey (Stephens and Krebs, 1986; Kolling et al., 2012), algorithms maximising their reward in a reinforcement learning settings (Kaelbling et al., 1996), and humans visually searching for a lost item (Wolfe et al., 2005), or solving a complex problem (Dry et al., 2006; Fu and Pirolli, 2007). How do people solve such search tasks?

In the present work, we focus on such type of problems by addressing two research questions:

1. How do people explore their environment when only gradual movements are possible (i.e. jumps are not feasible)?
2. When do people decide to terminate the exploration and start exploiting one solution when these two phases are temporally separated?

We address these two questions separately, by means of a dedicated experimental design. In a first experimental phase, we study specifically how people explore a two-dimensional solution space when only gradual movements are allowed. In a second experimental phase, we study the decision to exploit a solution, when exploration and exploitation are separated. We show that these two behavioural components are well described by a simple model based on the take-the-best heuristic (Gigerenzer and Goldstein, 1996;

Gigerenzer and Goldstein, 1999). A third experimental phase, combining exploration and exploitation, confirms that the full model has captured the participants search strategies, both in rich and poor solution spaces. We conclude by comparing the model to alternative approaches proposed in the literature.

4.2 Methods

We conducted an experiment in which participants were instructed to search for the best possible solution in a *landscape* – a conceptual euclidean representation of a solution space (Alexander et al., 2015; Mason et al., 2008; Lazer and Friedman, 2007). In a landscape, each field represented one solution and was associated to one fixed payoff. Participants were given 30 rounds of search. In each round, they could move to one of the neighbouring solutions or stay at their current one. Participants indicated their decision by clicking on the solution they wanted to move to (see figure A1 in the supplementary materials for the experimental interface). Movements to distant solutions that were not adjacent to the currently occupied one were not allowed (gradual exploration). Participants saw the payoffs associated to their current solution and to the eight adjacent ones. We call *trajectory* the sequence of solutions a participant moved through during the 30 rounds of the experiment. The experiment was divided in three phases (see also table 4.1):

1. **The exploration phase.** In the first phase, participants were positioned in the centre of a squared landscape containing 63×63 fields. The landscape was large enough to ensure that participants could not reach its border within the allocated time. Participants were instructed to search for the best possible solution and were rewarded based on the highest payoff they found after 30 rounds of exploration. In such a way, we could focus solely on the exploration pattern, leaving out the exploitation decision.

2. **The exploitation phase.** In the second stage, participants were placed at one end of a uni-dimensional landscape, that is, a vector containing 63 solutions. They were rewarded according to the payoff of the field they occupied in the last round. With this design, we focus on how and when the participants decide to stop exploring the solution space and start exploiting one solution.

Phase	Landscape	Size	Start	Reward
Exploration	Two-dimensional	63×63	$(32, 32)$	Highest payoff
Exploitation	Uni-dimensional	1×63	(1)	Payoff in last round
Combined	Two-dimensional	63×63	$(32, 32)$	Payoff in last round

Table 4.1. Description of the three experimental phases. Every phase consisted of 20 landscapes (divided in 10 rich and 10 poor landscapes) played for 30 rounds each.

3. **The combined phase.** In the third phase, participants were positioned in the middle of a quadratic landscape containing 63×63 (as in the exploration phase) and rewarded according to the payoff of the position they occupied in the last round (as in the exploitation phase).

In each phase, participants played a total of 10 rich landscapes containing a high number of peaks, and 10 poor landscapes containing a low number of peaks. Rich and poor landscapes were presented to the participants in a random order.

Landscapes. The two-dimensional landscapes used in the exploration and combined phase were produced according to the following procedure:

1. We first generated n sub-landscapes. Each sub-landscape consisted of a 63×63 matrix filled with zeros, except for one randomly selected field that contained a random value drawn from a normal distribution with mean zero and standard deviation one. We call this non-zero field a peak. We then squared the peak value to avoid negative payoffs.

2. We then applied a Gaussian filter with a standard deviation of one on each sub-landscape to create a local gradient around the peak.

3. We finally merged the n sub-landscapes into a single one by selecting the highest payoff across all sub-landscapes at each coordinate.

We used $n = 32$ and $n = 512$ to create poor and rich landscapes, respectively. The uni-dimensional landscapes used for the exploitation phase were generated by randomly selecting one horizontal line from a two-dimensional landscape of the same type.

Finally,the payoffs were rounded to the closest integer and linearly scaled between zero and a random value between 30 and 80. This procedure generates landscapes similar to those shown in figure 4.1. We call the normalised payoff of a solution its actual payoff divided by the highest payoff of the landscape.

Procedure and participants. Participants were recruited from the Max Planck Institute for Human Development's participant pool and gave informed consent to the experiment. The experimental procedure was approved by the Ethics Committee of the Max Planck Institute for Human Development.

At the beginning of each phase, participants received information about the goal of the search, the size of the landscape, the moving rules, and completed a practice search. We recruited 50 participants (28 female, mean age = 26.1, SD = 4.4). They received a flat fee of 12 € plus a monetary bonus based on their aggregated performance (0.15 € per 100 points, mean bonus = 2.46 €, SD = 0.48 €). The average completion time was 35.31 minutes (SD = 10.67 minutes).

4.3 Results

Exploration phase. In the first phase of the experiment, we focused on how people explore their environment when jumps are not permitted. For this, participants were instructed to search in a two-dimensional landscape of size 63×63 and rewarded based on the highest payoff they found during 30 rounds of search. Figure 4.1 shows two illustrative trajectories of participants in a poor and a rich landscape.

Overall, participants performed better in rich than in poor landscapes (the average normalised payoff was 0.33 with SD = 0.21 in rich landscapes and 0.17 with SD = 0.26 in poor landscapes), but explored a similar number of unique solutions (on average 26.1 and 27.2 fields visited in rich and poor landscapes respectively, with an SD of 6.64 and 5.39 respectively). In both environments, participants avoided revisiting a previously visited solutions. On average, the fraction of solutions visited more than once was 0.14 (SD = 0.20). As a comparison, this fraction goes up to 0.57 (SD = 0.10) for a completely random exploration process, suggesting that participants are actively avoiding previously visited solutions.

To better understand the exploration mechanisms at play, we aggregated all trajectories (in poor and rich landscapes separately) to generate the corresponding density maps. These maps indicate how often each field has been visited relative to the others, irrespective of the peaks positions.

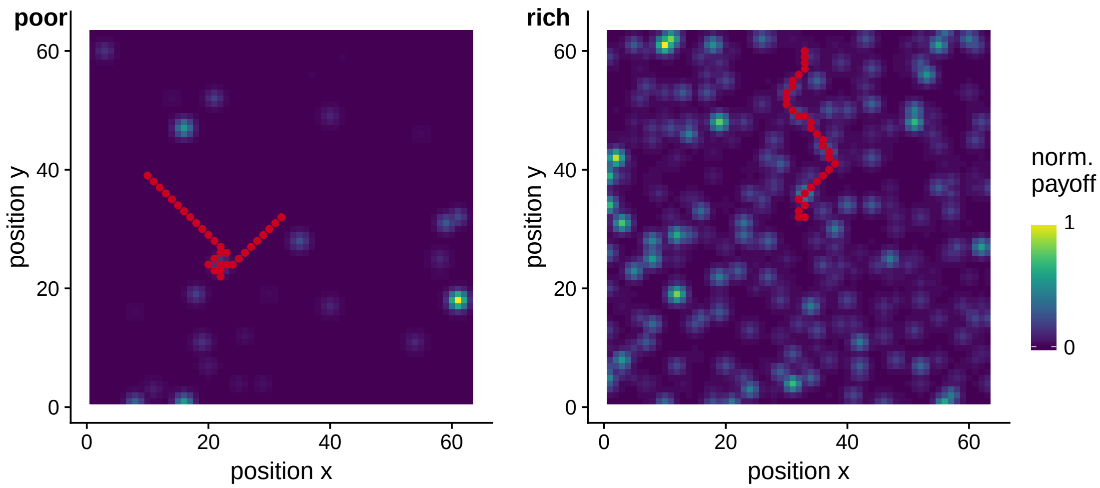

Figure 4.1. Two examples of exploration trajectories (in red) in a poor (left) and a rich (right) landscape. The red dots indicate the participant's trajectory, i.e. the spatial position at each round. The colour-coding of the landscape indicates the normalised payoff associated to each position (x, y). Participants always started in the middle of the landscape, at position $(32, 32)$.

As shown in figure 4.2, the density map for the poor landscapes reveals a surprising X-shaped exploration pattern, suggesting that participants have a preference for diagonal movements. This pattern, however, is not visible in the rich landscapes.

Why do participants tend to explore along diagonal lines when peaks are rare but not when they are abundant? Diagonal movements uncover up to five new solutions because it enables participants to move simultaneously along the x- and y- dimensions. By contrast, vertical or horizontal moves can only reveal up to three new solutions. Therefore, moving diagonally constitutes an efficient strategy to extend one's exploration range. The absence of the X-shaped exploration pattern in rich landscapes suggests that participants might rely on another cue when peaks are frequent: the surrounding payoff values. In this case, participants are most likely using a hill-climbing process consisting in moving to the most rewarding adjacent solution (Marshall and Neumann, 2012). Overall, our data suggests that three rules are guiding the exploration: 1) not returning to previously visited solutions (using the *non-visited cue*), 2) maximising the immediate payoff by moving to the most-rewarding neighbouring solution (using the *payoff cue*), and 3) maximising the number of new solutions revealed (using the *novelty cue*). Figure 4.3 confirms the important role played by these three components. We formalise these three rules in a

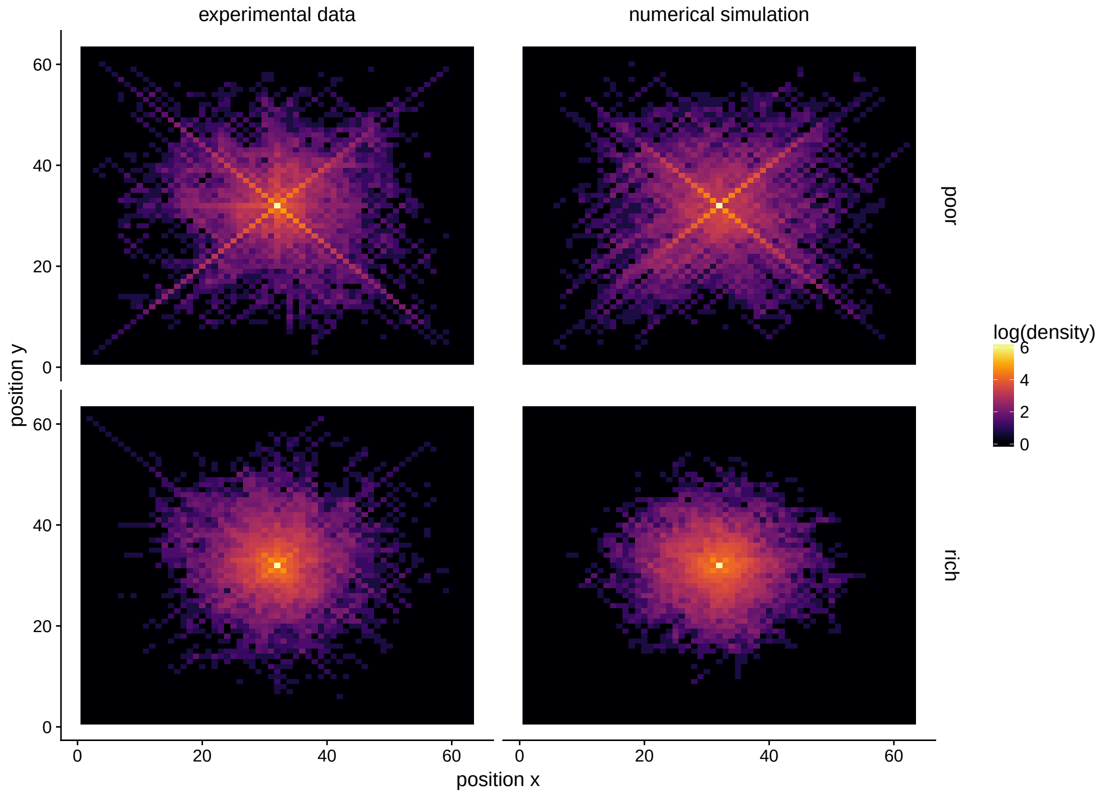

Figure 4.2. Density maps for poor (upper line) and rich (lower line) landscapes in the exploration phase, as observed in the experimental data (left) and obtained from numerical simulations (right). The colour coding indicates how often a given position (x, y) has been visited at the aggregate level, represented in logarithmic scale. The starting point of the search is located in the middle of the map, at coordinates $(32, 32)$. For the simulations, we randomly selected the same number of trajectories as in the behavioural data to ensure comparable density scales.

simple lexicographic model based on the take-the-best heuristic (TTB) (Gigerenzer and Goldstein, 1996; Gigerenzer and Goldstein, 1999). TTB assumes that decisions between multiple options are made by ranking cues and then looking at only one cue at a time. If a cue discriminates, a decision is made for the best option, and only otherwise the next cue is evaluated.

