Ecological Rationality of Social Learning

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English summary

Humans rely extensively on social learning in their everyday lives. The capacity for learning from others is thought to underlie the complexity of human cultures and to influence all domains of life. How people learn from others and when it is adaptive to rely on social learning have been major questions in several disciplines including psychology, biology, anthropology and economics. Despite the shared interest of these diverse fields, many of the results remain isolated and are often incomparable, in part because the study of social learning still lacks a general theoretical framework that would make results comparable or explain why different strategies perform well in different contexts. In this thesis I propose such a framework that is grounded in the study of ecological rationality. I use this framework to explore three primary questions: i) how can social learning strategies be modeled as cognitively plausible strategies composed of simple building blocks (search, stopping and decision rules), ii) what are key characteristics of social and task environments in which social learning takes place, and iii) how do social learning strategies composed of different building blocks interact with the structure of the environment to produce different levels of success. Through addressing these three questions I map out the conditions under which different strategies are adaptive and explain how the building blocks of different strategies contribute to their performance in certain environments. The thesis focuses on three representative classes of social learning strategies, namely, frequency-dependent, payoff-biased, and unbiased copying. Different chapters focus on important everyday social learning settings, identify key environmental characteristics defining the setting and demonstrate how the building blocks of social learning strategies interact with these environmental structures to produce different outcomes. In the final chapter I discuss the implications, possible extensions and future challenges of the framework.

Keywords: Social learning; Ecological rationality; Wisdom of crowds; Decision making

Zusammenfassung

In ihrem Alltag nutzen Menschen soziales Lernen. Die Fähigkeit von anderen zu lernen bildet die Basis für die Komplexität menschlicher Kulturen und beeinflusst alle Bereiche menschlichen Zusammenlebens. Wie Menschen von anderen lernen und wann es adaptiv-rational ist sich auf soziales Lernen zu verlassen sind wichtige Fragen in vielen Disziplinen einschließlich der Psychologie, der Biologie, der Anthropologie und den Wirtschaftswissenschaften. Trotz der geteilten Interessen dieser Disziplinen sind viele der vorhandenen Resultate voneinander isoliert und oft nicht vergleichbar, teilweise weil es der Forschung zum sozialen Lernen immer noch eines theoretischen Rahmens fehlt, welcher die gewonnen Erkenntnisse vergleichbar machen würde sowie erklären würde warum unterschiedliche Strategien in Abhängigkeit vom sozialen Kontext erfolgreich sind oder nicht. In meiner Arbeit schlage ich einen solchen theoretischen Rahmen vor, welcher sich auf der Forschung zur ökologischen Rationalität gründet. Ich benutze den theoretischen Rahmen der ökologischen Rationalität sozialen Lernens, um drei Fragen zu beantworten: i) Wie können soziale Lernstrategien als kognitiv plausible Strategien modelliert werden, die auf drei einfachen Building Blocks beruhen (Such-, Stopp- und Entscheidungsregeln), ii) was sind die wichtigsten Faktoren von sozialen Umwelten und Problemumwelten, in denen soziales Lernen stattfindet und iii) wie interagieren soziale Lernstrategien, die auf unterschiedlichen Building Blocks beruhen, mit der Struktur von Umwelten, um unterschiedliche Erfolgsniveaus zu erreichen. Indem ich diese drei Fragen adressiere, erarbeite ich die Bedingungen unter denen unterschiedlichen Strategien adaptiv-rational sind und erkläre wie unterschiedlichen Strategien in bestimmten Umwelten erfolgreich sind. Meine Arbeit fokussiert auf drei repräsentative Klassen von sozialen Lernstrategien: Frequency-Dependent, Payoff-Biased und Unbiased Copying. Jedes der Kapitel behandelt eine wichtige alltägliche soziale Lernsituation, identifiziert die Schlüsselcharakteristiken der Situation und demonstriert wie die Building Blocks des sozialen Lernens mit diesen Umweltstrukturen interagieren, um unterschiedliche Erfolgsniveaus zu erreichen. Im letzten Kapitel diskutiere ich Implikationen, mögliche Erweiterungen und künftigen Herausforderung des theoretischen Rahmens der ökologischen Rationalität sozialen Lernens.

Schlagwörter: Sozialen lernen; Ökologischen Rationalität; Intelligenz der Masse; Entscheiden

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Chapter 1

Introduction

1.1 Social learning

Humans make many decisions by relying on social information. From choosing consumer products (e.g., books, movies, music, food items) to deciding how to behave in cultural settings, people often imitate the choices of others. Social learning is central in the lives of most social animals (Laland, 2004) and is a core element of human social cognition already present in pre-verbal infancy (Gergely, Bekkering, & Király, 2002; Heyes, 2012; Meltzoff, 1988). Starting from a few months of age, infants imitate adults' gestures, tool use, and avoidance behavior, and imitation remains an important element of development and learning throughout adolescence and adulthood (Bell, 1970). On a large scale, organizations such as firms also rely on social learning when, for example, developing business models (Segerstrom, 1991). Social learning underlies much of human behavior and is considered to be the major driving force of cultural evolution (Boyd & Richerson, 1985).

The study of social learning broadly construed is central to a large number of disciplines including psychology, biology, anthropology, economics, management, and artificial intelligence. Many studies, in particular in biology and anthropology have focused on developing mathematical models for understanding the conditions under which different social learning strategies can evolve and can outperform each other. However, for the sake of analytical tractability, most of these models are rather abstract and tend to ignore the cognitive processes underlying social learning (e.g. how information is searched) as well as many important characteristics of real-world social and task environments (Boyd & Richerson, 1985; A. R. Rogers, 1988; Schlag, 1999). Meanwhile, in psychology, social learning has typically been studied using vague terms, such as conformity or social influence, that lack the precision needed to distinguish between different strategies in empirical settings or to formalize them computationally (Mesoudi, 2009). Both approaches have their strengths and weaknesses and combining them would contribute to a better understanding of social learning. However, despite the fact that these disciplines are concerned with very similar questions, they tend to study social learning independently, with very little or no communication between them. Several recent attempts have been made to address this issue by providing a taxonomy of social learning strategies for the behavioral sciences (Laland, 2004), trying to foster communication between the biological and psychological sciences (Mesoudi, Whiten, & Laland, 2006) or running interdisciplinary computer tournaments on social learning in the spirit of Robert Axelrod's famous tournament on cooperation (Rendell, Boyd, et al., 2010). In addition, some biological and anthropological models have tried to test hypotheses put forward in Bandura's social learning theory (Aoki, Wakano, & Feldman, 2005; Bandura, 1971; Boyd & Richerson, 1985), thereby connecting insights from psychology with formal mathematical models developed in biology.

However, the study of social learning still lacks a unifying theoretical framework with most results being difficult to compare due to the different methodologies used, different interpretations of social learning and the different journals these studies are published in.

The purpose of this thesis is to fill this gap in the study of social learning by proposing a novel framework based on the notion of ecological rationality for the study of social learning. This framework is composed of three elements:

(1) Modeling social learning as cognitively plausible process-level strategies composed of building blocks (search, stopping, and decision rules).

(2) Studying important elements of the social and task environments in which social learning takes place.

(3) Building computational and analytical models to study the match between social learning strategies and different environments in order to explain why a given strategy is successful in a given environment.

1.2 Ecological Rationality

The study of ecological rationality emphasizes the role played by the match between the strategy and the structure of the environment in producing good decisions (Gigerenzer & Gaissmaier, 2011; Gigerenzer, Todd, & the ABC Research group, 1999). Following this approach, I model social learning strategies (rules that describe whom to imitate) as cognitive strategies composed of three basic building blocks: search, stopping, and decision rules. Search rules specify how information is searched in the environment, stopping rules prescribe when search is stopped, and decision rules determine how the collected information is used to make a final decision.

Consider a simple heuristic called take-the-best (Gigerenzer & Goldstein, 1996) that can be applied to make binary decisions about which of two options has a higher value on a given criterion. For example, when judging which of two cities is larger on the basis of several cues, such as whether a given city has a university, is a state capital, or has a soccer team, the take-the-best heuristic searches for cues in terms of their validity (i.e., the relative frequency with which a given cue leads to the correct inference), stops searching as soon as one of the cues discriminates (i.e., the cue has a positive value for one city and a negative value for the other) and decides by picking the city with the positive cue value. Take-the-best is a process model describing each phase of making a decision, including information search, stopping search and making a decision. By studying each building block of the strategy and properties of the environments in which it can be applied one can map out the conditions under which it is a good strategy. Theoretical analyses have shown that take-the-best performs well in environments where cue validities follow a J-shaped distribution (Todd & Gigerenzer, 2012) (see Gigerenzer & Brighton, 2009; Şimşek, 2013, for other ecological conditions). These theoretical predictions have been subsequently justified in empirical studies (Gigerenzer, Hertwig, & Pachur, 2011).

Another heuristic that can be used for the same task is the recognition heuristic which makes a decision about which of two cities has a larger population by selecting the option that is recognized [1]. This strategy is ecologically rational when the most famous cities are also the biggest cities, i.e., recognition correlates with the criterion (Goldstein & Gigerenzer, 2002). This approach has been fruitful in modeling individual decision strategies and studying the environmental conditions influencing their performance.