In our experiment, participants need to decide between nine different options in every round (that is, moving to one of the eight neighbouring solutions or staying at the current one). To make that decision, we assume that participants first look at the not-visited cue and stop if the cue discriminates (i.e. if only one option has not been visited, that partic-

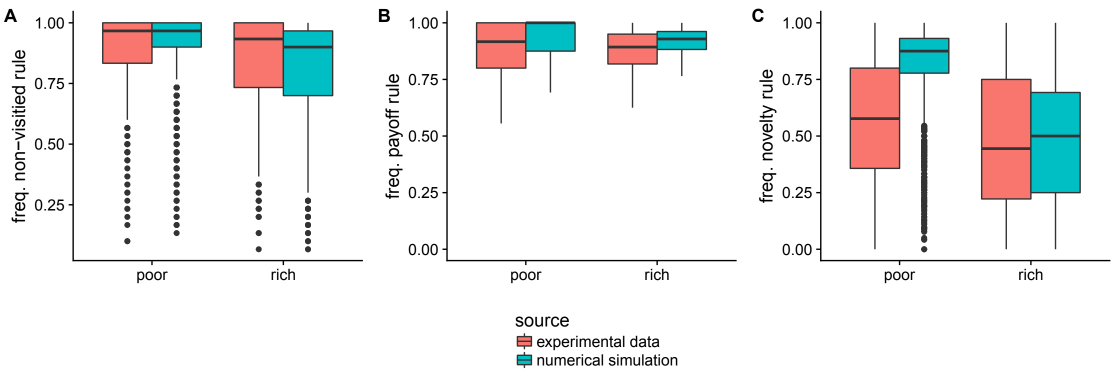

Figure 4.3. Frequency of decisions based on the three rules as observed in the experimental data and in numerical simulations (for poor and rich landscapes). Box plots indicating the interquartile range (box), the median (horizontal line) and 1.5-times interquartile range (whiskers). Outliers are shown as a single dot. A) Non-visited cue. Proportion of movements towards a non-visited solution. B) Payoff cue. Proportion of movements towards a non-visited solution with the highest payoff. C) Novelty cue. Proportions of movements maximising the number of new solutions revealed, when the non-visited cue and the payoff cue do not discriminate. In C, the decisions based on the novelty cue in poor landscapes are less frequent than predicted by the model, but remain nevertheless higher than what a random search model predicts (40%). Overall, the three cues presented in A, B, and C account for 68.8 % of all the decisions made by the participants.

ular option is chosen and a decision is made). If the *not-visited cue* does not discriminate, they consider the *payoff cue* of the remaining options (if exactly one option has a higher payoff than all other options, that option is chosen and a decision is made). If the payoff cue still does not discriminate, they finally consider the *novelty cue* (that is the option that reveals the largest number of new solutions is chosen). If two or more equivalent options remain at the end of the process, a random decision is made between them. Finally, we add an uniform noise parameter ϵ to the model, defined as a low probability to make a random choice between all available options. Table 4.2 shows an example of how decisions are made according to our model. The model has one unique parameter, namely, the noise level ϵ. We fitted ϵ by systematically varying it between zero and one and comparing the highest payoff per round to the experimental data (averaged over $8,000$ simulated trajectories). The value $\epsilon = 0.17$ minimises the squared difference to the experimental observations (figure 4.4). We keep ϵ constant in the remainder of the study.

Once fitted to the payoff curves, the resulting model also produces consistent patterns on other aspects of the search behaviour, such as the X-shaped exploration pattern (figure 4.2), and the influence of the three cues (figure 4.3). In the next section, we will extend

Cues \ Options	∅	N	NE	**E**	SE	S	SW	W	NW
Non-visited	0	0	1	1	1	1	1	1	1
Payoff	0	45	5	**25**	10	5	0	0	0
Novelty	0	0	2	3	5	3	5	3	2

Table 4.2. Example of the take-the-best heuristic. The decision-maker can choose between nine options (as columns: the eight cardinal directions and staying (∅)) knowing the three cue values for each option (as rows: non-visited, payoff and novelty). In this example, the decision-maker would first look at the non-visited cue for all options. This stage leaves seven possible non-visited options that are then compared based on the payoff cue. At this stage, one option scores better than the others (the "East" option marked in bold letters) and a decision is made in favour of it. The novelty cue is not examined. Green cells (resp. red cells) indicate cue values that are considered (resp. ignored) during the decision.

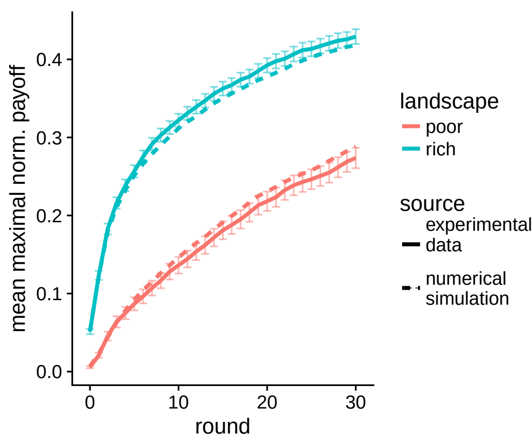

Figure 4.4. Performance in the exploration phase. The highest normalised payoff found as a function of time averaged over all participants (plain line) or produced in simulations (dashed line). Error bars for the experimental data indicate the standard error of the mean.

this model to include the decision to exploit.

Exploitation phase. In the second phase of the experiment, we examine how people decide to stop their search and exploit a previously discovered solution. For this, participants are positioned at one end of an uni-dimensional landscape, and are rewarded based on the payoff of the field they occupy at the last round. Unlike the exploration phase, participants can only navigate along a line (i.e., by moving left or right). Furthermore, they face a tradeoff between the benefits of exploring as far as possible and the need to be positioned at a sufficiently good solution after 30 rounds. Figure 4.5 illustrates this experiment.

The type of landscape directly impacted the participants' performances (average final payoff 0.60 in rich landscapes and 0.47 in poor landscapes, with a SD of 0.36 and 0.46 respectively). On average participants moved 20.6 fields ($SD = 9.93$) and 13.2 fields ($SD = 8.71$) away from their starting point in poor and rich landscapes, respectively.

The trajectory shown in figure 4.5-B illustrates that, after discovering a new best solution, participants tend to continue searching for a more advantageous one before eventually returning back to it if no better solution is found.

At any moment of time, we call X_{best} the best payoff that the participant has discovered so far, and P_{best} the position of that best payoff. We first ask the following question: how far do participants continue their exploration after discovering P_{best}, before coming back to it if no better one is found? From a normative point of view, participants should start returning to P_{best} as late as possible, such that their chance to discover a better solution is maximised. This optimal exploration range simply equals to $D_{optimal} = \lfloor T_{left}/2 \rfloor$, where T_{left} is the remaining number of rounds. In such a way, the participant would arrive back at P_{best} exactly at the last round while having maximised her exploration range.

Looking into the behavioural data, however, it seems that participants only use a certain fraction of the optimal exploration range (see, e.g., the example in figure 4.5-B). That is, they start returning to their best option too early with respect to $D_{optimal}$. Some participants even stop their exploration immediately when a new P_{best} is discovered, without using any of the remaining rounds for further exploration. In contrary, it also happens that participants continue searching longer than $D_{optimal}$ and hence do not return to P_{best} at all.

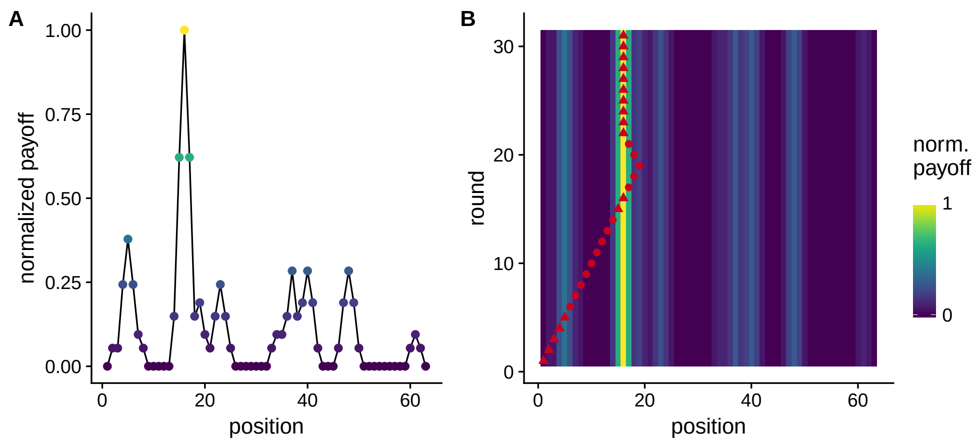

Figure 4.5. Exploitation phase. A) Example of a rich landscape used in the experiment. Participants always started at position $x = 1$ and could see the payoffs associated to their current position and to the two neighbouring ones. In the first round, they could only move to the right. Participants were rewarded based on the payoff of their final position. B) Trajectory of a participant navigating in the landscape shown in A). The red markers indicate the position in each round and the colour coding shows the normalised payoff of each position. In this example, the participant discovered a first peak at round 5 (at position $x = 5$) but continued her exploration. At round 15, a better solution is found (at position $x = 15$). The participant continued her exploration for 3 rounds before returning to her best solution and settling there until the end of the 30 rounds. Triangles indicate that the current solution is the best that has been discovered so far (named X_{best} in the main text).

To study this process, we measured the safety level S of our participants, defined as the fraction of the optimal exploration range they used before returning to P_{best}. That is, $S = R/D_{optimal}$, where R is the distance a participant has actually moved away from P_{best} before returning to it. With this definition, $S = 1$ indicates that all remaining rounds were used efficiently, $S = 0$ indicates that the exploration has stopped immediately after the discovery of the peak, and $S > 1$ indicates that the participant did not return to P_{best} at all. Figure 4.6 shows the values of the safety levels S observed in our experiment, as a function of the payoff value X_{best}.

Figure 4.6-A reveals multiple zones of interest: 1) On the upper part of the figure, the stronger density of data points around $S = 0.9$ indicates that participants often continued their search up to about 90% of the optimal exploration range. 2) On the lower part of the figure, however, the stronger density of data points along $S = 0$ indicates that participants often decided to stop their search immediately after discovering a new peak. In this case, the probability to stop seems to be linearly increasing with the payoff value

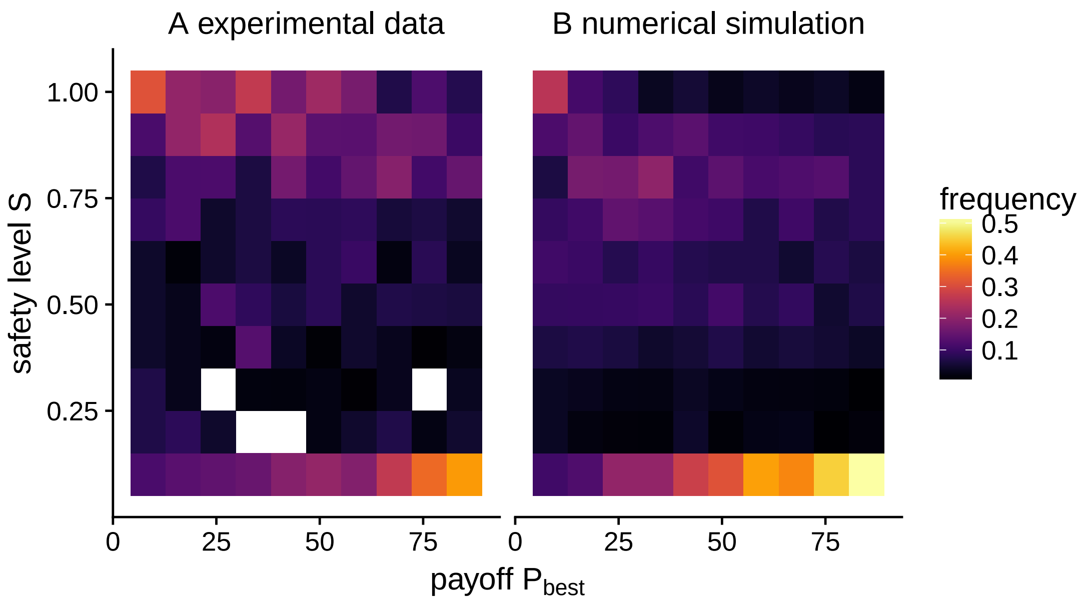

Figure 4.6. Safety level S as a function of the payoff X_{best}, A) as observed in the experimental data. B) and obtained from numerical simulations. All incidents where $D_{optimal} \leq 2$ or $S > 1$ were excluded, as these cases neither show return nor staying behaviour. In total the removed incidents account for 26% of the data, of which 75% are cases where no payoff bigger than zero is found at all. To generate the heatmap, we first determined the safety level S for all trajectories where the participants returned to a previously visited P_{best}. We then calculated the relative frequency for S given a certain X_{best}, which are indicated by the colour coding.

X_{best}. The cases where $S > 1$ is most frequent when the value of X_{best} is low (mean payoff for $S > 1 = 9.38$, $sd = 9.05$). In sum, participants tend to stop immediately if a sufficiently good peak is found and otherwise continue their exploration before coming back to it with a certain safety time. If the payoff of the discovered peak is too low, however, they do not return to it.

Formally, the exploration range R around a newly discovered best solution P_{best} can therefore be defined as $R = 1$ with a probability of $k \times X_{best}$, $R = \infty$ with a probability of $1 - l \times X_{best}$, and $R = S_0 \times D_{optimal}$ otherwise, where $D_{optimal} = \lfloor T_{left}/2 \rfloor$ as previously defined. The parameter k describes the linear influence of X_{best} on the stopping probability (fitted value $k = 0.0051$, $SE = 0.0003$ using a linear model applied to cases where $S = 0$). The parameter l describes the linear influence of X_{best} on the probability to ignore a peak (fitted value $l = -0.027$, $SE = 0.005$ using a linear model applied to cases where

$S > 1$). The parameter S_0 is the safety level that a person adopts and is sampled from a truncated normal distribution $\mathcal{N}(\mu, \sigma^2)$ bounded between zero and one (fitted values $\mu = 0.806$, $SE = 0.04$ and $\sigma^2 = 0.364$, $SE = 0.03$ using a maximum likelihood estimator applied to all observations with $S > 0$ and $S \leq 1$).

How can the exploration model described in the previous section be extended to account for this stopping process? Remarkably, only one additional cue in the TTB heuristic is sufficient to do so: the *exploration-radius cue*, indicating whether a given option lies within the exploration radius R or not. The general model is therefore composed of four cues — exploration-radius, not-visited, payoff, and novelty — that are considered one at a time and in this order. In other words, the model simply ensures that only options that are not too far from the current best payoff are considered. Interestingly, the returning behaviour does not need to be explicitly implemented in the model. Instead, it emerges naturally. In fact, the exploration range R shrinks towards the current best solution P_{best} as the end of the allocated time is approaching (due to the dependency of R on the remaining time T_{left}). Therefore, after a certain time, only decisions towards P_{best} are considered, gradually driving the individual back to its best solution.

The model reproduces the trends observed in the experimental data, in terms of payoffs and individual behaviours (figure 4.7) and shows a similar relationship between the payoff X_{best} and the safety level S (figure 4.6).

Combined phase. In the third experimental phase, participants performed the search task in two-dimensional landscapes (as in the exploration phase) but were rewarded based on the payoff of the field they occupy at the last round (as in the exploitation phase). This phase, therefore, combines the exploration and the exploitation processes that we previously studied separately, and allows us to evaluate the full model that we have elaborated.

The average payoff in the rich landscapes is higher than in the poor landscapes (average final payoff 0.36, with a $SD = 0.20$ and 0.24 with a $SD = 0.29$ in the rich and poor landscapes, respectively). When looking at the density maps, the X-shaped exploration pattern is visible in the poor landscapes but not in the rich landscape, similar to the exploration phase (figure 4.8).

Does our full model reproduce these patterns? The same fitting procedure as in the exploitation phase yields the parameter values $k = 0.011$ ($SE = 0.003$), $l = -0.022$ ($SE = 0.012$), $\mu = 0.386$ ($SE = 0.02$), and $\sigma^2 = 0.275$ ($SE = 0.01$). Interestingly, these

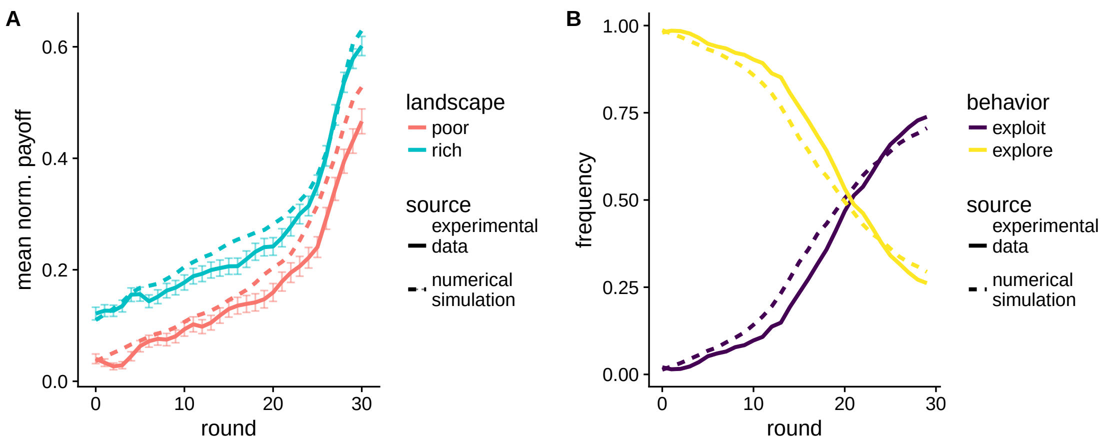

Figure 4.7. Performance and behaviour in the exploitation phase. A) Observed and simulated average normalised payoff as a function of time. B) Frequency of exploration (moving away from P_{best}) and exploitation (moving towards or staying at P_{best}) as a function of time. Error bars for the experimental data indicate the standard error of the mean.

values are different from those fitted in the exploitation phase. The decrease of k (the influence of X_{best} on the stopping probability) and μ (the mean safety level) reflect the fact that participants were satisfied with a lower payoff and adopted a lower safety level than in the exploitation phase. This can be explained by the greater complexity of the task, which reduced the participants willingness to move away from a discovered solution (Mehlhorn et al., 2015). Despite this overall decrease of μ, we find a strong correlation between the participants' safety level in this phase and in the exploitation phase (Pearson's correlation = .42, df=47, $p < 0.003$, see also figure A6 in the supplementary materials), suggesting that the difference between the individual safety levels remained somewhat stable.

The model predicts the emerging X-shaped exploration pattern (figure 4.8) as well as the evolution of the average payoffs (figure 4.9). Overall, this confirms that the full model has captured some of the key mechanisms involved in the search process of the participants.

Model comparison. How well does our full model perform compared to alternative modelling approaches? Because most models in the literature either focus on the exploration (e.g., Wu et al. (2018), Gittins (1979), and Gershman (2018)) or the exploitation mechanism (e.g., Hertwig et al. (2004), Ferguson (1989), and Seale and Rapoport (1997)),

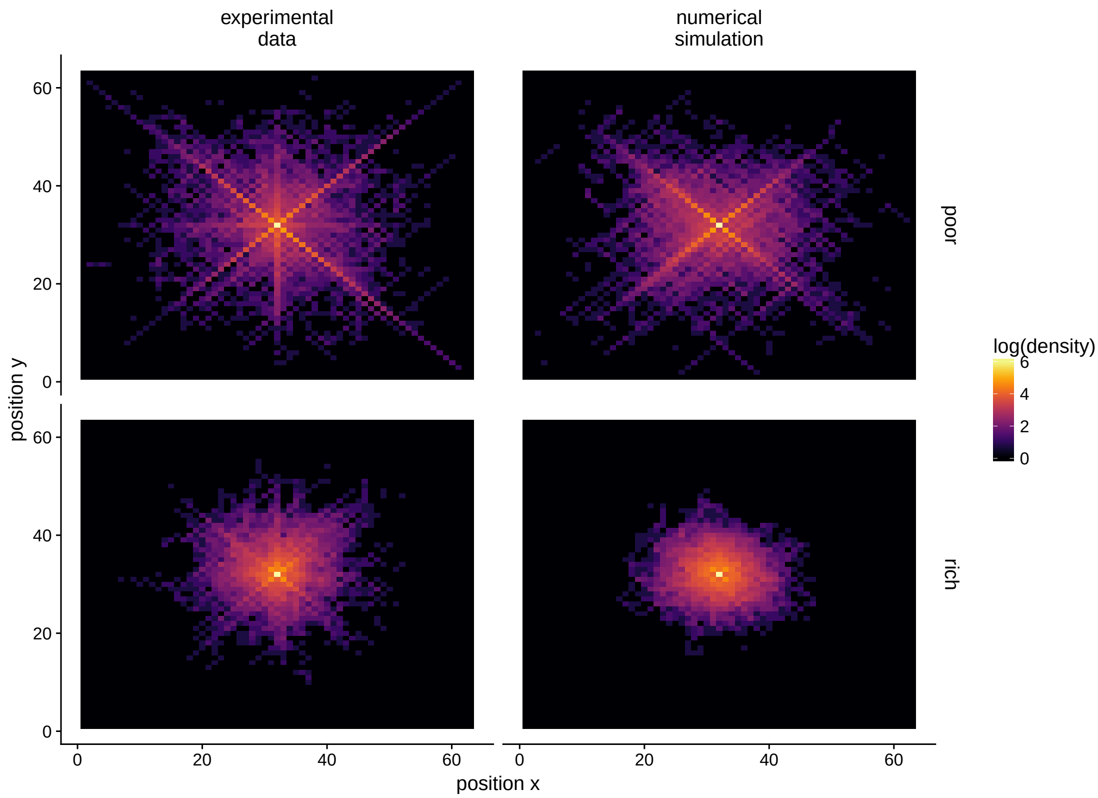

Figure 4.8. Density maps for poor (upper line) and rich (bottom line) landscapes in the combined phase, as observed in the experimental data (left) and obtained from numerical simulations (right). The colour coding indicates how often a given position (x, y) has been visited at the aggregate level, represented in logarithmic scale. The starting position is located in the middle of the map, at coordinates $(32, 32)$. For the simulations, we randomly selected the same number of trajectories as in the behavioural data to ensure comparable density scales.

we tested these two main components separately. For this, we first kept the exploitation mechanism unchanged, and tested five different models for the exploration phase: 1) our *take-the-best* model, 2) a *probabilistic* variation of that model in which the individual chooses to rely on the payoff cue or the visibility cue based on the most rewarding neighbouring solution (Wilson et al., 2014; Cogliati Dezza et al., 2017), 3) a typical *hill-climbing* model where exploration is always directed towards the most-rewarding adjacent position (Barkoczi and Galesic, 2016), 4) a "*blind search*" model in which the exploration is only guided by novelty, and 5) a *random search* model in which the next position is randomly chosen among the adjacent solutions. For the probabilistic model, we fit a logistic regres-

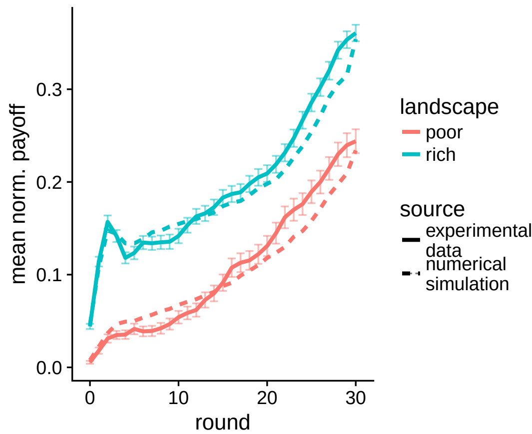

Figure 4.9. Performances in the combined phase. Evolution of the average normalised payoff, aggregated over all participants, as a function of time in the experimental data and model simulations. Error bars for the experimental data indicate the standard error of the mean.

sion to predict the probability of using the payoff cue over the novelty cue, depending on the most-rewarding neighbouring solution. The probability to rely on the payoff cue is $1 - 1/e^{-1.509+0.301pn_{max}}$, where pn_{max} is the payoff of the most-rewarding neighbouring solution (see figure A7 in the supplementary materials).

The results are presented in table 4.3. It appears that take-the-best predicts the experimental data best, in terms of both the payoff and the density map. Specifically, the three models that use the payoff cue (take-the-best, probabilistic, and hill-climbing) are in good agreement with the observed payoffs pattern. However, the X-shaped pattern observed in the experimental density maps can only be predicted when using the novelty cue (see also the figures A2 and A3 in the supplementary materials).

We then evaluated the exploitation mechanism analogously, by keeping the exploration mechanism unchanged, and tested four possible models for the exploitation phase: 1) a *normative* model in which the individuals return the their best solution with no safety time, 2) an *early-stop* model in which the individuals stop exploring whenever the first peak is found (Alexander et al., 2015) 3) our *returning model*, and 4) *simple returning*, a variation of our model where individuals do not ignore peaks with low payoff (Simon, 1990). The results are shown in table 4.4. The normative model strongly deviates from the observed payoff pattern, as participants tend to stop exploration and return to their best solution much earlier than the simulated agents. Likewise, the early-stop model produces

Name	$dist_{payoff}$	$dist_{density}$	parameters	cues
Take-the-best	2.83	0.68	1	3
Probabilistic	3.34	0.77	2	3
Hill-climbing	5.07	0.79	0	2
Blind search	69.6	1.06	0	2
Random search	82.0	0.934	0	0

Table 4.3. Comparison of different exploration mechanisms. The first column indicates how much the model predictions deviates from the observations with regard to the payoff pattern shown in figure 9. Formally, $dist_{payoff}$ measures the squared difference between the observed and the predicted payoff curves. The second column indicates the deviation of the predictions with regard to the density map (figure 8). Here, $dist_{density}$ measures the absolute average difference between each position of the observed and the predicted density maps. To assess the *prediction accuracy* we used a k-fold cross-validation (k=5) and out-of-sample predictions for calculating $dist_{payoff}$ and $dist_{density}$ (Daw, 2011). The last two columns indicate the number of free parameters of the model and the number of cues used in the exploration mechanism. All five exploration models are tested in combination with the *returning model* for exploitation (see table 4.4).

Name	$dist_{payoff}$	$dist_{density}$	parameters	cues
Returning	2.83	0.68	4	1
Simple returning	3.48	0.73	3	1
Early-stop	17.7	0.75	0	0
Normative	39.4	0.85	0	1

Table 4.4. Comparison of different exploitation mechanisms. The values of $dist_{payoff}$ and $dist_{density}$ measure the difference between observations and model's predictions, in terms of payoff patterns and density maps, respectively (see table 4.3 for formal definitions). All four exploitation models are tested in combination with the *take-the-best model* for exploration (see table 4.3)

payoff patterns that are inconsistent with the observations (see figures A4 and A5 in the supplementary materials). The two remaining models have similar performances: the returning model predicts the experimental data slightly better whereas the simple returning model has one less free parameter (Daw, 2011). Remaining deviations from observed data in the TTB model can be attributed to some of the model's simplifications, such as ignoring a possible time-dependency of the safety level S (see figure A8 in the supplementary materials)

4.4 Discussion

Search problems can vary on many different dimensions. We investigated how people search for a rewarding outcome in problems characterised by gradual exploration (i.e. when jumps between distant solutions are not allowed) and a temporal separation between exploration and exploitation. This type of search is relevant for numerous real-life situations, such as visual search, spatial search and most problem-solving situations (Wolfe et al., 2005; Dry et al., 2006; Kaelbling et al., 1996; Fu and Pirolli, 2007). On that account, we have developed a dedicated experimental design enabling us to isolate the exploration from the exploitation mechanisms. We then modelled these two components separately, before merging them in a full and comprehensive model of search.

We described the participants behaviour by means of the TTB heuristic. With that approach, four cues can describe the exploration and exploitation behaviour of the participants: the exploration-radius cue, the non-visited cue, the payoff cue, and the novelty cue. While TTB constitutes a valid model to describe how people make decisions between two options (Bröder, 2000), we have shown that it can also be used to describe search behaviours.

Recent research on human search behaviours distinguishes between directed and undirected exploration (Wilson et al., 2014; Gershman, 2018; Wu et al., 2018). In multi-armed bandit tasks undirected exploration refers to the stochasticity of the search process causing random exploration decisions. In contrast directed exploration seeks out solutions that are informative about the underlying reward distribution (Wilson et al., 2014). Both components play a important role in solving exploration exploitation dilemma and are often considered as "two core components of exploration" (Gershman, 2018). Our full model stands along the same lines: the noise parameter ϵ accounts for undirected exploration, whereas the novelty cue guides the exploration towards unknown regions of the solution space and hence accounts for directed exploration.