The framework of ecological rationality has also been applied to the social domain including group decision making, cooperation, mate choice, moral decision making, and advice taking (Hertwig & Hoffrage, 2013; Kämmer, Gaissmaier, Reimer, & Schermuly, 2014). Hertwig and Hoffrage (2013) classified problems faced in the social work into two broad classes: *games against nature* and *social games*. Games against nature refer to situations where individuals need to predict something occurring in nature (e.g. the yield of a crop) while social games involve making decisions in situations where outcomes also depend on the decisions of other individuals. The heuristics proposed within the adaptive toolbox that can be applied to such problems include social learning (imitation), however, very few studies have focused on fleshing out the properties of imitation strategies and

[1] Note that this strategy requires that only one of the two cities is recognized, otherwise, the take-the-best strategy can be applied.

the ecological conditions in which they perform well. One of the few such attempts have been made by Boyd and Richerson (1985) who studied the environmental conditions that favor genetic transmission, individual learning or social learning. They found that when the environment is stable, natural selection should favor genetic transmission, when the environment is very turbulent individual learning is favored and when the environment changes at intermediate rates, social learning can evolve (Boyd & Richerson, 1985). This is a useful approach for mapping out the ecological rationality of social learning, however, it is only an initial step. How to define environmental change, what are other environmental conditions that favor or disfavor social learning and what forms of social learning are favored have not been addressed.

In social learning, strategies have typically been defined by one word descriptions (e.g. imitate the best) without reference to the underlying decision process. This is problematic for a couple of reasons. First, it results in most studies modeling only the decision phase of implementing a social learning strategy (e.g., Garcia-Retamero, Takezawa, & Gigerenzer, 2006) without specifying how the information on which the decision is based is collected. Second, it leaves the exact implementation of the strategies open, resulting in different studies using different implementations and, as a result, in contradictory results (see for example Garcia-Retamero et al., 2006; Woike, Bonardi, & Garcia-Retamero, 2013).

Linking the study of social learning to the framework of ecological rationality, allows us to build psychologically plausible process models of social learning. Specifically social learning strategies can be modeled by the same building blocks (search, stopping, and decision rules) and their performance can be studied in different social and task environments. Before describing this approach in more detail, in what follows I briefly review the literature on social learning in psychology and biology and discuss their limitations.

1.3 Social learning in Psychology and Biology

The study of social learning has a long history in social psychology. Psychologists and sociologists have considered imitation to be a fundamental aspect of human behavior and human culture (Bandura, 1971; Tarde, 1903). For example, Bandura's Social Learning Theory put forward that much of human behavior is acquired via social learning rather than learning through trial-and-error (Bandura, 1971) and several experiments have demonstrated that children imitate aggressive acts after observing them or that they tend to copy prestigious individuals (Bandura, Ross, & Ross, 1961, 1963). Festinger (1954) argued that individuals compare themselves to others when they are uncertain about their own behavior and tend to adjust their own behavior accordingly. Other studies have focused on situations where individuals conform to the behavior of others in experimental settings (Asch, 1956; Latané & Wolf, 1981; Sherif, 1936). These studies from social psychology provide rich information regarding the kinds of situations in which individuals use social information as well as about the kinds of social information they consider. However, most of these studies lack precise models of social learning strategies and an understanding of how they interact with the structure of the environment (Mesoudi, 2009). They use rather vague definitions of social learning that obscure the exact mechanisms underlying individual decisions. As a result, the same vaguely defined mechanism can be consistent with several different patterns of behavior.

To illustrate, consider the case of conformity. In a large population 60% of individuals choose option A and 40% choose option B. If an individual was to conform by copying the majority behavior of a random sample of, say, nine members of the population, her probability of choosing option A would be higher than 60% [2]. If, however, she would follow a random other individual then she would have a 60% chance of choosing the most frequent option (A). In both cases, the observed pattern of results would indi-

[2]This can be verified by simply calculating the cumulative probability of sampling a majority or more 'correct' instances from a set of Bernoulli trials where the probability of being 'correct' is 0.6 in this case. Doing the calculation yields 73% for this example.

cate that the individual conformed to the most popular option since an individual is more likely to choose the more frequent option using both strategies (Claidière & Whiten, 2012; Mesoudi, 2009). However, the underlying mechanisms are different: in the first case an individual samples multiple people from the population and picks the majority option, while in the second case she considers only one randomly sampled individual. As I will demonstrate in this thesis, these mechanisms can produce very different results when interacting with different environmental structures and, therefore, distinguishing between them is crucial.

The literature on social learning in biology and anthropology has studied social learning more formally (albeit only the decision phase of strategies), but studied them in very simplified environments to allow for analytical tractability. In general, this line of research has identified three main classes of social learning strategies: (1) frequency-dependent, (2) payoff-biased, and (3) unbiased social learning.

Frequency-dependent social learning refers to any strategy that adopts a behavior as a function of its frequency in the population. Within this class, positive and negative frequency dependence can be distinguished, where the former refers to adopting a behavior the more frequent it is and the latter to adopting a behavior the less frequent it is. This class is also commonly referred to as conformity and anti-conformity, respectively. Commonly studied strategies within this class are the majority and plurality rules (Hastie & Kameda, 2005) as examples of positive frequency dependence, and the copy-the-minority strategy as an example of negative frequency dependence (Claidière, Bowler, & Whiten, 2012; Efferson et al., 2008). Frequency-dependent social learning, in particular the majority rule is very similar in structure to a decision heuristic called *tallying* which chooses the option with the highest number of positive cue values (Dawes & Corrigan, 1974).

Payoff-biased strategies use the payoff, success, or prestige of other individuals as cues to decide whom to copy. Common strategies studied in this class are the imitate-the-best, imitate-the-successful and imitate-the-prestigious heuristics (Henrich & Gil-White, 2001). These strategies are thought to underlie the evolution of prestige relationships in human cultures and have been studied in economic and business settings (Schlag, 1999). Note that they have a very similar structure to the *take-the-best* heuristic which searches for cues in a lexicographic order starting with the best cue.

Finally, unbiased copying refers to a strategy that does not bias its decision towards frequency, payoff, or some other cue, but instead, it simply copies another individual at random. This strategy is typically referred to as random copying. Random copying has been shown to be consistent with several cultural trends in human societies, including the adoption and abandonment of popular music, first names or dog breeds (Bentley, Hahn, & Shennan, 2004). Unbiased copying is analogous to the *minimalist* heuristic studied in binary choice which searches for cues at random.

In addition, several combinations of these three classes also exist, for example a strategy can be simultaneously frequency-dependent (copy the majority behavior) and payoff-biased (adopt it only if it has a higher payoff).

While these strategies have been studied formally in biology and anthropology, they have typically been modeled as decision rules (e.g. *imitate-the-majority*) while ignoring the other building blocks required for implementing these strategies. This is problematic because, as we will see later on, these strategies can produce very different outcomes depending on how they search for information or on the size of the sample on which they based their decisions.

In summary, building more precise, psychologically plausible models and studying them more formally could inform both social psychological studies as well as biological and anthropological models of social learning. The importance of linking these two perspectives has also been highlighted by (Mesoudi, 2009). As outlined above, I develop a framework that aims to fill this gap, and address three main goals.

1.4 Goals of the thesis

The first goal of the thesis is to model social learning as cognitively plausible process-level strategies. To this end I will model frequency-dependent, payoff-biased and unbiased social learning strategies as combinations of three building blocks: search, stopping, and decision rules. To illustrate, in this framework, social learning strategies can be modeled as follows: (1) search (randomly in the population; among most similar individuals; among kin; among peers); (2) stopping (stop searching after consulting n other people; after reaching a threshold); (3) decide (majority rule; best member; random member). By modeling strategies in terms of search, stopping, and decision rules it is possible to understand how each phase contributes to the overall performance of a given strategy. This allows for an explanation of why a given strategy might perform well and provides insight on how to modify a certain strategy to improve performance.

The second goal of the thesis is to identify important properties of social and task environments that may influence the success of social learning. To achieve this I study important everyday social learning settings such as innovation diffusion, organizational learning, judgment aggregation in the context of the wisdom of the crowds and advice taking in matters of taste. In each situation, I identify key environmental characteristics of the task and the social network in which interaction takes place and study the match between the building blocks of a strategy and the environmental structures.

I identify five important dimensions of environments based on reviewing a the literature in psychology, biology, anthropology and management science:

(1) Simple versus Complex environments: In some cases what we copy consists of whole units, (e.g., a stock to invest in or a camera to buy) and options can be ranked by their payoffs. I call these simple environments because the payoff space is characterized by a single peak (the best option). I contrast these environments with complex ones, where what is being copied consists of several components that are interdepen-

dent(Simon, 1965). In complex environments the payoff space is multi-peaked due to interdependence. Copying all components correctly is crucial for obtaining good payoffs. Examples of complex environments include technological innovation, copying business models or agricultural practices. For example, planting the exact same crop in the exact same way under the exact same environmental conditions are all crucial components to success. Implementing one of these steps differently (planting the same crop in a different environment) can result in completely different outcomes, hence the multi-peaked payoff space. Contrast this example with buying a camera, where it matters much less whether it is used in the exact same way or purpose.

(2) One-shot versus Repeated social learning settings: Some settings involve making one-shot decisions, such as voting in a committee, while other settings evolve over time, e.g. making a decision about whether to adopt an innovation. In repeated settings there is a feedback loop between the choices of individuals and the information available for imitation, thereby altering information available to copying over time.

(3) Uniform versus Varying task difficulties: Some decision environments consist of relatively homogeneous task difficulties, while other tasks can vary substantially in difficulty.