Our experimental data revealed that the decision to stop exploration and start exploiting a solution relies on a satisficing behaviour (Simon, 1990). That is, participants exhibited a tendency to terminate their exploration immediately when a good enough solution is found, even though more time was still available. In this context, the idea of satisficing seems inefficient as individuals overlooked an opportunity to explore new solutions and come back to their best solution only when time was running out. Research has shown that satisficing – and thus deliberately reducing the exploration range – can be adaptive when the number of solutions is much larger than the individual's search horizon (Simon, 1990) and when exploration is too difficult compared to its expected reward gain (Gigerenzer et al., 2012). In our design, continuing the exploration after the discovery of a sufficiently good solution creates a risk of not finding it again when returning to it. This uncertainty should grow as the size of the solution space increases. In agreement with this idea, we observed that participants were satisficed earlier in two-dimensional landscapes than in uni-dimensional ones.

We also observed a correlation between the participants' safety levels across the different phases of the experiment. That is, participants who exhibited a higher safety level in the exploitation phase were also more likely to show a higher safety level in the combined phase (and respectively, for a lower safety level). Interestingly, the safety level reflects the participant's propensity to take risks: the longer individuals continue to explore after finding a peak, the higher their risk of not finding the peak again. The consistency of the observed safety levels across phases thus agrees with risk research showing that people's risk preferences tend to be stable over time and tasks (Frey et al., 2017).

In our experiments and simulations, we systematically compared two specific types of search environments: rich and poor landscapes, which differ in the number of peaks that are present. Nevertheless, other structural aspects of the search environment could be varied as well, such as the peaks widths, heights, or locations. This last feature is particularly useful to create "patchy" landscapes in which peaks tend to be clustered in specific regions of the search space (Pacheco-Cobos et al., 2019). Additional simulations presented in figures A2, A3 and A4 in the supplementary materials show that our heuristic model seems to behave realistically in this new type of environments, although these predictions still need to be tested experimentally. Future work will investigate if heuristic models similar to our TTB approach could be generalised to describe people's search behaviour in different types of environments, including such patchy landscapes.

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Chapter 5

The Social Dynamics of Collective Problem-Solving

Yahosseini, Kyanoush S. and Moussaïd, Mehdi. In Prep.

Abstract

When searching for solutions to a problem, people often rely on the observation of their peers. How does this process of social learning impact the individual and the group's performance? On the one hand, research has shown that individuals benefit from social learning in numerous situations and across many domains. Through social learning, individuals can access good solutions found by others, improve them, and share them in turn. On the other hand, this individual benefit may come at a cost: An excessive tendency to copy others often decreases the overall exploration volume of the group, thus reducing the diversity of discovered solutions, and eventually impairing the collective performance. Here we investigate the conditions under which social learning can be beneficial or detrimental to individuals and to the group. For that, we model problem-solving as a search task and simulate various amounts of social learning. We avoid model specific considerations by relying on a simple framework whereby individuals gradually explore the search environment – a two-dimensional landscape of solutions – while being attracted to the best solution of the group.

Our results highlight a *collective search dilemma*: When group members learn from one another, they tend to improve their own individual performance at the expense of the collective performance. How is this dilemma affected by the structure of the search environment? By varying two structural aspects of the search environment, our results reveal that the negative effect of the dilemma is mitigated in more difficult environments.
Finally, we show that single individuals can profit from a high propensity of social learning, which in turn is damaging for the other group members. As a consequence, if individuals continually adapt their behavior to maximize their own payoff, groups converge to a sub-optimal level of social learning. Unraveling these intricate social dynamics helps to understand the complex picture of collective problem-solving.

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5.1 Introduction

Humans and other social animals seldom solve problems in isolation. When searching for a solution, individuals often rely on the observation of their peers to decide where to explore, and when to exploit a previously discovered solution (Laland, 2004; Danchin et al., 2004; Goldstone et al., 2013). Social learning, or the act of learning by observing the solutions of others, has been shown to be beneficial to individuals in numerous situations and across many species (Rendell et al., 2010; McGrath, 1984; Galef and Laland, 2005; Boyd et al., 2011). Social learning enables good solutions to spread between individuals (Mason et al., 2008), who can further improve them and share their refined solutions with others (Mason and Watts, 2012). Recent studies have demonstrated that collective search can succeed in solving highly complex optimization problems, such as reconstituting protein structures (Cooper et al., 2010), mapping neurons connectivity (Kim et al., 2014), or improving quantum transport (Sørensen et al., 2016).

However, research has also shown that under certain conditions, relying on social learning can have negative consequences at the collective level (Giraldeau et al., 2002; Laland, 2004). An excessive tendency to copy others can decrease the overall exploration volume, reduce the diversity of discovered solutions and thus impair the group's performance (Lazer and Friedman, 2007; Lorenz et al., 2011). In particular, in "rugged" search environments characterized by numerous local optima, the risk that the group converges to a suboptimal solution is increased (Barkoczi and Galesic, 2016) – a phenomenon labeled maladaptive herding (Toyokawa et al., 2019), premature convergence (Pandey et al., 2014), or negative information cascades (Bikhchandani et al., 1998).

These two opposed effects of social learning have sparked rich interdisciplinary research between cognitive sciences, biology, and economics (Lamberson, 2010; Bernstein et al., 2018; Hills et al., 2015; Berdahl et al., 2013). Most research agrees that a high collective performance requires a delicate balance between social learning and independent individual search (Bernstein et al., 2018; Rendell et al., 2010; Toyokawa et al., 2019; Derex et al., 2018). Yet, it remains unclear what social dynamics drives this phenomenon, how the structure of the search environment influences it, and what would be the optimal strategy to adopt – for the group and for the individuals.

For instance, one inconsistent aspect in extant research concerns the measurement of performance: whereas some studies rely on the average payoff of the group members (Mason et al., 2008; Lazer and Friedman, 2007; Barkoczi and Galesic, 2016), others focus on the best solution found by the group (Cooper et al., 2010; Kempe and Mesoudi, 2014; Derex et al., 2018). In fact, these two measurements assess different aspects of the group dynamics: the average performance indicates how much group members can *individually* benefit from social learning, while the best solution is an indicator of the group's *collective* performance. Here, we rely on numerical simulations to address two specific research questions: (1) How does the amount of social learning impact the individual and the collective performances, and (2) how do the search environment and the social environment influence what is best for the individual and what is best for the group?

We model problem-solving as a search task in which individuals explore a vast, two-dimensional landscape of solutions, while assuming that each group member is trying to maximize its personal payoff (Barkoczi and Galesic, 2016; Lazer and Friedman, 2007). In order to avoid model-specific considerations, we use a generic model where individuals rely on a simple hill-climbing exploration strategy, while being attracted by the best solution of the group (Yahosseini and Moussaïd, 2019; Barkoczi and Galesic, 2016). We first study how the amount of social learning impacts the individual and the collective performance of the group, and highlight the existence of a strong tension between the two measurements. Second, we study the influence of the search environment, that is, the structure of the solution space, on both performance measurements. Third, we take a prescriptive viewpoint and investigate how much an individual should rely on social learning to maximize its own payoff, considering the behavior of its peers. Finally, we propose an approach to explain how a certain level of social learning could have developed through repeated social interactions.

5.2 Results

The collective search dilemma

The performance of a group can be assessed in two ways: (1) By evaluating the average payoff of each group member, the *individual performance*, and (2) by evaluating the payoff of the best solution that has been discovered by the whole group, the *collective performance*. We first investigate how individual and collective performances depend on the amount of social learning. For that, we introduce a social learning parameter S describing the degree to which an individual's exploration is influenced by social information. Formally, S expresses the fraction of a simulation run where the individual is influenced by the solution of its peers rather than searching independently (see the model description in the method section). For instance, a social learning level of $S = 0.8$ indicates that the individual searches independently during the first 20% of the simulation run and relies on social learning for the remaining 80%.

As shown in figure 5.1A, an increase of social learning causes opposed effects on the two performance measurements: It increases the individual performance (up to a maximum for $S_{opt} = 0.733$), while at the same time decreases the collective performance. This conflicting effect reflects the collective search dilemma (Bernstein et al., 2018): When group members are influenced by each other, they improve their own individual performance at the expense of the collective performance.

We use the simulation results to better understand the dynamics of this dilemma. First, why is social learning improving individual performances? Having access to social information allows all individuals to profit from the best solution discovered by any of the other group members (figure 5.1B) (Bernstein et al., 2018; Mesoudi, 2011). Second, why is social learning hindering collective performance? An increase in social learning reduces the total number of explored solutions (figure 5.1B). As individuals are attracted by each other, they inevitably tend to explore the same region of the environment. Hence the group explores less and is thus less likely to find a good solution than when searching independently.

Figure 5.1A additionally highlights an optimal social learning level $S_{opt} = 0.733$ at which the individual performance is maximized. Excessive social learning (for $S > S_{opt}$) causes a *premature convergence* effect whereby the agents explore too little and converge too early on the first discovered solutions – missing out potentially better ones. This effect lowers both the individual and collective performances (the individual and collective performances of a group of fully social agents with $S = 1$ are reduced by 11.7% and 16.5% compared to a group with social learning S_{opt}).

Impact of the search environment

For now, we have assumed that the size and distribution of the peaks in the landscape (i.e., the local optima) are unstructured. In such a search environment, all peaks are evenly distributed and their payoffs are uncorrelated with their width. We introduce two continuous dimensions to study the effects of structural changes of the search environments: the kindness k and the dispersion d (see figure 5.2A). Kindness k manipulates the

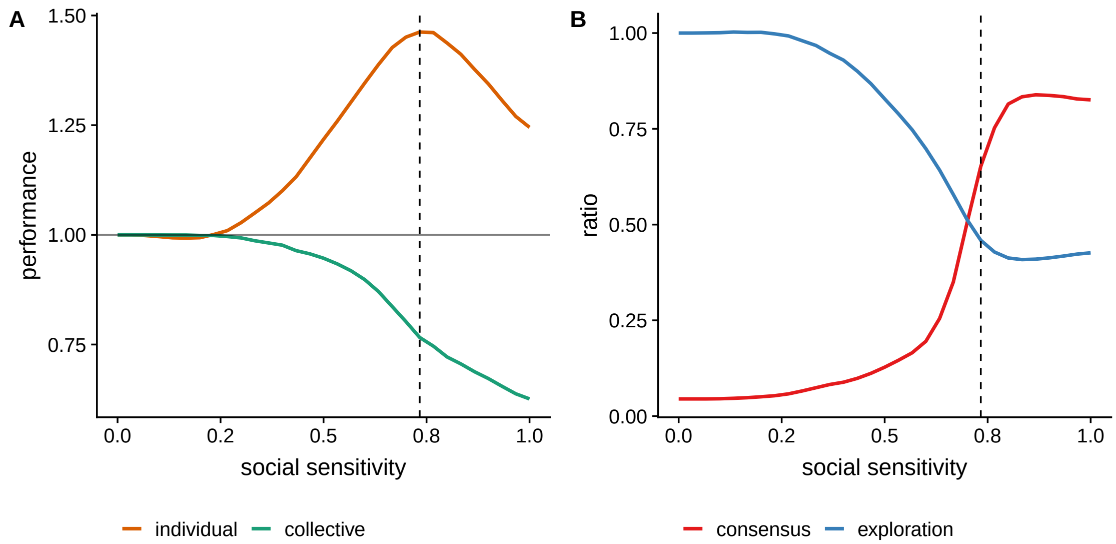

Figure 5.1. The collective search dilemma. (A) Impact of social learning on the individual (orange) and the collective (green) performance, relative to a group of independent searchers. Social learning yields an increase in individual performance at the expense of the collective performance. Individual performance is maximized for a learning level $S_{opt} = 0.73$ (dashed line). (B) The dilemma results from a drop in exploration (in blue; measured as the ratio of explored solutions relative to a group of independent searchers) and a boost of group consensus (in red; measured as the ratio of solutions shared by all agents). The best individual performance is achieved when exploration and group consensus are well-balanced.

correlation between a peak's width and payoff. For a negative correlation, higher peaks tend to have a smaller width (the environment is low in kindness) whereas for a positive correlation higher peaks tend to have a wider width (the environment is high in kindness). Dispersion d determines the structure of the locations of the peaks. For low d, peaks are more concentrated in one area (the environment is low in dispersion), while for high d they are more evenly distributed over the search environment (the environment is high in dispersion).

How does the structure of the search environment impacts the performances of a group? We find that the social search dilemma and the premature convergence persist across different physical environments, but change in amplitude (figure 5.2B). Overall, the beneficial effect of social learning on individual performances is larger in less kind environments, because social learning facilitates the discovery of hidden good peaks by the entire group (figure 5.3A). In addition, the negative effect of social learning on collective

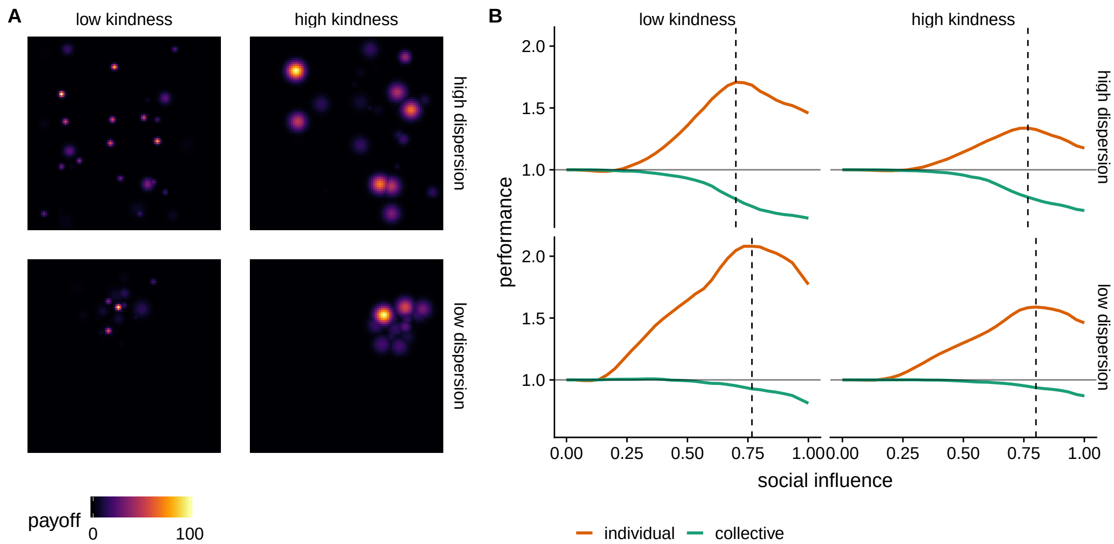

Figure 5.2. The structure of the search environment. (A) Illustrative examples of environments with low and high levels of kindness k (as columns), and low and high levels of dispersion d (as rows). Kindness refers to the correlation between the height and the width of the peaks. Dispersion determines the extent to which the peaks are clustered in the same area or scattered across the environment. (B) Corresponding patterns of individual and collective performances for different search environments. The search environments are of the same type as those illustrated in (A). Performances are relative to groups of independent searchers. The dashed vertical lines indicate the social learning levels S_{opt} that maximize the individual performance for each type of environment.

performance is smaller in when dispersion is lower (figure 5.3B). If no agent has found a satisfying peak at all, which is common when dispersion is low, social learning does not impair exploration and, thus, the collective performance.