(4) Learning about Matters of Fact versus Matters of Taste: many decision problems involve making inferences about options that have a universal, objective criteria (i.e., matters of fact) while in other problems the best option depends on the tastes of the individuals, and different options might be good for different individuals (i.e., matters of taste).

(5) Clustered versus Unclustered social environments: In some environments agents have access to the decisions of all other individuals within their group (e.g. in a group decision making environment) while in many real life situations agents from small cliques within a larger network and interact within those cliques.

The third goal of the thesis is study the match between strategy and environment using computational and analytical modeling. Here I show that the best way of learning socially depends crucially on the building blocks of social learning strategies and the environmental dimensions in which learning takes place. Table 1.1 illustrates the environmental characteristics studied in each chapter. The goal here is not to study all possible combinations of environmental properties, but rather to characterize each everyday setting along the five proposed environmental dimensions and to demonstrate how they interact with the building blocks of different strategies to produce different outcomes in terms of performance.

1.5 Overview of the chapters

The thesis is organized as follows. Chapter 2 demonstrates what to expect from social learning in a simple task environment with the goal of building intuition for subsequent chapters. In a simulation, agents made repeated choices between two options, where at any point in time one option had a higher payoff than the other option. Over time, the environment could change, making the previously correct option incorrect and vice versa. Agents could learn about the state of the environment either via individual learning or social learning by copying (1) the most successful agent, (2) the majority of the agents in the sample, or (3) a random agent. Agents searched randomly among other agents with whom they were connected and stopped after consulting either a small ($n = 3$) or a larger ($n = 9$) number of others. In separate scenarios we varied the communication network agents were embedded in, starting from a fully connected network where agents could communicate with all other agents to a clustered network, where agents formed cliques and different agents belonged to different cliques. Results show that as long as payoffs can be accurately observed, copying the best member always outperforms both copying the majority and random copying and more connected networks (i.e., fewer clusters) improve the performance of all strategies. In addition, taking smaller samples in the case of copying the majority leads to higher performance compared to larger samples. Again, the goal of this chapter is to provide a simple and comprehensible overview of what to expect from strategies and to facilitate the understanding of subsequent chapters.

In chapter 3 this work is extended to the setting of organizational learning or collective problem-solving where instead of having a simple environment with clearly identifiable payoffs, the environment is complex in a sense that options to be copied consist of several components that are interdependent. The number of components and the level of interdependence between these components in a system have been suggested as two important elements of complexity (Simon, 1965) and have been studied in models of technological innovation, organizational learning, and biological evolution (Kauffman, 1993; Levinthal, 1997). In such settings, different solutions form a fitness landscape with multiple peaks, depending on the level of interdependence between components. The decision task becomes a combinatorial optimization problem where the goal is to improve the payoff of a solution by modifying its components and, therefore, shares many properties with the famous traveling salesman problem or cue-order learning in the heuristics research program (Garcia-Retamero et al., 2006). In this study agents used one of three different social learning strategies (1) best member, (2) conformity (majority/plurality) and (3) random copying, each of which could be composed of different building blocks. Agents by default engaged in social learning and switched to individual learning if the default strategy could not find a better solution. Results show that in the short run the best member strategy outperforms other strategies (as in Chapter 2), however, in the long run the conformity strategy relying on small samples outperforms all other strategies. In addition it is shown that depending on the social learning strategy used by agents, both well and poorly connected networks can be beneficial.

Chapter 4 investigates in greater detail the reasons why relying on small samples in the case of conformity is beneficial (as has been found in the previous two chapters). In the context of innovation diffusion it is shown that when agents face the task of choosing repeatedly between two options where one option has a better long-run payoff than the other, sampling fewer individuals leads to both higher individual- and population-level outcomes. Here a simple mathematical model based on Condorcet's Jury theorem is developed and utilized to study the performance of conformity (or copy the majority). The results are then explained both in terms of basic probability theory as well as in more practical terms. The basic findings are supported in several sensitivity checks and implications for studying the diffusion of innovations are discussed.

Chapter 5 moves from decision tasks where learning unfolds over time, to one-shot situations such as voting in groups or forecasting binary outcomes in the case of sports or politics. Many important decisions are made in committees of small to moderate sizes. Consider governing bodies, electoral committees, councils or policy boards. These groups typically have between three to 40 members. Work on the wisdom of the crowds and Condorcet's Jury Theorem predicts that when average individual accuracy in a group is higher than chance, decision accuracy should reach near certainty as group size goes to infinity. Why aren't the empirically observed group sizes larger then? This project points out an important environmental characteristic missing from these theoretical models: the fact that groups face tasks of varying difficulty. I show that when groups face several one-shot decisions where tasks vary in difficulty, decision accuracy often peaks at small to moderate group sizes even if average individual accuracy is above chance. I analyze the conditions necessary for this to happen using a simple mathematical model and illustrate its plausibility by means of empirical data from political predictions and economic forecasts.

In Chapter 6 social learning strategies are applied to matters of taste rather than matters of fact. Most studies of social learning and social decision making in general study situations where there is a universal, objectively best option for all individuals. In contrast, in many real life situations different options (e.g., books, movies, restaurants) are good for different individuals. The literature on recommender systems has long been concerned with finding strategies that work well for matters of taste. Therefore, this project first undertakes an exercise in theory integration, finding parallels between (1) models in recommender systems and (2) models of social learning and inference from psychology, biology and anthropology. The performance of these models is then investigated in a large real-world dataset of joke ratings. It is shown that when individuals have little experience with a domain it is best to rely on the wisdom of the crowds by averaging the ratings of other individuals, while if individuals are experienced with a domain, it pays to apply a search rule based on similarity to other individuals.

Chapter 7 summarizes and discusses the implications of the framework.

	Task studied	Repeated vs. One-shot	Task difficulty	Simple vs. Complex environment	Matters of Fact vs. Taste	Social environment
Chapter 2	Abstract example	Repeated	Uniform	Simple	Fact	Clustered and Unclustered
Chapter 3	Organizational learning / collective problem-solving	Repeated	Uniform	Complex	Fact	Clustered and Unclustered
Chapter 4	Innovation diffusion	Repeated	Varying	Simple	Fact	Clustered and Unclustered
Chapter 5	Committee decision making	One-shot	Varying	Simple	Fact	Unclustered
Chapter 6	Consumer choice	One-shot	Uniform	Simple	Taste	Unclustered

Table 1.1: Illustration of the environmental conditions studied in each chapter.

Chapter 2

Building Blocks of Social Learning Strategies

This chapter is based on Barkoczi, D., & Galesic, M. (2013). Social learning in complex networks: the role of building block and environmental change. In M. Knauff, M. Pauen, N. Sebanz, & I. Wachsmuth (Eds.) *Proceedings of the 35th Annual Conference of the Cognitive Science Society* (pp. 1821 – 1826). Berlin: GER: Cognitive Science Society.

2.1 Introduction

Humans and other animals obtain information via social learning. This is an efficient way to save the time and effort involved in individual trial-and-error learning and is known to underlie our capacity for culture. Despite the diverse list of empirical evidence for its use in the wild (Laland, 2004; McElreath et al., 2008), theoretical models exploring the adaptive nature of social learning strategies lack sufficient detail to explain when we should expect to observe them. Most models study unstructured groups and focus only on the decision phase of implementing a strategy (e.g. *copy- the-majority*), leaving open an important dimension affecting strategy performance: the interaction between the building blocks of a strategy and the structure of the environment. The main goal of the chapter is to highlight the importance of studying the building blocks of social learning strategies in a simple, transparent environment.

Social learning is often based on limited samples of the social environment. Most communities consist of sizable groups where an individual cannot survey all other group members within reasonable time before making a decision. Consider migrating animals deciding between multiple directions, individuals in an organization trying to jointly solve a problem or stock traders trying to predict the best investment option (Couzin, Krause, Franks, & Levin, 2005; March, 1991). In such situations the way information about options is sampled from the social environment is likely to be an important aspect of any strategy. The structure of the social network in which social learning takes place can then in turn affect the options available for sampling. Previous work has shown that different network structures and their efficiency can affect the diversity of behaviors in the population and the time it takes groups to converge on good solutions (Lazer & Friedman, 2007; Mason & Watts, 2012). How does the performance of different strategies depend on the way they sample information and on the social environment in which they are embedded?

To address this question we study three representative social learning strategies:

copy-the-best, *copy-the- majority* and *random copying* (Boyd & Richerson, 1985; Cavalli-Sforza & Feldman, 1981; Laland, 2004) and model them as decision heuristics that consist of different building blocks: search, stopping and decision rules (Gigerenzer et al., 1999). By explicitly modeling these three phases we are able to test their relative contribution to strategy success in different environmental structures.

Overall, a general characteristic shared by many social learning strategies, including those we study here, is that they alter the structure of the social environment by changing the frequency of different options in the population over time. This property has been extensively studied in the context of biased cultural transmission (Boyd & Richerson, 1985) and suggests a key factor influencing strategy success in a changing environment: the speed with which they are able to increase the frequency of the correct option in the group and, therefore, their ability to respond to environmental change. Our goal here is to show how this speed can be influenced by the building blocks of a strategy (i.e., its search, stopping and and decision rule) on the one hand, and by the structure and efficiency of the social network in which interaction takes place on the other hand.

In what follows we derive specific expectations, based on previous literature and preliminary analytic calculations, about the effects of different building blocks and network structures on *copy-the-best*, *copy-the-majority* and *random copying*. We consider a hypothetical situation where a group of agents make repeated choices between two options (one correct, the other incorrect). Whenever the environment changes, the previously correct option becomes incorrect and vice versa.