Further manipulations of kindness and dispersion reveal a correlation between the difficulty of the environment, i.e. how well individual searchers solve it, and the beneficial influence of social sensitivity (see figure 5.3C). We find that, for more difficult environments, social learning leads to a bigger increase in individual performance and a smaller decrease in collective performance. Consequently in the most difficult search environments, the social search dilemma is mitigated.

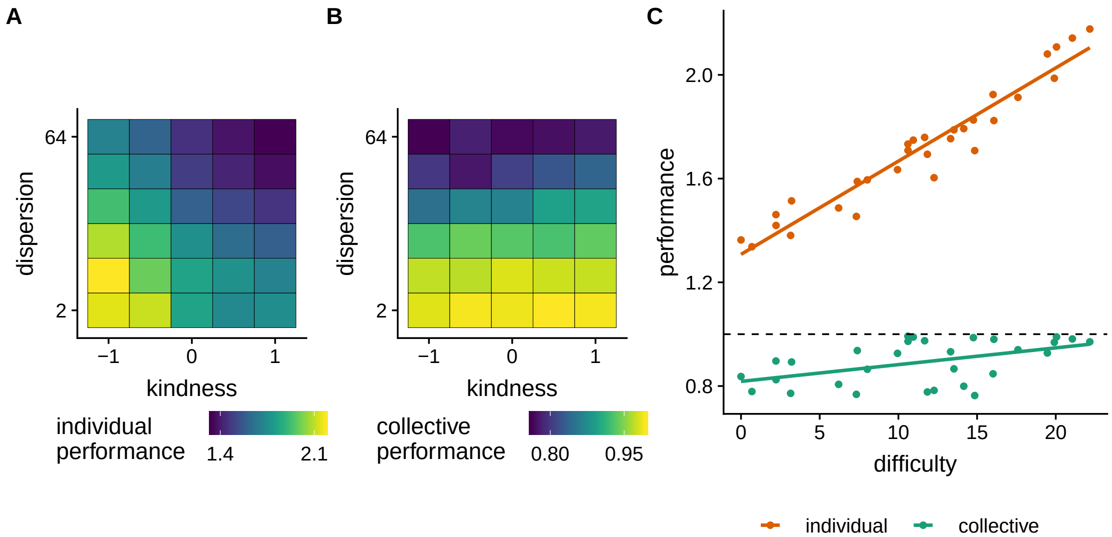

Figure 5.3. (A) Individual performances and (B) collective performances as the search environment varies in kindness (from low kindness $k = -1$ to high kindness $k = 1$) and dispersion (low dispersion $d = 2^1$ to high dispersion $d = 2^6$). See the method section for more details. The color-coding indicates the performances at the optimal social learning levels S_{opt} (see dashed lines in figure 5.2B). (C) Individual and collective performances as a function of the difficulty level. Difficulty is measured as the inverse average individual performance of a group of independent searchers (higher is more difficult). Each dot represents the performances for a given combination of kindness and dispersion, taken at the optimal social learning level S_{opt}. The dashed line indicates the performance of a group of independent searchers in that environment. Individual and collective performances increase with difficulty (linear model $r^2 = 0.93$ and 0.25 for individual and collective performances, respectively).

Impact of the social environment

The environment is not limited to the search environment, but also concerns the social environment. How much should an individual rely on its peers, given the peer's own social learning level? To answer this question, we systematically varied the social learning level for one individual in the group and for the rest of the group independently. That is, all agents except one are homogenous and share the same social learning level.

We find that the payoff of an individual highly depends on its social environment (figure 5.4A). From the perspective of an individual, the best performance is reached when all peers are independent searchers. In this case, the agent will be able to learn from others without undergoing the risk of premature convergence. On the contrary, social environments where other people have a high social sensitivity are the worst because the

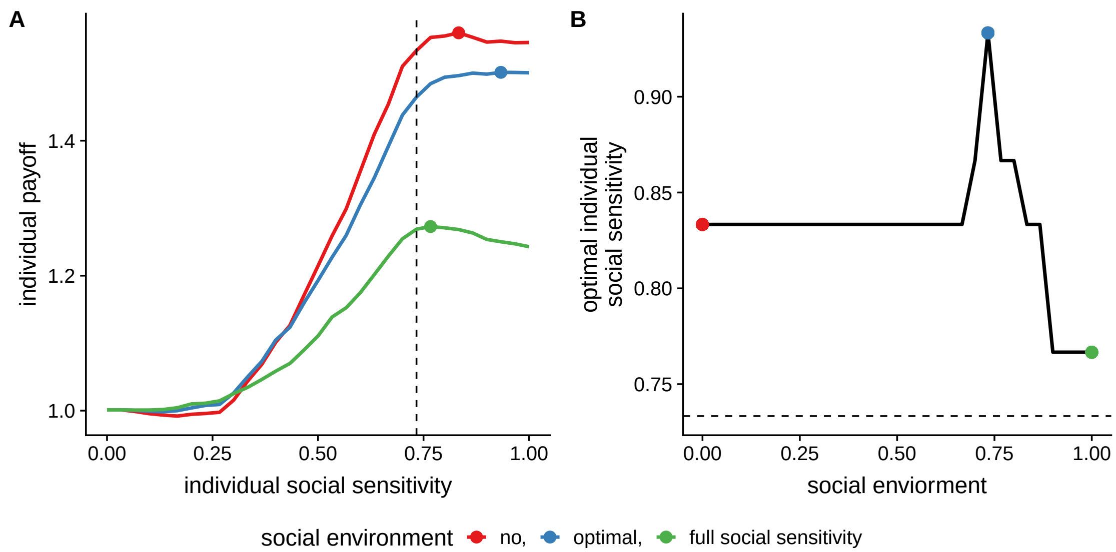

Figure 5.4. Influence of the social environment, measured as the level of social learning of one's peers. (A) Impact of one agent's social learning level on its payoff in different social environments (all other agents share the same social sensitivity, color coded). Dashed line indicates the optimal social learning for the group S_{opt}. Points mark the curves maxima. (B) The social learning level maximizing an individual's payoff in different social environments. These learning levels are consistently above the optimal group level S_{opt} (dashed line). Colored points indicate the social environments shown in A.

peers copying each other will reveal few solutions.

Our results also reveal that, in order to maximize its own payoff, an individual should rely on more social learning than the optimal level S_{opt} highlighted in figure 5.3B. Hence, what is optimal for an individual is different from what is optimal for the group, which might further increase the risk of premature convergence.

To study this hypothesis, we set up a simple model in which agents gradually adapt their individual social learning level S to maximize their own payoff (see figure 5.5 and method section). As expected, the average level of social learning increases slightly above S_{opt}. That is, each individual is better off copying others more than what is optimal for the group, which leads to a decrease of performance when everybody does so. Hence, this model can explain why individuals often over rely on social information and account for the behavioral origins of premature convergence in some natural systems (Pandey et al., 2014).

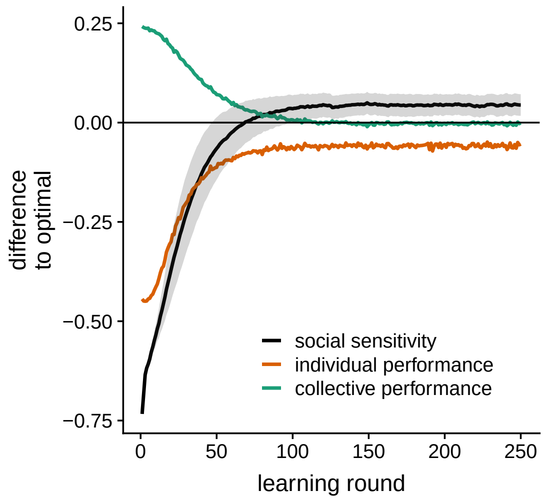

Figure 5.5. Simulation of a model in which the agents gradually update their propensity for social learning to maximize their own individual payoff (see methods for more details). The figure shows the development of the group's average social learning level (black line, gray band shows variance) and the individual and collective performances over 150 learning rounds. Values are shown relative to a group of agents with optimal social learning $S_{opt} = 0.73$ (negative is lower and positive is higher than S_{opt}). The group converges to a learning level slightly higher than the optimal value, causing a decay in individual performances.

5.3 Discussion

In our study, we used generic model of collective search (Gigerenzer et al., 1999; Barkoczi and Galesic, 2016; Yahosseini and Moussaïd, 2019) to address two questions. First, how does the amount of social learning impact the individual and collective performances? We find that social learning introduces a collective search dilemma. When individuals rely on social learning, their individual performances increase, whereas the collective performances decrease. We find that this dilemma can be explained by a reduction of the overall exploration volume and an increase in the ratio of consensual solutions. Social learning, therefore, is beneficial to the individual but can cause maladaptive premature convergence when individuals excessively rely on it.

Second, how does the environment moderate what is best for the individual and what is best for the group? By varying some features of the search environments, we find that social learning is a more profitable to individuals in difficult environments than in easy ones. In addition, we show that social learning is less detrimental to collective performances when all peaks are clustered in the same area.

We also studied the social environment, that is, how the features of one's peers impact an individual's performance. We show that any single individual can profit from a high level of social learning, but only when others are not doing so. Simulations show that this dynamics can generate a group in which individuals trying to maximize their personal payoffs by copying others end up breaking down their collective potential.

Overall, our study shows that, depending on the chosen measure of performance, the impact of social learning can change dramatically. Social learning has different effects, depending on whether one is interested in the collective performance (e.g., the group comes up with a unique collective solution (Kempe and Mesoudi, 2014) or develops a new cultural innovation (Derex and Boyd, 2016; Derex and Boyd, 2015), or in the average individual performance (see, e.g., Lazer and Friedman, 2007; Mason and Watts, 2012; Barkoczi and Galesic, 2016). Here, it is interesting to point out that the measures of performance are not limited to the two instances that we have studied in this work. Other research has, for instance, considered the group's ability to find the problem's global optimal solution (Cooper et al., 2010; Derex and Boyd, 2016). In this case, any solution that is not the optimal one is not taken into account in the calculation of success, which comes down to considering landscapes with very low dispersion. The results of our study suggests that social learning would then have little negative effect on collective performance in that case.

Our results outline the importance of correctly balancing independent exploration and social learning (Bernstein et al., 2018; Rogers, 1988). This fact connects to a current debate about whether sparse networks that spread information slowly between individuals yield better performances than dense networks that support a rapid dissemination of information within the group.

We argue that the role of the network structure can only be understood when put in perspective with the individuals' behavior (Barkoczi and Galesic, 2016). Sparse networks, for instance, can be beneficial when individuals tend to rely too much on each other, by regulating the flow of social information within the group (as in, Lazer and Friedman, 2007). On the contrary, dense networks are favorable when individuals have a propensity to explore independently, by supporting the rapid dissemination of a few good solutions (as in, Mason and Watts, 2012; Derex et al., 2018). In other words, the network structure and the behavior of the individuals are two forces that can modulate the flow of social information. A good match between them supports an efficient social dynamics during collective problem-solving.

More generally, our work helps understanding the complex dynamics that operate within interacting groups of problem-solvers and contributes to current research on collective intelligence. Future work will expand our findings to more complex problems such as NK-landscapes (Kauffman and Levin, 1987), to concrete tasks such as the traveling salesman problem (Yi et al., 2012), or to other fields that require a tradeoff between individual and collective search (March, 1991).

5.4 Methods

We model problem-solving as a search in a landscape – a conceptual representation of a solution space (Wu et al., 2018; Yahosseini and Moussaïd, 2019). In such a landscape, each field represents one solution and is associated to one payoff. We develop a model describing how individuals search in such a landscape when trying to maximize their own payoff while at the same time observing other people's solutions. This model extends previously validated approaches for independent (Yahosseini and Moussaïd, 2019; Gigerenzer et al., 1999) and social search (Laland, 2004).

Search model

The individual search behavior is composed of (1) a social search rule, and (2) an independent search rule. We assume that the agent relies on the independent search rule during a certain number of simulation rounds at the beginning of the search process, and then switches to the social search rule. The fraction of rounds during which the social search rule is applied is given by the social learning parameter S. For example, a value of $S = 0.8$ indicates that the agent applies the independent search rule during the first 20% of the rounds, and applies the social search rule for the remaining 80%.
The independent and the social search rule are defined as follows:

1. Independent search rule: In every round, the agent maximizes its immediate payoff by moving to the neighboring solution that offers the highest payoff. If more than one solution fit this criteria, the agent maximizes the number of explored solutions by moving away from visited areas of the landscape. If multiple solutions are still equivalent, the agent chooses among them at random. If all neighboring solutions

offer a lower payoff than the current solution (i.e. if the agent is occupying a local optimum), then the search stops.