Effects of decision rules. In general, as long as the correct option is used by the majority of agents in a group and the environment is stable, all three strategies will converge to the correct option. However, under the assumption that the best member can be reliably identified within the sample, *copy-the-best* will always converge faster than the other strategies because it requires only a single agent with the correct solution to reach a decision, whereas *copy-the- majority* requires at least two out of three and *random copy-*

ing will select the correct option equal to that options frequency in the population. As soon as the environment changes, the correct option will be in minority. In this case, *copy-the-best* and *random copying* will still be able to find it, however, as predicted by the Condorcet Jury Theorem (CJT), *copy-the-majority* will never find the correct option because it requires that the proportion of agents with the correct option be higher than 0.5 (e.g., Grofman, Owen, & Feld, 1983).

Effects of information sampling and sample size. The CJT prediction may no longer hold when sampling is involved. Even if the correct option is in minority, *copy-the-majority* may still be able to find it. Sampling as opposed to group-level aggregation can create situations where the correct option is more frequent in one's sample than overall in the group. When agents with such samples choose the correct option, this further increases the correct option's frequency in the group, assuming that agents retain the option if it is better than what they were using before (Lazer & Friedman, 2007). Smaller samples are more likely to produce such situations, both because they are more likely to be biased and because they require fewer agents with the correct option in order to reach a decision. This suggests two situations where smaller as opposed to larger samples should benefit *copy-the-majority*. First, whenever the group is converging toward the incorrect option, smaller samples will delay this process and keep the payoffs of the group higher for the longer time. Second, when the correct option is in minority, smaller samples will make it more likely to accidentally have a majority of agents with the correct option. In contrast, for *copy-the-best* larger samples are always more advantageous, because they increase the chance of finding at least one agent with the correct solution, while for *random copying* sample size does not matter since by definition it copies a random behavior and has a chance of selecting the good option equal to its frequency in the population regardless of sample size.

Effects of network structure. Previous studies have demonstrated that for simple problems, higher network efficiency (i.e., the speed with which different networks spread useful information) lead to higher performance. More efficient networks should, therefore, favor all strategies by increasing the speed with which useful information can spread. Network efficiency depends on a variety of factors (Mason & Watts, 2012); here we focus on clustering (number of isolated cliques in the networks) and average path length (i.e., the average number of agents separating two randomly selected agents in the network). As networks become more clustered and average path lengths increase, their efficiency decreases, and they maintain diversity for a longer time (Lazer & Friedman, 2007). In such networks, the speed with which different strategies can find the correct option will become more important. As a result, the difference in performance between *copy-the-best* and *copy-the-majority* should become even larger. More clustered networks could have an additional effect by enabling the occurrence of relatively homogeneous clusters using the same option. If this option is incorrect, *copy-the-majority* using a sample within that cluster will not be able to find the correct option. In contrast, *copy-the-best* and *random copying* should be less affected by diversity of information as they only require a single agent with the correct option.

2.2 Method

2.2.1 Overview

We simulated a situation where multiple agents ($N = 100$) had to make repeated choices between different number of options by acquiring information from their contacts. The choices they made directly affected their payoffs. We created three social networks differing in their efficiency (as measured by clustering and average path length). Each agent had the same number of contacts in the network ($d = 10$)[1] and was assigned one of five decision strategies. Each strategy sampled randomly among one's contacts but differed in its stopping and decision rule. The agents' task was to make repeated choices between

[1]Except for the fully connected network where each agent was connected to each other agent.

different number of options (2 or 10) at each time step using their decision strategy. The environment could change on each time step (t_i) with some probability (pc) affecting the payoff of options at the next time step (t_{i+1}). The simulation was run for $t = 400$ time steps and each condition was replicated 100 times [2]. More specifically the simulation consisted of the following steps:

(1) At $t = 0$ agents were placed in the networks and randomly assigned a social learning strategy and an initial option.

(2) From $t = 1$ onwards, agents sampled the options and corresponding payoffs at t_{i-1} of their contacts.

(3) Agents made a choice between the sampled options based on the decision rules of their social learning strategies.

(4) The environment changed with a certain probability (pc), making the previously best option worse and vice versa.

(5) Payoffs for the choice from step (3) were determined.

Note that there is a lag between the information acquired from contacts and the realization of an agent's payoff in the sense that information is collected before environmental change occurs, thus allowing for the possibility of acquiring outdated information when the environment changes to a new state.

2.2.2 Social Learning Strategies

We studied five social learning strategies that differed in their building blocks (see Table 2.1). For each strategy we assumed that agents sample among their contacts randomly,

[2] Sensitivity analyses revealed that running the simulation for longer time periods and more replications produce identical results.

and stop after collecting either a small (n=3) or a large sample (n=9)[3], except for random copying where sample size was set to n=1[4]. They then decide to try an option that is either endorsed by the majority of the sample contacts; by the agent that had the best payoff in the last time step or by a random agent. In all cases agents only switch to a new option if that option's payoff was higher at the previous time step than the option they are currently using. In situations where these two payoffs are equal or when the majority rule results in ties, agents chose randomly.

Table 2.1: Social learning strategies and their building blocks.

Sampling rule	Stopping rule	Decision rule
Random	n=3 or n=9	*copy-the-best*
sample of	n=3 or n=9	*copy-the-majority*
contacts	n=1	*random copying*

2.2.3 Decision environment

Two factors affecting the decision environment were varied in different simulations: (1) the number of options available and (2) the rate of environmental change. To manipulate the first factor we assumed that agents choose either between 2 or 10 options with payoffs ranging from 1 to 2 and from 1 to 10 respectively, with higher numbers implying higher payoffs. At any given time, only one option had the highest payoff. On the first time step agents were assigned options randomly. In conditions with 2 options, we varied the initial proportion of the correct option in the group ($ps = 0.2$, 0.5 or 0.7). For 10 options each option had the same initial proportion. For the second factor we assumed that the payoffs of options can change on each time step with probability pc=0.001, 0.01, 0.1 or 0.4 reflecting a discreet scale between slow and fast rates of change. We ran all possible combinations of environmental change in all three network structures described below.

[3]Sensitivity analyses with other sample sizes produced similar results and we do not report them here.
[4]Note that in the case of random copying all sample sizes will lead to the same performance level.

2.2.4 Network structure

Three different networks were created, ranging from most efficient to least efficient as measured by two standard indicators in the network science literature (Mason & Watts, 2012): clustering coefficient and average path length. The clustering coefficient measures the extent to which the network is dominated by isolated cliques, which from a communication perspective decreases the efficiency of a network by making it harder for information to spread the higher the clustering. Consider an example where small groups of tightly connected agents exchange information but because groups are isolated from other groups information spreads much slower between these small units.

Another measure of efficiency is average path length, the average number of steps it takes to get from any agent to any other agent in the network. The shorter the path length the more easily information can spread. The efficiency of a network is known to affect how quickly information spreads from one part to another, however, it can also enable maladaptive information to spread more rapidly as in the case of panics following flu pandemics or stock bubbles. Many real-world networks are known to have both high clustering and low average path lengths thus representing an intermediate level of efficiency. These small-world networks (Watts & Strogatz, 1998) can be mimicked by performing random re-wirings on edges of a locally connected network. In line with previous studies (e.g., Schwenk & Reimer, 2008), we started by first generating a random directed locally connected network and then randomly rewired it (i.e., changed the links between nodes) with a 0.1 probability to obtain a small-world network [5]. In addition we created a fully-connected network to represent unstructured groups (see Table 2.2 and Figure 2.1). All networks had a fixed degree of 10 and a total of 100 nodes ($d = 10$, $n = 100$) except for the fully connected network where all nodes where connected to all other nodes.

[5] Other networks with lower values of rewiring produce similar results, therefore, we omit them.

Table 2.2: Social networks studied in the simulation.

Network	Clustering coefficient	Average path length	Rewiring probability
Locally connected	0.67	5.55	p=0
Small world	0.31	2.35	p=0.1
Fully connected	1	1	p=1

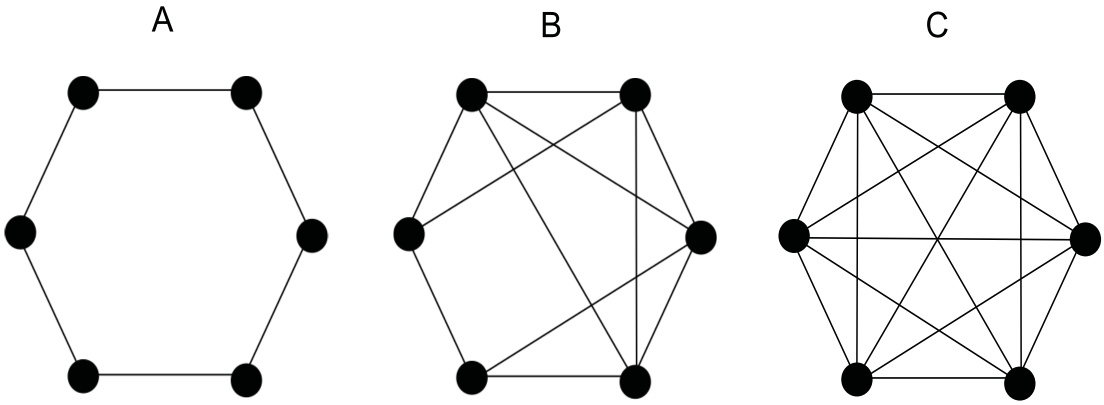

Figure 2.1: **Illustration of the three social networks studied.** Panels **A**: locally connected network, **B**: small world network , **C**: fully connected network. Nodes represent agents and lines represent connections between agents. In the locally connected network each agent is connected to its direct neighbors and form small isolated cliques with two neighbors each; in the small world network agents also form small cliques but some agents are connected to other agents outside of these cliques, thereby decreasing the distance between cliques in the network; in the fully connected network all agents are connected to all other agents.

2.3 Simulation results

Figure 2.2 shows the overall performance of the five different strategies, measured by their rate of environmental tracking (percentage of agents using the correct option on each time step). We show the results for 2 options, probability of environmental change $pc = 0.001$, and initial probability of correct option $pinit = 0.5$, averaged across networks[6]. Overall,

[6]Results for 10 options and other rates of environmental change and initial probability of correct option do not change the main conclusions and we do not present them here.

copy-the-best proves to be the best strategy in terms of speed of spreading information, followed by *random copying* and *copy-the-majority*. This result holds in all network structures and environmental conditions.

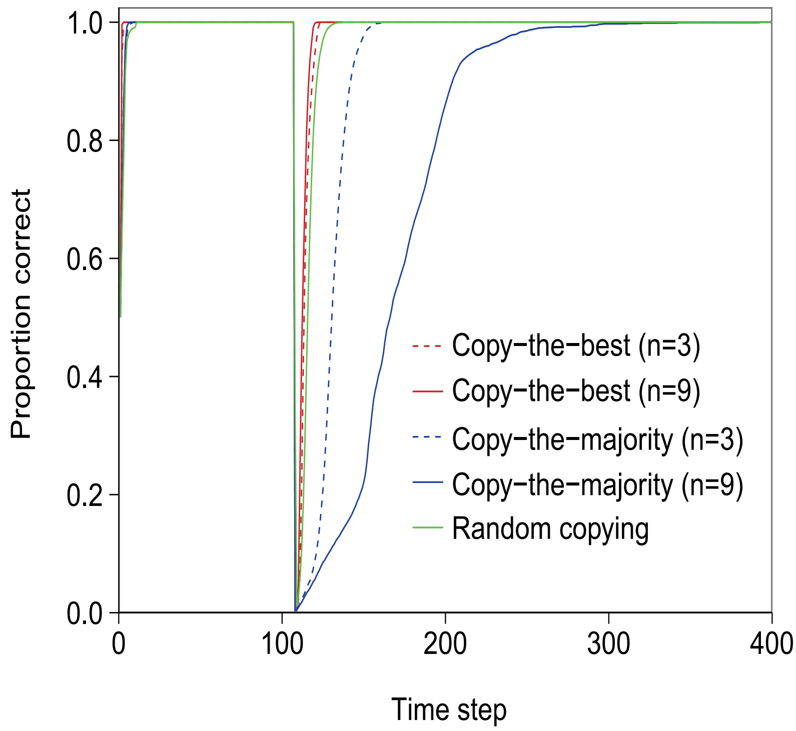

Figure 2.2: **Performance of strategies over time averaged across the three different social networks.** Results are shown for environmental conditions $pc = 0.001$ and $ps = 0.5$. Y-axis: Proportion of agents with the superior option.

2.3.1 Effects of buildling blocks

From Figure 2.2 we can see the number of time steps it takes groups using each of the strategies to converge on the correct solution after the environment has changed. As expected, *copy-the-best* benefits somewhat from larger samples, however, even its small sample version outperforms both *random copying* and *copy-the-majority*. The opposite is the case for *copy-the-majority*, which is hurt by larger samples and actually performs better when it samples fewer people. This result highlights that speed with which different strategies can recover after environmental change is crucial to their success and demonstrates that different sampling regimes should be adopted depending on the decision rule used.

As mentioned before, without sampling, *copy-the- majority* will converge on an incorrect option whenever the proportion of agents using the correct option is smaller than 0.5. As expected, these results do not hold when decisions are based on sampled information as opposed to overall group aggregation. As visible in Figure 2.2, *copy-the-majority* is able to find the correct option even when the proportion of agents using it falls under 0.5. This happens because samples sometimes include a majority of the less frequent but superior option and, by agents selectively retaining it over time, increases in frequency, making it more and more likely to appear as the most frequent option over time (this effect will be studied in greater detail in Chapter 4).

However, when the correct option is in majority in the group (as on $t = 1$) larger samples are slightly better than smaller samples as predicted by Condorcet's Jury Theorem. In addition, in such situations, *copy-the-majority* becomes slightly better than *random copying*. This can be seen in Figure 2.3 which zooms in on the first 30 time steps of the simulation. Note that the population started from $ps = 0.5$ on the first time step. The reason why these results do not translate to situations where individuals start from lower frequencies of correct behavior (as in Figure 2.2) is that the initial advantage gained by the faster strategies when the correct behavior is rare cannot be overtaken later on (as can be seen in Figure 2.2).

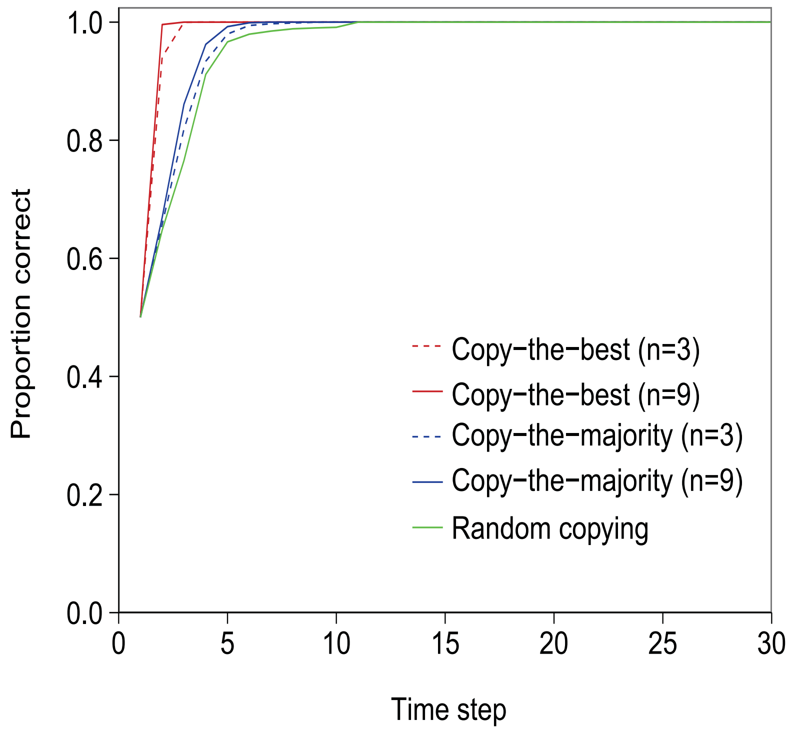

Figure 2.3: **Performance of strategies on the first 30 time steps (when** $ps => 0.5$**) averaged across the three different social networks.**

2.3.2 Effects of network structure

Overall, we find that regardless of strategy, more efficient networks are faster at spreading information and that this helps groups in all conditions. However, we observe an effect for network structure on the relative difference between strategies. Figure 2.4 shows that the difference between strategies is least pronounced in the fully connected network absent of any structural properties, however, as networks become more structured (thereby decreasing the efficiency and speed with which information flows), the difference between *copy-the-majority* and the other two strategies becomes more pronounced.

The effect of network structure is especially visible immediately after environmental change. In networks with high clustering and long path lengths such as a locally connected network, relatively isolated agents may form homogeneous groups possessing the same information. In these situations, *copy-the-majority* has problems finding the correct option. The larger the sample, the more prone is this strategy to get stuck. As expected, the performance of *copy-the-best* and *random copying* is less affected by network structure.

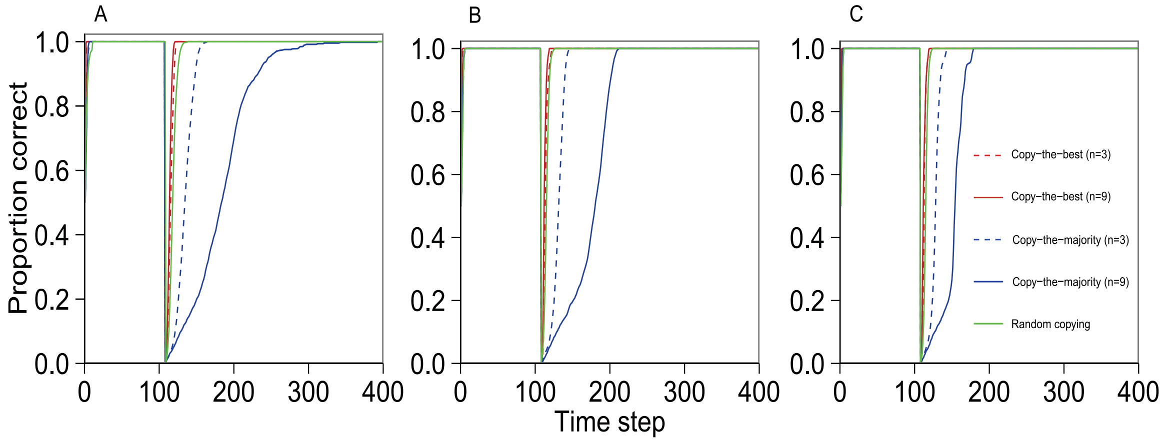

Figure 2.4: **Performance of different strategies in the three network structures over time.** Panels **A**: locally connected network, **B**: small world network , **C**: fully connected network. Results are shown for environmental conditions $pc = 0.001$ and $ps = 0.5$.