2. Social search rule: In every round, the agent first looks at the current solutions of all its peers. The solutions that cannot be reached within the remaining time are ignored. If one of these solutions offers a higher payoff than the agent's current solution, it moves one step towards that solution, following the shortest path. If multiple solutions are on the shortest path the individual rule is applied to those. If none of one's peers' solutions meet these criteria, the agent resorts to the independent search rule.

Search environment

We implement the search environments as a landscape with multiple local optima (also denoted as "peak"). We use the following procedure to generate these landscapes (Yahosseini and Moussaïd, 2019; Wu et al., 2018):

1. We first generate 32 sub-landscapes. Each sub-landscape consists of a 99×99 matrix filled with zeros and will serve as layers for each of the 32 peaks. We select one random coordinate P around which all the peaks will be clustered.

2. For each of the 32 sub-landscapes, we draw one coordinate from a normal distribution with $mean = P$ and $SD = d$ that will serve as a location for the peak p. The parameter d determines how much the 32 peaks are clustered around P.

3. The height of the peak p (i.e., the payoff of that solution) is drawn from a normal distribution with $mean = 0$ and $SD = 1$, and is subsequently squared to avoid negative payoffs.

4. To create a local gradient around the peak p, we apply a Gaussian filter with $SD = f(w)$ on each sub-landscape. Here w controls how much the width of the peak p and the payoff correlate.
   The function $f(w)$ is defined as $f(w) = (1 - w) \times random + w \times payoff(p)$, where $random$ is a random number between 1 and $payoff(p)$. That is the width of a peak p is determined by a combination of its payoff and a random factor controlled by w. $f(w)$ is linearly scaled between 1 and 4 over all peaks in the 32 sub-landscapes,

resulting in a width (controlled by the Gaussian filter's SD) of all peaks between 1 and 4.

5. The 32 sub-landscapes are merged into a single one by selecting the highest payoff across all sub-landscapes at each coordinate.

6. Finally, all payoffs are linearly scaled between 0 and 100.

This procedure generates landscapes similar to those shown in figure 5.2A.

Simulation procedure

For each simulation run, we randomly position ten agents in the landscape within an area of size 10×10 solutions. Each simulation run lasts 30 rounds. In each round, the agents behave according to the previously described model. The size of the landscape, the starting solution and the total number of rounds are balanced in such a way that the "borders" of the landscape can never be reached. At the end of each run, the payoff of each individual agent is the payoff associated to the current occupied solution. We report the individual performance as the groups mean payoff and the collective performance as the highest payoff found by any member of the group. For better comparison, we generally report performance measures relative to the performance of a group of non-interacting agents, that is, a group of agents with no social learning ($S = 0$). Hence, a performance higher than one indicates a better performance compared to groups of non-interacting agents.

Simulating changing social learning levels

In the simulations presented in figure 5.5, we describe how a specific social learning level could develop. For that, we assign an individual social learning level S_i and a direction parameter D_i to each agent. The direction parameter D_i describes the direction in which the social learning level of that agent is changed after each learning round (i.e., whether it increases or decreases). In each learning round, all agents search 50 landscapes as described in the simulation procedure. At the end of this process, each agent compares its average payoff to the payoff obtained in the previous learning round. If the payoff has decreased, the agent switches the direction D_i (i.e., from increase to decrease and vice versa). Afterwards, all agents change their social learning level by one round according to D_i and a new learning round starts (i.e., depending on D_i agents either rely more or less on the social search rule). Here, we assume that all agents start from a non-social state ($S = 0$) and initially increase their social learning level. The results are robust to different parameter values.

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Chapter 6

General Discussion

When people work together, they are able to solve problems that no single individual can solve on its own. Yet, efficiently merging the capabilities of many people is often not an easy task. Indeed, numerous examples have highlighted that not all groups are effective in problem-solving. What makes some groups more successful than others? How does the nature of the problem and the structure of the environment influence the group's performance? Following Newell and Simons definition, I considered problem-solving as a *search for solutions* (Newell and Simon, 1972). Many different methods for *collective* problem-solving have been identified. For easier comparison, I classified them according to information exchange among individuals: (1) non-interacting groups, which do not share information, (2) social groups, where individuals freely exchange information during their search, and (3) solution-influenced groups, where individuals only share their solution at the end of their individual search process. In this thesis, I described and studied solution-influenced groups, which have received relatively little attention in current research. The findings of my thesis indicate that solution-influenced groups can be an effective method for structuring groups in collective problem-solving (chapter 2 and 3). Furthermore, I investigated how numerous features of the environment, such as the nature of the problem, the difficulty of the task, the measure of success, the group composition, and the behavior of the individuals can impact the performance of the three classes of methods (chapter 2 to chapter 5).

In chapter 2, I described the performance of the transmission chain, a particular type of solution-influenced groups. I applied this method to binary choice problems and compared it to the majority rule (and to the confidence-weighted majority) in non-interacting groups. By means of numerical simulations, I found that transmission chains excel in environments where the individual accuracy is low and where confidence is a reliable indicator of performance. Why is that so? In binary choice tasks, individuals are limited to one possible action: switching the collective solution from one answer to the other. Individuals only do so when they strongly believe that the current answer is wrong, which translates into having a high confidence level. Therefore, a strong consistency between confidence and accuracy is a necessary condition for the success of transmission chains in binary choice tasks. In addition, majority rules are typically very effective if the average individual accuracy is high. As a result, transmission chains outperform the majority only when two conditions are met: (1) individual accuracy is low, and (2) confidence is indicative of accuracy. However, two experimental datasets indicate that these environments are rare.

My initial study suggested that transmission chains might be better suited for problems where the contributions of individuals can *accumulate* – each one adding to the solution of the predecessors. This is typically the case for problems that have a complex solution structure, which led me to my second project.

In chapter 3, I therefore evaluated transmission chains for problems that have such a complex solution structure. For that, I modeled problem-solving as a search in a multidimensional landscape. As in chapter 2, I compared transmission chains with non-interacting groups. I measured the performance of both methods in numerical simulations and in experimental data, while manipulating the problem difficulty and the skills of the individuals. My results indicate that transmission chains can indeed outperform independent groups in two specific environments: either (1) when problems are easy to solve, or (2) when the group members have a low skill-level. These environments are ideal for transmission chains as the poor skills of the individuals can sum up, gradually improving the collective solution.

I then focused on the dynamics of social groups, that is, when individuals influence each other during the search. I used a bottom-up approach to investigate these dynamics: First I described the individual search process (chapter 4), and second I figured out how this process is affected by social information (chapter 5). In chapter 4, I first investigated how lone participants search for solutions. The findings indicate that the individual search behavior can be described by a take-the-best heuristic guided by the immediate payoff or by the novelty of a solution. This simple model can reproduce a diversity of behavioral search patterns observed experimentally.

Chapter 5 raises the question of how this individual search process is affected by the presence of other problem-solvers in a social group. In simulations, I showed that attraction between group members leads individuals to search in similar areas of the landscape, and hence reduces the overall diversity of solutions. This induced a collective search dilemma: compared to non-interacting groups, social influence improves the quality of the average individual's solution, but this comes at the expense of the collective performance (here measured as the best solution found by the group). Nevertheless, this dilemma disappeared for very difficult problems where acceptable solutions are so rare that individuals can benefit from other peoples search without impairing the overall diversity of discovered solutions.

6.1 Major contributions

Solution-influenced groups in collective problem-solving

Indirect interactions – interaction through a shared collective solution – are ubiquitous in natural and artificial systems (Heylighen, 2016). They structure the contributions of thousands of volunteers editing a Wikipedia article, enable the cultural evolution of primitive artifacts into extremely sophisticated ones, and guide the "invisible hand" when sellers and buyers interact via the price for a product (Parunak, 2005). Despite this wide diversity of applications, indirect interaction methods have gathered relatively little attention in the domain of collective problem-solving (Moussaïd and Yahosseini, 2016; Heylighen, 2016). In fact, only two categories of collective problem-solving methods are commonly suggested: social groups, such as group discussions, and non-interacting groups, such as the wisdom of the crowds (Koriat, 2015). One contribution of this thesis is the addition of a third category, namely, solution-influenced groups, where individuals work separately on a shared collective solution.

In this context, I introduced and studied transmission chains – a simple form of solution-influenced groups (Kempe and Mesoudi, 2014; Tomasello et al., 1993) – as a means of problem-solving. My findings indicate that transmission chains have several beneficial properties. In contrast to non-interacting groups, transmission chains *combine* the skills of group members, allowing each one to optimize a specific part of the problem. In contrast to social groups, they enable collaborative projects for large human crowds, even when no easy means of communication are present. Yet, solution-influenced groups also have drawbacks, such as decreasing the individuals willingness to search by initially exposing them to another person's "good enough" solution (Yahosseini et al., 2018). Transmission chains also suffer from an order effect. Late individuals in the chain have, in principle, the capacity to undermine the contributions of all the predecessors causing the "loss" of good solutions. To prevent these effects, more sophisticated implementations of transmission chains that retain a "collective memory" of past solutions have been suggested (Mesoudi, 2007; Mesoudi and Whiten, 2008). These more complex implementations are closer to what is typically observed in practical projects or in cultural evolution processes. Wikipedia articles or open-source software projects, for instance, keep a history of changes. Thus, any previous version can be easily recovered whenever deemed necessary. Likewise, transmission chains in cultural evolution consist of groups – and not individuals – at each chain position, reducing the likelihood that a discovery is "forgotten" (Kempe and Mesoudi, 2014; Derex et al., 2013). By examining transmission chains in detail, my thesis paves the way for more complex implementations of solution-influences groups in collective problem-solving.

No free lunch in collective problem solving

My results highlights that the *no free lunch in search* theorem delineated in optimization research (Wolpert and Macready, 1997; Wolpert and Macready, 1995) also holds true for collective problem-solving. The theorem states that no problem-solving strategy works best on all problems or, translated to my research, that no collective problem-solving method works best in all environments. In fact, my results underline that the success of a group depends on whether its organization suits the features of the environment. These features can be the structure and the difficulty of the problem, the individuals skills, the diversity of competences, and their motivations.

Specifically, chapter 2 shows that the relationship between confidence and accuracy determines whether transmission chains will perform better or worse than a majority rule. Transmission chains are efficient in environments where the average accuracy is low, as long as the correlation between confidence and accuracy is positive. In contrast, the success of a majority rule requires environments where the individual's accuracy is sufficiently good (i.e. better than chance). Along the same lines, chapter 3 demonstrates that the skills of the individuals and the problem difficulty dictates whether transmission chains will outperform non-interacting groups. While transmission chains are preferable for easier problems or in groups of less skilled individuals, non-interacting groups are superior for more difficult problems or when individuals are highly skilled.

My findings complement the growing body of research pointing to similar conclusions. For instance, Barkoczi and Galesic (2016) found that collective performance depends on the nature of interactions between individuals, the group's structure, and the problem difficulty. Similarly, Toyokawa and colleagues (2019) find that the group's performance greatly depends on the interplay between the uncertainty of the environment and the behavior of the individuals.

Another determinant of success relates to the way performance is measured. As discussed in chapter 5, altering the definition of performance can drastically change which group structure is best suited for the problem. Whether one is interested in the best solution of the group (Kempe and Mesoudi, 2014; Derex and Boyd, 2015), the number of times the optimal solution has been found (Cooper et al., 2010; Derex and Boyd, 2016), or the performance of an average individual (Lazer and Friedman, 2007; Mason and Watts, 2012) causes the "best" collective problem-solving method to change.

More generally, it is essential to better understand how each component of the environment favors or undermines a given method, and how to pick the right tool in the right circumstances. My work contributes to that.

6.2 Outlook

Combining collective methods

In this thesis, I studied three *strictly separated* categories of collective problem-solving methods. For instance, in my implementations of non-interacting groups or transmission chains, not a single information is directly exchanged between group members (which is exclusive to social groups). In more realistic conditions, however, the methods at play are not so strictly separated. When predicting the weight of an ox, as in Galton's seminal study, members of the non-interacting crowd might have, at least to some extent, discussed their estimates before giving their final judgment. Likewise, contributors in Wikipedia, a typical instance of solution-influenced groups, can indeed interact directly through the "discussions" page of each article.

The open question, therefore, is the extent to which such "mixed" methods could further enhance the collective performances. As I argued earlier, no collective problem-solving method performs best for all situations. The same conclusion seems to apply to mixed methods, which opens numerous interesting lines of investigation. For instance, research has shown that injecting direct interactions in conventional *wisdom of crowds* techniques can sometimes be detrimental (Lorenz et al., 2011) and sometimes beneficial to the group's accuracy (Farrell, 2011; Jayles et al., 2017). These conflicting results suggest that other unknown factors could promote or undermine these mixed methods.

Similarly, chapter 5 and related research consistently point to the fact that balancing independent and social search is beneficial to the group's performance under most conditions (Barkoczi and Galesic, 2016; Bernstein et al., 2018).

Mixed methods can also be considered for solution-influenced groups. For instance, members of transmission chains could work in small groups at each chain position. Indeed, research on cumulative cultural evolution has proposed such a combination of methods by organizing group discussions in which the most experienced person is regularly replaced by a new individual (Caldwell and Millen, 2008). Future research should continue to investigate how to best combine these different methods.

Combining men and machines

One implication of Newell and Simon's vision of *problem-solving as a search process* is that humans and computer programs can be described within the same framework. This connection could allow us to build groups where men and machines work together, potentially compensating each other's shortcomings. Humans are (for now) better at finding "leaps" – truly novel and substantially improved solutions (Miu et al., 2018) – and have a better ability to generalize when learning from few examples (Wu et al., 2018). In contrast, algorithms excel in local optimization tasks, at a speed far beyond what humans can achieve. Solution-influenced groups – by sidestepping the issue of communication (Suchman, 1987) – constitute a good candidate method for combining the strength of human and algorithmic search. In fact, most citizen science projects have already implemented such a combination of cognitive systems: novel and innovative solutions are found by human crowds, which are further improved by local optimization algorithms (Cooper et al., 2010; Sørensen et al., 2016).