2.4 Discussion

Our goal was to study how information sampling and the structure of the social environment affect the performance of three representative social learning strategies: *copy-the-best* and *copy-the-majority* and *random copying*. We modeled social learning strategies as heuristics consisting of different building blocks and embedded them in three social networks in a task involving repeated choices between multiple options.

Overall, we find that *copy-the-best* consistently outperforms both *random copying* and *copy-the-majority* and our results suggest that the reason underlying this finding is the speed with which different strategies are able to respond to environmental change. This speed is affected both by different building blocks and the structure of the social environment. *Copy-the-best* is always faster at finding the good option because its decision rule requires fewer correct instances in the sample and larger samples are always beneficial. In contrast, sample size has a counter-intuitive effect on *copy-the-majority* with smaller samples increasing the likelihood and thereby the speed of finding the correct option. Sample size has no effect in the case of *random copying* and, therefore, has a probability of choosing the correct behavior equal to that behaviors frequency in the population. The relative difference between strategies, however, is moderated by network structure. *Copy-the-best* and *random copying* are less affected by network structure than *copy-the-majority*. More efficient networks (those with lower clustering and shorter path lengths) benefit all strategies and decrease the difference between them while less efficient networks (with more clusters and longer path lengths) increase the difference by having a worse impact on *copy-the-majority*.

Information sampling as opposed to group-level aggregation has an additional effect on *copy-the-majority*: it can still converge on the correct option, even if less than 50% of the group is using it. This result lies in contrast to the predictions of the Condorcet and related Theorems on full group-level aggregation of information in a single trial (Grofman et al., 1983). We study this finding in greater detail in Chapter 4.

The three strategies investigated in this chapter have been extensively studied both theoretically and empirically (e.g., Conradt & Roper, 2003; Garcia-Retamero et al., 2006; Hastie & Kameda, 2005; Katsikopoulos & King, 2010; McElreath, Fasolo, & Wallin, 2013). Much of this work has studied small and unstructured groups and focused exclusively on the decision-phase of implementing these strategies (but see Pachur, Rieskamp, & Hertwig, 2005; Schwenk & Reimer, 2008, for exceptions in other contexts). We believe that this leaves many important details affecting strategy success unaddressed and can be one reason why some studies reach different conclusions. The present chapter is a first step towards capturing the interactions between the building blocks of social heuristics and the structure of the social and task environments that they exploit.

The main focus of this chapter was to introduce the reader to the general setting we study and to illustrate the importance of studying the building blocks of social learning strategies. To achieve this goal we deliberately left many aspects of the simulation rather simplified. The next chapter extends this model to more complex task environments and uses insights from this chapter to explain the results. Chapter 4 then focuses more closely on the counter-intuitive effect of sample size on *copy-the-majority*.

Chapter 3

Social Learning in Complex Environments

This chapter is based on Barkoczi, D & Galesic, M. (2015). Social learning strategies, network structure and the exploration-exploitation tradeoff. *Proceedings of the 2015 Annual Meeting of the Computational Social Science Society*, Santa Fe, NM, USA

3.1 Introduction

The previous chapter introduced the reader to the basic setting of social learning, outlined the concept of building blocks and demonstrated their importance through a simple, transparent problem. This chapter extends the model from Chapter 2 to a more complex problem that characterizes many real world settings including organizational learning or collective problem-solving.

Many problems involving social learning require making a trade-off between exploration and exploitation (Gupta, Smith, & Shalley, 2006; Holland, 1975; March, 1991; Mehlhorn et al., 2015). Exploration involves the search for superior solutions in a problem space while exploitation involves the use of existing solutions in order to reap their benefits. Individuals, groups and organizations regularly face this problem when deciding whether to keep using an existing solution that works well (e.g., an organizational structure) or to search for new, potentially better solutions (Mehlhorn et al., 2015; Voss & Voss, 2013). A proper balance between the two behaviors is thought to be essential for long-term success (Levinthal, 1997; March, 1991; Voss & Voss, 2013).

When individuals interact through social learning, this trade-off manifests itself in the balance between innovation through direct environmental learning and the imitation of existing solutions in the population (Fang, Lee, & Schilling, 2010; Kameda & Nakanishi, 2002, 2003; Rendell, Boyd, et al., 2010; A. R. Rogers, 1988). Innovation is essential both for tracking changes in the environment and for introducing novelty in the population, while imitation serves the purpose of diffusing good solutions in order to increase individual and group-level performance (Boyd & Richerson, 1985).

In this chapter we study how the use of different social learning strategies contributes to the population-level balance of exploration (innovation) and exploitation (imitation) in complex environments where agents switch between exploration and exploitation depending on whether social learning (i.e., exploitation) proves useful.

Focusing on the three representative classes of strategies studied in the previous chapter: (1) *copy-the-majority/plurality* (hereafter conformity) , (2) *copy-the-best* (hereafter best member), and (3) *random copying* (Henrich & Boyd, 1998; Rivkin, 2000; A. R. Rogers, 1988) and implementing them as decision strategies grounded in basic building blocks that guide information search, stopping search and making a decision (Gigerenzer et al., 1999), we study: (1) how these building blocks affect the usefulness of the strategies and (2) how they interact with the structure and complexity of the environment to produce different outcomes in terms of performance.

We propose, based on the findings of the previous chapter, that different strategies vary on a continuum from efficient to inefficient, where efficiency is defined by the speed with which different strategies are able to diffuse information about more successful options in the population (see also Lazer & Friedman, 2007). The efficiency of a social learning strategy affects the level of exploitation and exploration the population engages in, assuming that agents switch between these two behaviors depending on their success (see e.g., Lazer & Friedman, 2007)[1]. More efficient strategies result in higher levels of exploitation and drive agents toward better solutions at any given point in time, while less efficient strategies result in higher levels of exploration through individual search, thereby maintaining higher levels of diversity in the population. The position of a strategy on this efficiency continuum will, therefore, determine the level of exploration and exploitation it promotes in the population. While exploration through individual search maintains diversity and ensures extensive search on complex problem spaces, too much exploration prevents the population from converging on more promising solutions. In contrast, exploitation is essential for adapting quickly and driving the population toward solutions with higher fitness, but it also has a homogenizing effect, leading to the presence of a single or only a few solutions in the population (Hanaki & Owan, 2013; Kandler & Laland, 2009). In a rugged problem space (where the correlation between payoffs of nearby

[1] To illustrate, if social learning proves successful in finding better options, individuals keep using it, whereas if it is unsuccessful they switch to individual search (i.e., exploration).

solutions is low) this can result in the population getting stuck on local peaks. Thus, a proper balance is required to ensure that groups can both search extensively and converge on high-payoff solutions (see also Hanaki & Owan, 2013; Kandler & Laland, 2009; Lazer & Friedman, 2007; Miller, Zhao, & Calantone, 2006).

What determines the efficiency of different strategies? First, note that we define strategy efficiency in terms of how fast it disseminates useful information.

To illustrate, the *best member* strategy would spread the solution of the best performing agent, the *conformity* strategy would spread the most frequent solution, and the *random copying* strategy would disseminate a random solution in a sample. With this consideration in mind, it is possible to classify different strategies on a scale from more to less efficient. The most efficient strategy is the *best member* strategy because it requires only a single instance of a superior solution in a sample in order to spread it. It is followed by *random copying*, which has a chance of spreading a superior option equal to the option's frequency in the population. When useful information is rare, it has a higher chance of spotting it compared to *conformity* which requires a majority or plurality of individuals with these solutions, making *conformity* the least efficient strategy when useful information is rare (Barkoczi & Galesic, 2013). However, when useful information becomes frequent, *conformity* becomes more efficient than *random copying*, as we have seen in the previous chapter. Larger sample sizes would increase the efficiency of both the *best member* and *conformity* strategies. This happens because larger samples increase the chances of identifying options with good payoffs, benefiting the *best member* strategy and also allow for a more precise estimation of the frequency of different behaviors, making it more likely that the *conformity* strategy will select a useful option when it is more frequent relative to other solutions in the population (i.e. in situations where $ps > 0.5$ in the two option case studied in the previous chapter). However, the efficiency of *random copying* would be unaffected by sample size since by definition it copies a random behavior from the population and, on average, the probability of sampling any behavior in the population will be equal to its frequency in the population, regardless of sample size.

Strategies varying in efficiency (as determined by their building blocks) will promote different patterns of explorative and exploitative behavior in the population, but whether different patterns of exploration and exploitation lead to good performance will also depend on the environment.

An ideal environment for studying exploration and exploitation is a fitness landscape such as the NK model (Kauffman, 1993; Kauffman & Levin, 1987; Levinthal, 1997), which belongs to a family of combinatorial optimization problems including the secretary and the travelling salesman problems. The NK model is a "tunably rugged" landscape defined by N, the number of components that make up each solution, and K, the level of interdependence between these components, which together define a problem space where different solutions in the space have different payoffs. Consider a technology composed of different parts or an organization with different departmental configurations. Identifying a way to improve a technology or an organization's configuration depends both on its components and on the interdependence between the components (Simon, 1965). For example, changing one component (e.g., increasing the number of departments in an organization) is likely to also have an impact on other components of the organization, and as a result, whether this change will increase overall performance depends on whether it also has a positive effect on the other components with which it is interdependent. Thus, search on such problem spaces becomes a combinatorial optimization problem where the goal is to modify components of different solutions in order to increase their overall payoff. Depending on the level of interdependence between components K, the landscape can be dominated either by a single peak ($K = 0$) in which case the payoffs of nearby solutions are highly correlated and local search is highly effective; by multiple local peaks ($0 < K < N$), where payoffs of nearby solutions can have very different payoffs (see Figure 3.1); or by almost completely uncorrelated landscapes where the payoffs obtained by local search become very similar to a random walk ($K = N - 1$). Whenever there are multiple local peaks in the problem space, individuals and populations can get stuck with inferior solutions that leave them unable to improve via local search. In this setting exploration involves searching for superior solutions that are not present in the population, while exploitation involves copying existing high-payoff solutions. The extent to which different strategies rely on these two forms of behavior evolves naturally depending on whether they are able to find superior solutions.