Another perspective on this topic consists in letting a computer program choose how to aggregate the contributions of multiple individuals (Laan et al., 2017). For instance, in an ongoing project, I am investigating how machine learning techniques – such as deep neural networks or random forests (LeCun et al., 2015) – could assemble the most efficient non-interacting groups. Such an approach, for instance, could *dynamically* select the best individuals for a specific task, based on how they previously performed on similar problems.

A landscape of collective intelligence

Collective intelligence is a wide and diverse field of research. It incorporates concepts from psychology, biology, computer science, and economy. As a result, existing work on collective intelligence typically focuses on one specific subdomain. While in some parts of the literature, a very broad definition of collective intelligence is used, others concentrate on distinct aspects of it. Here, I have adopted the latter approach by focusing specifically on collective problem-solving. In the long run, however, scholars should aim at building a broader, more comprehensive taxonomy unifying existing concepts of collective intelligence. Such a framework can promote the scientific exchange between the numerous communities involved in this research by introducing shared definitions and a common working ground, and ultimately reveal explanatory laws connecting the different perspectives of collective intelligence.

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Appendices

Appendix A

Supplementary Materials to Chapter 2

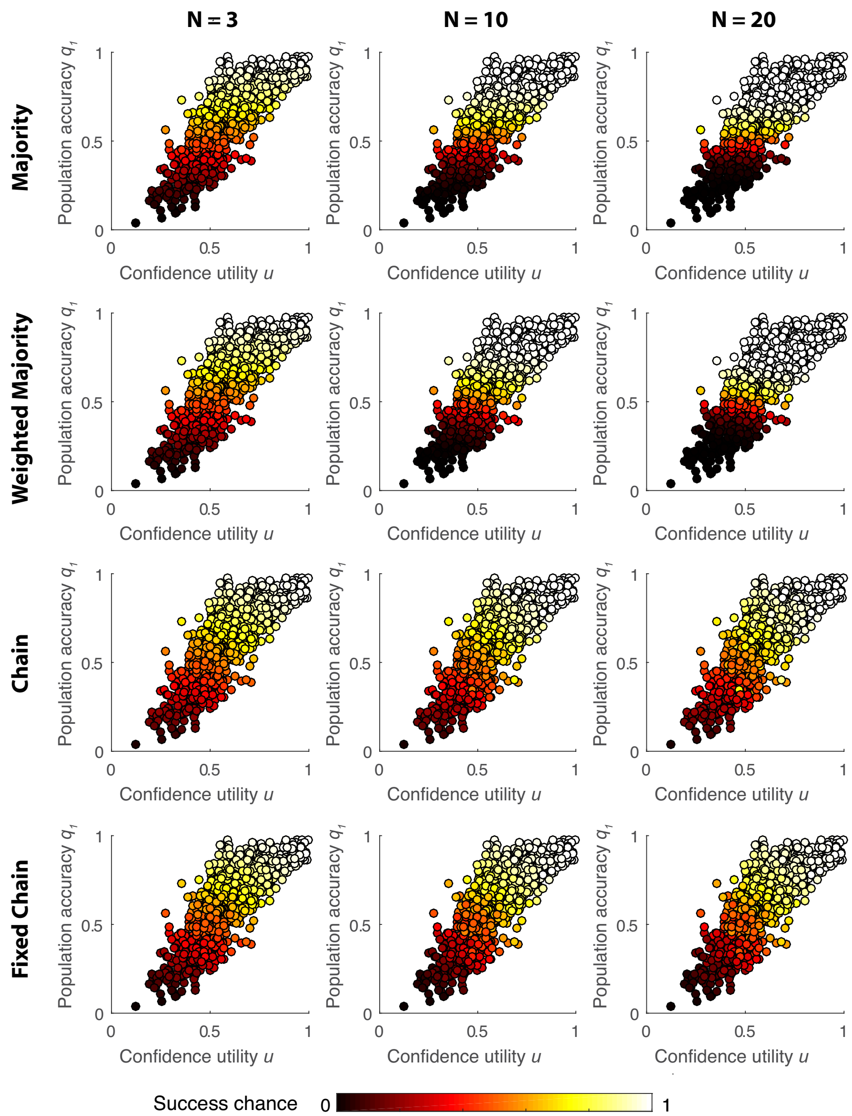

Figure A1. Performance of different aggregation method for groups of size $N = 3, 10, 20$ in the cities dataset. Each line corresponds to one aggregation method. The fixed chain has the contribution threshold fixed to $\tau = 0.8$ for all instances of the task (in contrast to the chain for which the contribution threshold is adjusted between instances of the task). Each point in the graphs corresponds to one city comparison task. The position of each point indicates the proportion of participants who provided the correct answer (y-axis), and the confidence utility (x-axis) for that task. The colour of each point indicates the success chance of each method for that particular task.

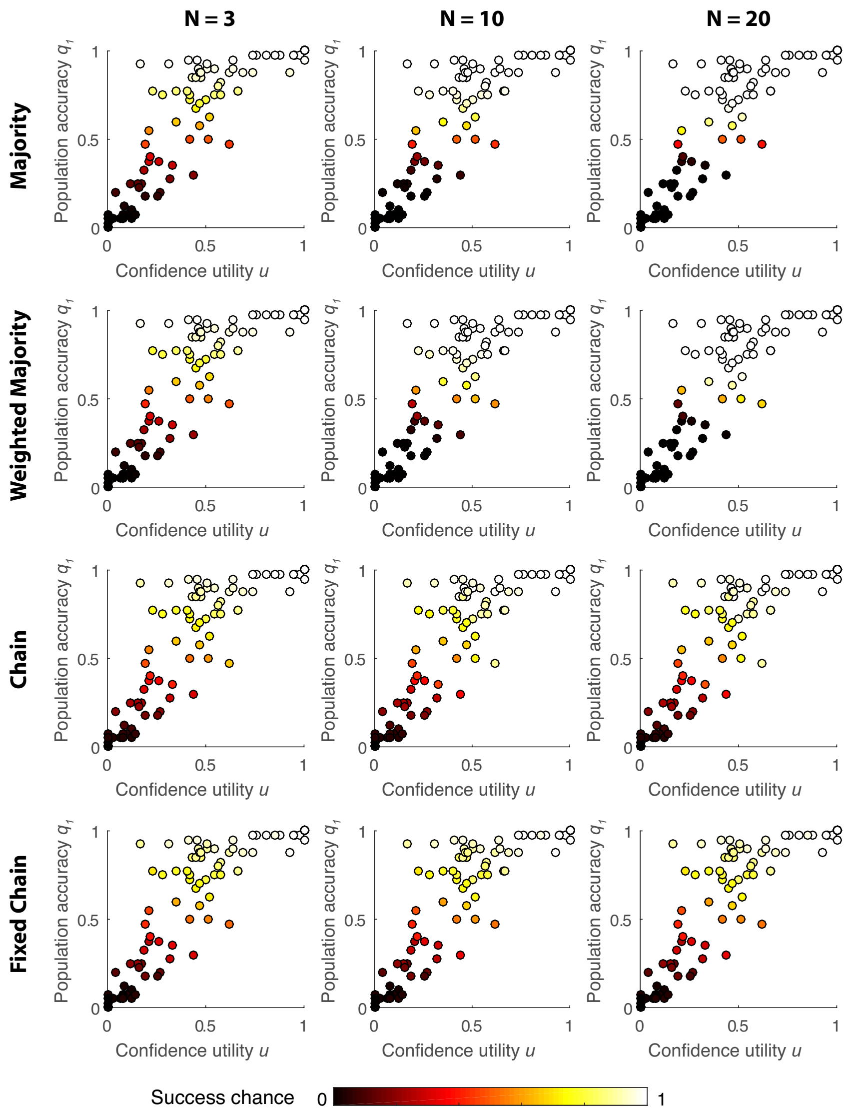

Figure A2. Performance of different aggregation methods for groups of size $N = 3$, 10, 20 in the doctors dataset. Each line corresponds to one aggregation method. The fixed chain has the contribution threshold fixed to $\tau = 3$ for all instances of the task (in contrast to the chain method for which the contribution threshold is adjusted between instances of the task). Each point in the graphs corresponds to one medical case. The position of each point indicates the proportion of doctors who provided the correct answer (y-axis), and the confidence utility (x-axis) for that case . The colour of each point indicates the success chance of each method for that particular case.

Appendix B

Supplementary Materials to Chapter 3

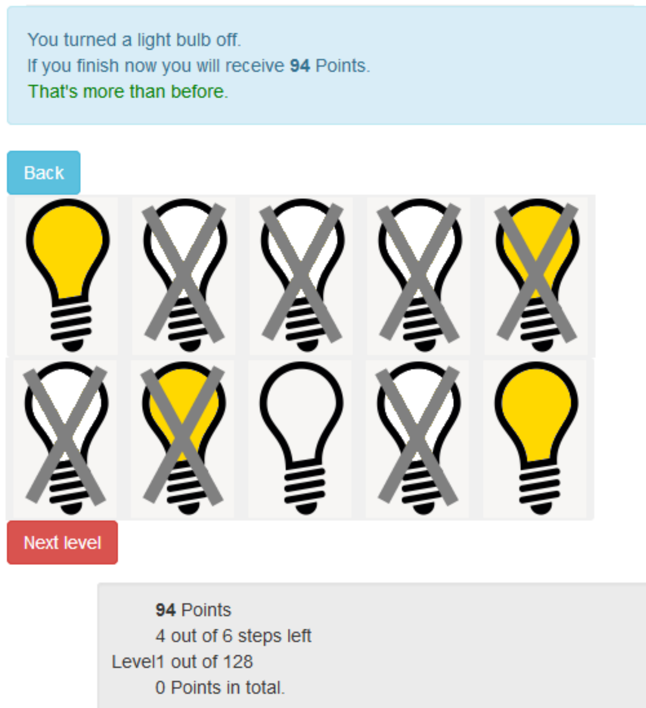

Figure B1. Experimental interface (translated from German to English). The ten light bulbs correspond to the ten dimensions of the the NK-landscape, and the state of each light bubble ('on' or 'off') represents the values 1 and 0. Grey crosses indicate dimensions that cannot be manipulated due to the restrictions imposed by the individual's skill S ($S = 3$ in this example). Information about the experiment, such as total number of points and remaining number of landscapes ('level') are provided in the grey box at the bottom. The blue box at the top shows information related to the previous decision. In each round, participants could either change the state of one light bulb (by clicking on the desired one), skip the remainder of a level if satisfied (by clicking the 'next level' button), or return to their previous solution (by clicking the 'back' button).

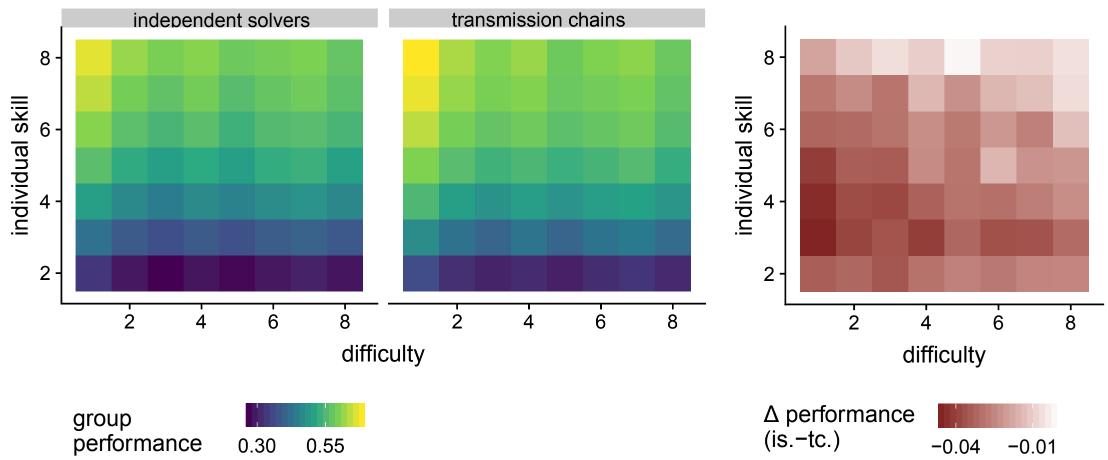

Figure B2. Performance of the transmission chains and groups of independent solvers with a rate of risky decisions $r = 0.8$ and reporting the best solution found. **(A)** Group performance for varying degrees of difficulty K and individual skill S. **(B)** Difference in performance between the two methods. Positive values indicate that independent groups outperforms the transmission chain, and vice versa.

Appendix C

Supplementary Materials to Chapter 4

Experimental paradigm

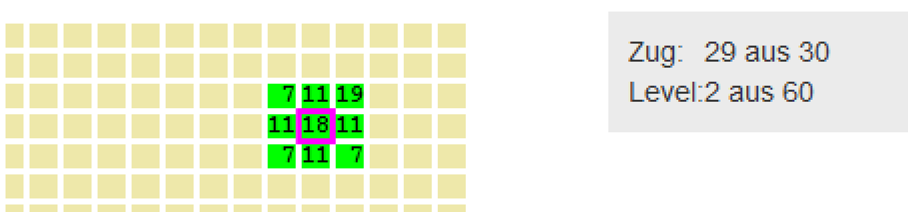

Figure B1. Experimental interface. The current position of the participant is indicated by the magenta square. The nine possible moving options and their respective payoffs are represented by the green cells. The grey text box on the right-hand side shows the number of remaining rounds (*Zug*) and landscape number (*Level*).

Patchy landscapes generation

In addition to the number of peaks in the landscape (i.e., rich vs. poor), we also varied the spatial distribution of the peaks to create patchy landscapes. Patchy landscapes are generated by the same procedure as the other landscapes, with the exception that the peaks positions are sampled from a normal distribution with $mean = P$ and a standard deviation $sd = d$, where P is a random location in the landscape and $d = 6$ determines the peak's dispersion range.