Our concept of strategy efficiency is related to work by Lazer and Friedman (2007), who studied the question of how the efficiency of social networks affects group-level outcomes. In a series of simulations, they varied the efficiency (i.e., the speed with which networks disseminate information) of the communication networks in which agents were embedded and found that efficient networks reached highest performance in the short run while in the long run inefficient networks outperformed efficient ones. Similar results were reported in a behavioral experiment by Mason, Jones, and Goldstone (2008) and in an organizational model by Fang et al. (2010). A recent behavioral experiment came to the opposite conclusion, however, finding that groups connected by highly efficient networks reached higher outcomes (Mason & Watts, 2012). Note though, that the above studies either focused on a single strategy (*best member*) or did not model the behavioral strategies underlying individual decisions. We connect our work to these results and demonstrate that different levels of efficiency in a population can be achieved both by social learning strategies composed of different building blocks as well as by the communication network agents are embedded in. We also show that the two can interact in ways that are either beneficial or harmful for overall performance. This allows us to reconcile the contradictory findings of Lazer and Friedman (2007) and Mason and Watts (2012) by showing that these results depend on the underlying social learning strategies in addition to the network in which interaction takes place.

In summary, our goal in this chapter is two-fold: first, we aim to understand how social learning strategies varying in their building blocks result in different levels of performance and second, how social learning strategies and network structure interact.

3.2 Model

3.2.1 Overview

We consider agents searching a space of possible N-digit solutions by modifying digits in their current solution in order to improve their performance. Examples include trying to identify an organizational configuration that maximizes performance or modifying components of existing technologies to improve them. These problems share the characteristic of being path dependent and interdependent in nature; getting to a solution usually involves modifying previous solutions and the success of changing some feature depends on the other features within the structure. The extent to which these characteristics dominate the problem space can be straightforwardly captured by tunably rugged fitness landscapes (see Environment). Agents by default engage in social learning (exploitation) and switch to innovation (exploration) if the former does not prove successful (see Agents and Strategies). Thus a strategy that often proves useful will engage in more exploitation and less exploration. We measured the performance of different strategies by the average payoff achieved relative to other strategies and to the highest obtainable performance level in the environment.

3.2.2 Environment

The environment is characterised by a tunably rugged NK landscape, where N denotes the number of components of the system and K represents the number of interdependencies between the components. A value of $K = 0$ produces single peak environment, while $K = N - 1$ produces a completely rugged landscape with no correlation between adjacent solutions, making local exploration ineffective. Intermediate values of K produce landscapes with both local and global peaks, with some correlation between nearby solutions. Each solution in the environment is an N-length vector composed of binary strings: that is, each element of the vector can take on two values, 0 and 1, leading to a total of 2^N possible solutions in the problem space. Each solution has a payoff that is calculated as the average of the payoff contributions of each element and the other elements with which they are interdependent. The payoff contribution of each element is a random number drawn from a uniform distribution between 0 and 1. In the case of $K = 0$, a simple average of the N elements is taken: $1/N * \sum_{i=1}^{N} N_i$, whereas with $K > 1$, individual payoff contributions are determined by values of the other $K-1$ elements, that is , $f(N_i \mid N_i, N_{i+1}, ..., N_K)$, where $f()$ is the payoff function and the total payoff is $1/N * \sum_{i=1}^{N} f(N_i \mid N_i, N_{i+1}, ..., N_K)$. In other words, when $K = 0$, changing any single element of the solution will affect only the contribution of that element, whereas when $K > 0$, changing a single element will change the payoff contribution of the $K-1$ other elements. As mentioned above, when $K = 0$, exploration of solutions through the modification of single components can prove effective, but as K increases, local exploration becomes less and less effective (Levinthal, 1997). In all results reported we let $N = 15$ and $K = 0$ or $K = 7$ to create two different environments that we call simple and complex, respectively. Figure 3.1 displays a graphical illustration of the environments studied. Panel A shows the simple environment where only one unique peak exists and it is possible to reach this peak by gradually modifying digits in one's solution. In contrast, Panel B shows a multi-peaked environment, which mean that agents can get stuck in a local peaks and be unable to reach higher payoffs via local search.

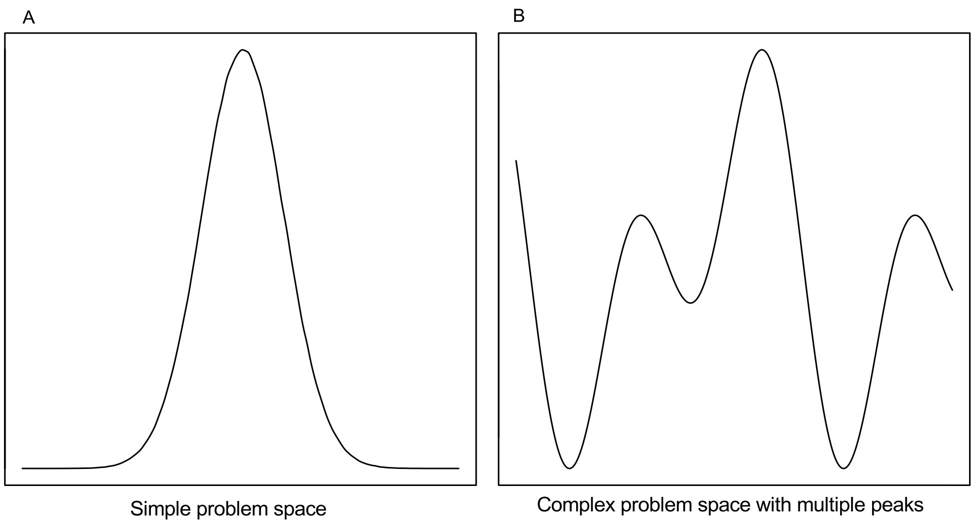

Figure 3.1: **Illustration of the two environments studied. A:** Simple environment with a single peak. **B:** Complex environment with multiple peaks. In the simple environment solutions one-digit apart from each other have very similar payoffs, therefore, modifying single digits in a solution will eventually lead to the global peak. In the complex environment payoffs of nearby solutions can be very different, therefore, search by single digit modification can lead to local peaks from which it is impossible to improve and, as a result, to find the global peak.

Our choices for values of N and K are representative of the literature, and sensitivity analyses revealed that changing these values would not affect our results. The simple environment ($N = 15, K = 0$) would correspond to the environment studied in the previous chapter since it is characterized by a single peak and all other solutions can be ranked by their payoffs.

Following several authors, we normalized the payoffs of different solutions by dividing them by the maximum obtainable payoff on a landscape $P_{Norm} = P_i/max(P)$ (Lazer & Friedman, 2007; Siggelkow & Rivkin, 2005). The distribution of normalized payoffs tends to follow a normal distribution with decreasing variance as K increases. This implies that most solutions tend to cluster around very similar payoff values. Following Lazer and Friedman (2007) we use a monotonic transformation $(P_{Norm})^8$ to widen the distribution, making most solutions "mediocre" and only a few solutions "very good". Note that this assumption does not change any of the results.

Since our main focus is on the properties of different strategies, the majority of our simulations is based on a fully connected network with $N = 100$ nodes. We compare the fully connected network with a locally connected network with 100 nodes and a degree of $d = 4$ (see Section 3.3.2 for network versus strategy efficiency and Figure 2.1 for an illustration of the networks) but omit the small-world network since we saw in the previous chapter that it lies in-between the two more extreme networks and, therefore, we do not expect anything unique to happen there. This allows us to compare more and less efficient networks as in previous studies (Lazer & Friedman, 2007; Mason & Watts, 2012).

3.2.3 Agents and Strategies

We simulated $N = 100$ agents. On each time step agents simultaneously interacted with the environment in order to avoid possible sequence effects (Bikhchandani, Hirshleifer, & Welch, 1992).

On the first time step agents started out with a randomly assigned solution of N digits and on each subsequent time step went through the following steps:

(1) Implement social learning by following the steps specified by the building blocks:

(i) Search rule: search randomly among the population

(ii) Stopping rule: stop searching after looking up the solutions of s[2] other individuals. We focused on two sample sizes, a relatively smaller (s=3) and a

[2] Note that the sample size s corresponds to n in the previous chapter

relatively larger (s=9) sample size [3].

(iii) Decision rule: select the best performing agent (*best member*); select the most frequent solution (*conformity*) [4]; select a random agent (*random copying*).

(2) Observe whether the solution identified via social learning produces a higher fitness score than the current solution. If yes, switch to the alternative solution; otherwise go to Step 3.

(3) Engage in exploration by modifying a single digit in the current solution and observe whether it produces a higher payoff than the current solution. If yes, switch to the alternative solution; otherwise keep the current solution.