Model comparison

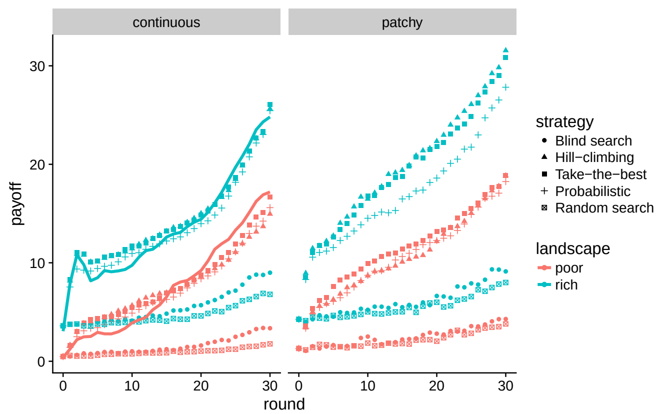

Figure B2. Payoff curves for different *exploration* mechanisms. Evolution of the average normalised payoff as a function of time as observed in the experimental data (plain line) and in simulations. Continuous landscapes (left) are those used in the experiment, whereas in patchy landscapes (right) peaks are clustered in one specific region of the landscape.

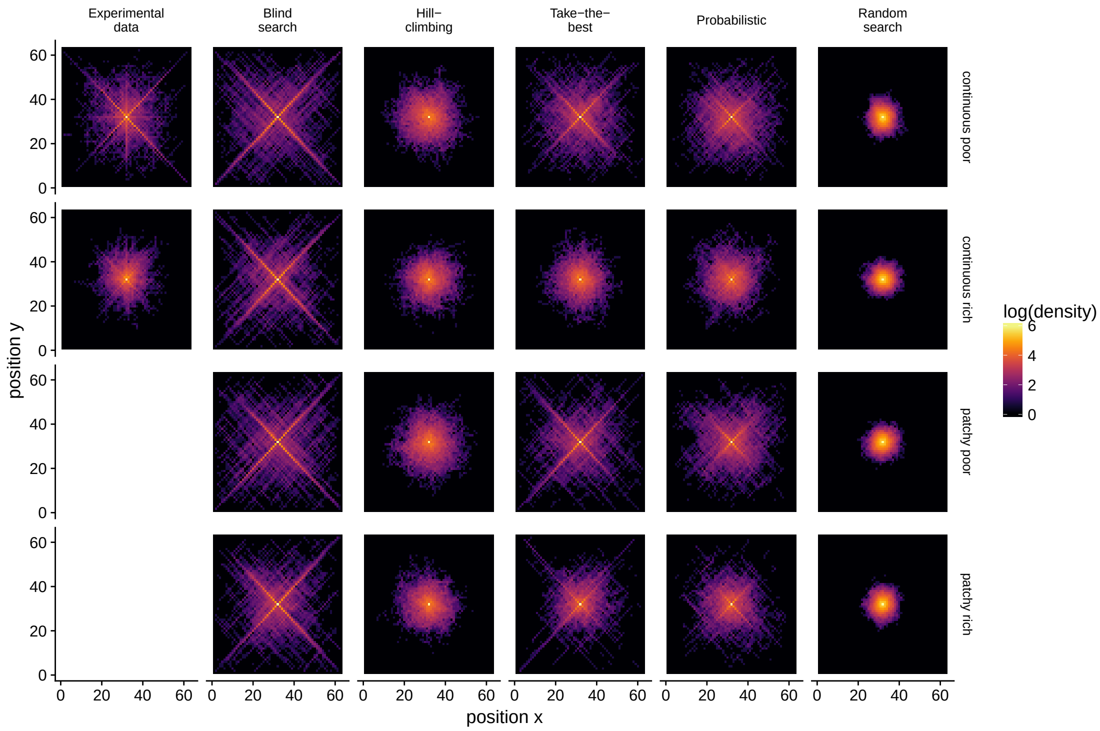

Figure B3. Density maps obtained for different *exploration* mechanisms (columns) and types of landscapes (rows) Experimental data are shown in the extreme left column. The colour coding indicates how often a given position (x,y) has been visited at the aggregate level, represented in logarithmic scale.

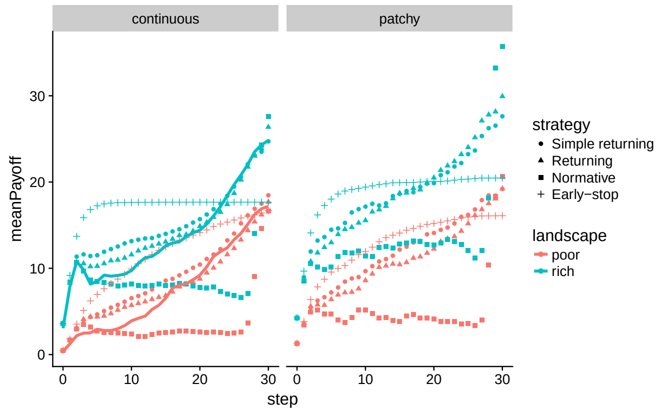

Figure B4. Payoff curves for different *exploitation* mechanisms. Evolution of the average normalised payoff as a function of time as observed in the experimental data (plain line) and in simulations. Continuous landscapes (left) are those used in the experiment, whereas in patchy landscapes (right) peaks are clustered in one location of the landscape.

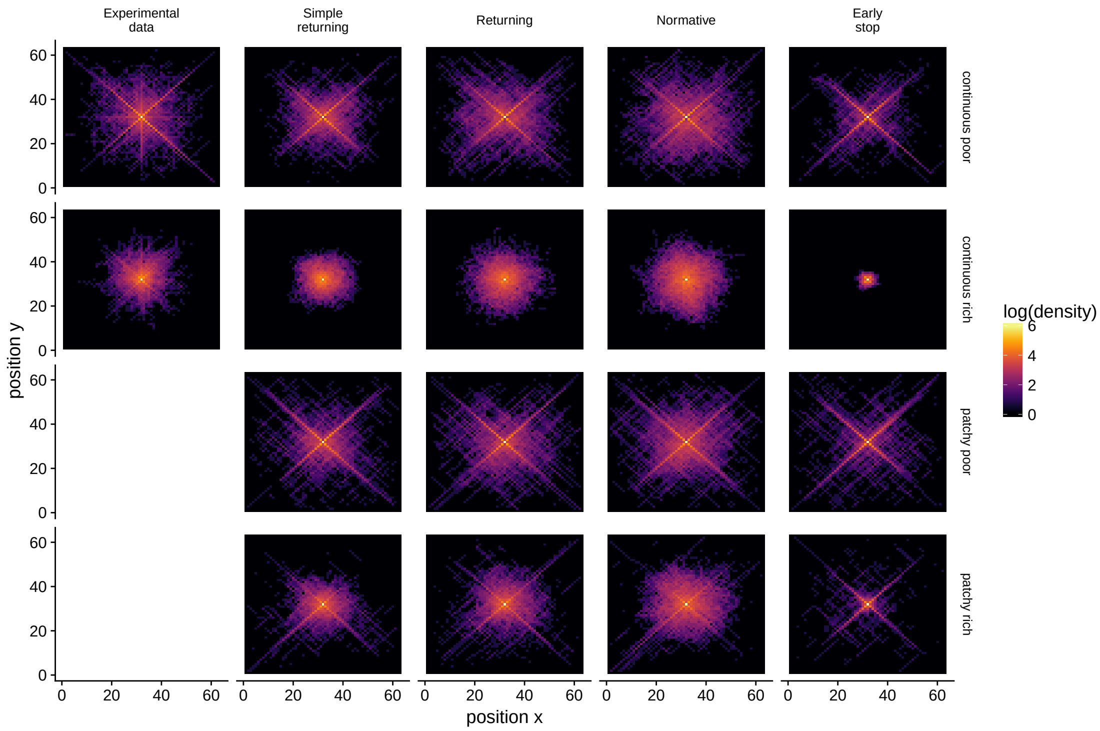

Figure B5. Density maps obtained for different *exploitation* mechanisms (column) and type of landscapes (row). Experimental data are shown in the extreme left column. The colour coding indicates how often a given position (x,y) has been visited at the aggregate level, represented in logarithmic scale.

Individual differences

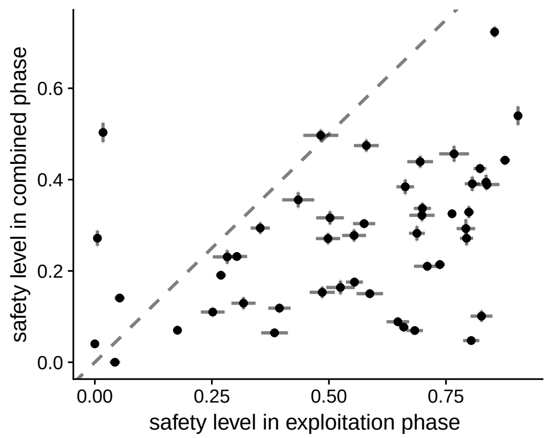

Figure B6. Safety levels displayed by the participants during the exploitation phase (x-axis) and the combined phase (y-axis). Each point indicates the average safety level of one participant. The error bars indicate the standard errors in the corresponding phase.

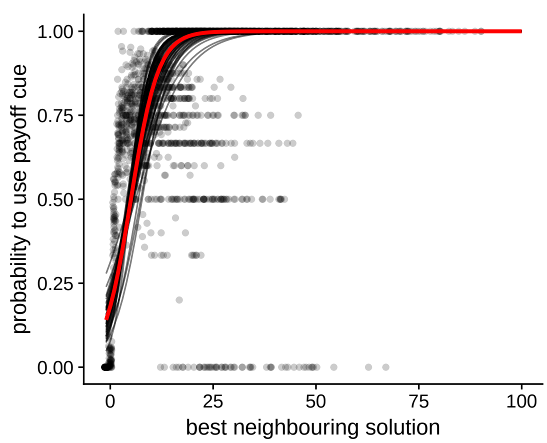

Figure B7. Relationship between the payoff of the most-rewarding neighbouring solution and the probability to rely on the payoff cue instead of the visibility cue. Each dot corresponds to one landscape. Each black line is the best fitted logistic function describing an individual's behaviour (mixed effect model with participants as a random effect, $BIC = 28949$). The red line indicates the best fitted logistic regression for the whole group, that is, not using the individual participant as a random effect ($BIC = 29261$).

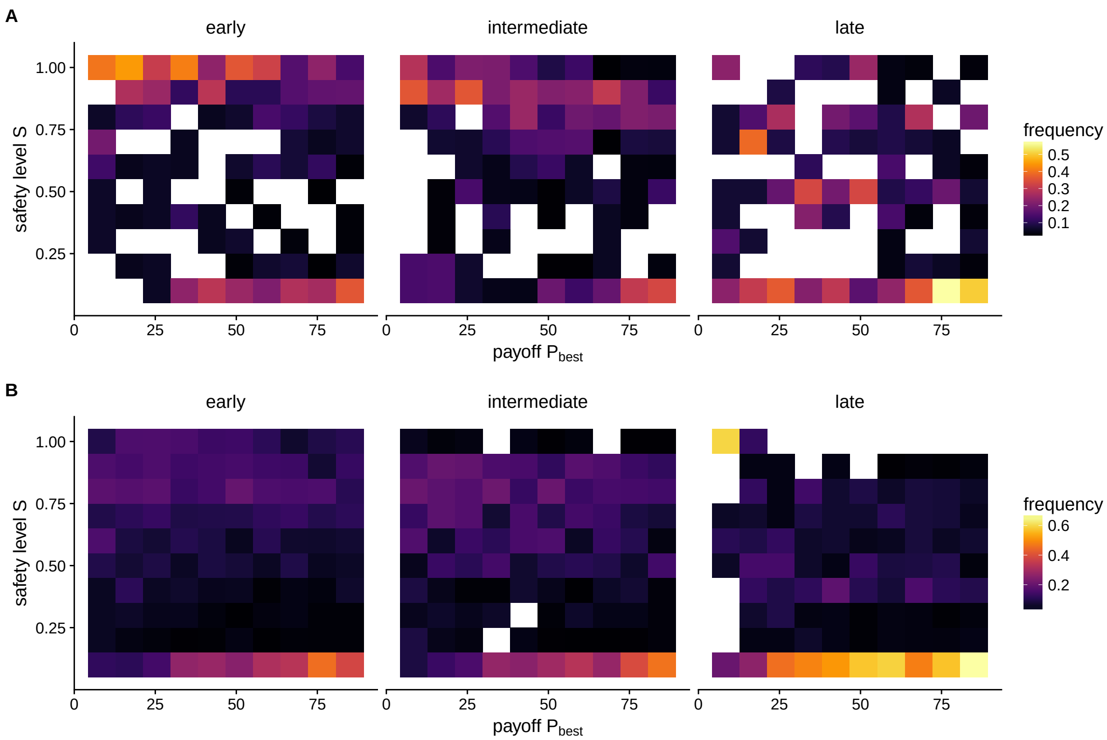

Figure B8. Safety level S as a function of the payoff P_{best} A) as observed in the experimental data, and B) as obtained from numerical simulations. Early, intermediate and late refer to the round where P_{best} is discovered, that is, round $1-10$, $11-20$, and $21-30$ respectively. The influence of remaining time on the safety level S is not captured by the numerical simulations.

Declaration of Independent Work

Chapter 2 has been published: https://doi.org/10.1371/journal.pone.0167223.
Chapter 3 is available as a preprint at https://www.biorxiv.org/content/10.1101/770024v1.
Chapter 4 is available as a preprint at https://www.biorxiv.org/content/10.1101/765107v1.
Chapter 5 is available as a preprint at https://www.biorxiv.org/content/10.1101/771014v1.

I hereby declare that I completed this doctoral thesis independently. Except where otherwise stated, I confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis. I have not applied for a doctoral degree elsewhere and do not have a corresponding doctoral degree. I have not submitted the doctoral thesis, or parts of it, to another academic institution. I have acknowledged the Doctoral Degree Regulations which underlie the procedure of the Department of Education and Psychology of Freie Universität Berlin, as amended on August 8th 2016. The principles of Freie Universität Berlin for ensuring good academic practice have been complied with.

Kyanoush Seyed Yahosseini

Berlin, September 2019