This procedure is repeated for $t = 200$ time steps and the average payoff in the population is recorded for different strategies and environments. Results reported are averaged across 1000 different NK environments.

3.3 Results

3.3.1 Performance

Figure 3.2 shows the average fitness level achieved by each strategy over time on two different landscapes: a simple landscape with a single peak ($K = 0$)[5] and a rugged landscape with multiple peaks (both local and global) ($K = 7$). First, note that in a simple landscape (Panel A), all strategies are able to find the globally best solution but differ in the time they take. The *best member* strategies are the fastest, followed by the small- and large-sample version of the *conformity* strategy. *Random copying* is the worst performing

[3]See section on Sensitivity checks for the best sample size for each strategy.

[4]This implies selecting the majority/plurality solution in the sample. In case each solution is equally frequent, agents choose randomly.

[5]This landscape is analogous to the problem studied in Chapter 2.

social learning strategy. Also note that all social learning strategies perform better than pure individual learning. This result replicates the findings from the previous chapter and validates our model. To see this, note that this setting corresponds to a case where the best solution is likely to be infrequent (i.e., $ps < 0.5$) in the beginning but will quickly become the most frequent solution [6]. This results can also be seen on Figure 2.3 in the previous chapter.

The result can be explained in the following way. As mentioned above, nearby solutions on the simple landscape are correlated and there is no interdependence between different components of a solution. These properties make local exploration highly effective and make it likely that someone in the population will be able to identify the globally best solution. As soon as the best solution is present in the population, the *best member* strategy will quickly drive the population toward this solution, since it requires only a single individual in a sample to identify it. *Random copying* will also quickly diffuse solutions that are better than the starting configurations on the first time step, but when when the best solution becomes the most frequent solution, *conformity* will drive the population toward this option faster. The *conformity* strategy promotes diversity through individual search in the beginning and since the problem is simple, a majority or plurality of individuals will quickly be able to identify the best solution. Once a plurality of individuals have found the best solution the *conformity* strategy will be biased toward this solution, allowing it to diffuse.

In more complex problem spaces, where the level of interdependence is high, identifying good solutions is not so straightforward. Figure 3.2B shows performance on a complex landscape. The *best member* strategies still reach the highest short-run outcomes, but they quickly drive the whole population toward a local peak, from which point individual exploration is not able to find better solutions. As a result the whole population gets stuck

[6] This happens simply because there are many possible options to choose from. As soon as a few individuals identify the best option through individual search, it will become the most frequent option available for sampling.

in an inferior state. In contrast, the *conformity* strategies converge more slowly to a solution. A striking result is that while the large-sample version of the *conformity* strategy performs poorly, the small-sample version converges to the highest long-run outcomes, outperforming the *best member* strategies by a large margin. *Random copying* performs on the level of individual learning. This pattern of results was replicated in all complex landscapes ($N > K > 0$).

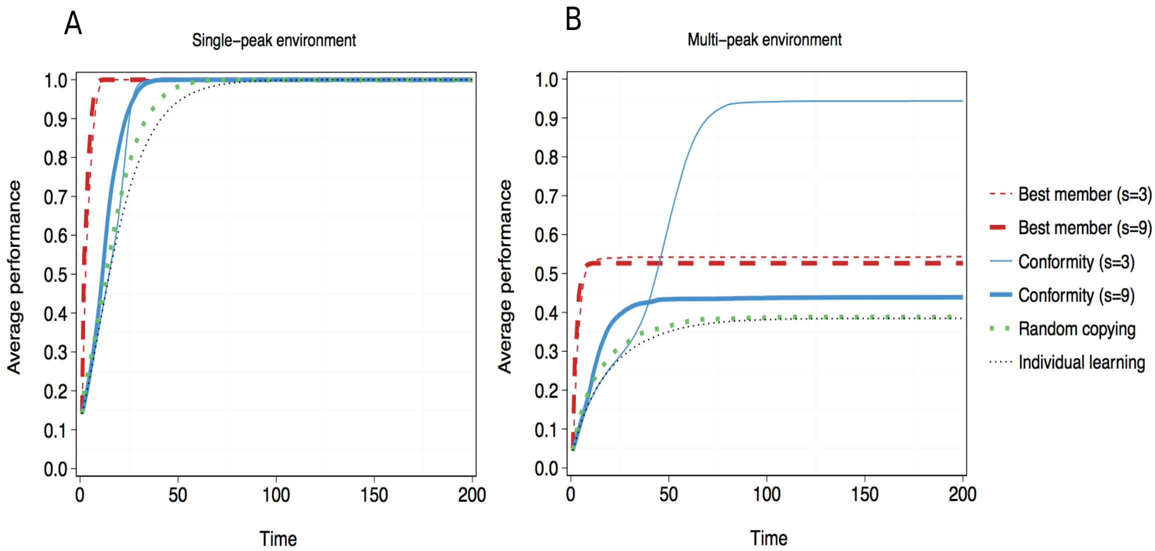

Figure 3.2: **Performance over time for different strategies.** Panel A: single peak environment ($K = 0$); Panel B: multi-peak environment ($N = 15$, $K = 7$); s stands for sample size.

The intuition underlying this result is the following. The *best member* strategies engage in the highest level of exploitation and lowest level of exploration early on and quickly drive the population towards a local peak. Their small-sample version performs slightly better than the large-sample version, because it leads to slightly less efficiency and thereby allows the population to explore and find a local peak that has a higher payoff. The second most efficient strategy, *random copying*, also engages in high levels of exploitation in the beginning and drives agents to several local peaks. Finally, the conformist strategy leads to very different outcomes depending on its building blocks. The large-sample version of the strategy is more efficient at diffusing the most frequent solution (analogous to $ps > 0.5$ in the previous chapter), so as soon as a plurality of individuals select solutions that are better relative to the starting solutions in the population, the group will converge to these solutions. However, even if a few individuals later identify a better solution, these solutions will never show up as the most frequent in a large sample, making them hard to diffuse and, therefore, lead the population to converge on several local peaks. In contrast, because of higher sampling variability, higher fitness solutions identified by a few people are more likely to sometimes appear as the most frequent solution in small samples, allowing infrequent but superior solutions to diffuse through the population (see also Chapter 4). In the long-run this leads to the highest outcomes because the group is able to search extensively as well as to converge on high fitness solutions.

That agents get stuck on multiple local peaks can be seen from Figure 3.3, which shows how the number of unique solutions in the population changes over time for different strategies. Since the *best member* strategies engage in high levels of exploitation and are biased toward high-payoff solutions, they drive out diversity from the population and lead the whole population to a single local peak. In contrast, in the case of the *conformist* strategies and *random copying*, the level of diversity in the group remains high for a longer period of time and groups discover multiple peaks on the landscape.

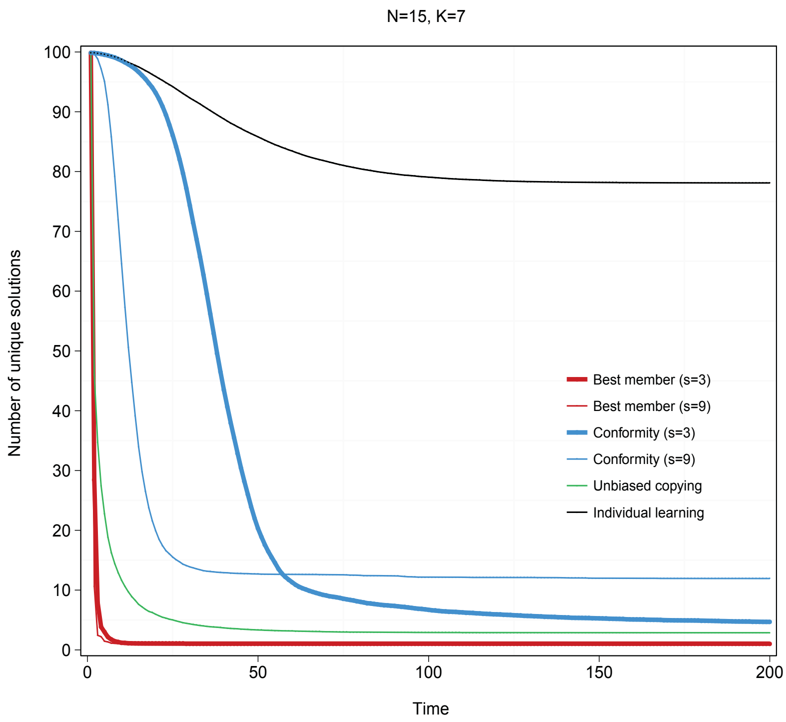

Figure 3.3: **Number of unique solutions over time.**

Taken together, these results indicate that strategies vary in their efficiency, leading to different patterns of explorative and exploitative behavior. The extent to which these behavior patterns are beneficial or harmful for a strategy will depend on the strategy's building blocks and the structure and complexity of the environment. Interestingly, strategies sharing the same decision rule (conformity) can achieve very different levels of performance depending on their other building blocks.

3.3.2 Network Versus Strategy Efficiency

In this section we study the connection between strategy and network efficiency. As mentioned above, two recent studies produced contradictory findings about the performance of efficient and inefficient networks (Lazer & Friedman, 2007; Mason & Watts, 2012). Lazer and Friedman (2007) used simulations to model social learning using the *best member* strategy with a sample size of two (each agent could communicate with two other neighbors), whereas Mason and Watts (2012) used behavioral experiments and did not model social learning strategies. The authors differ in how they defined network efficiency but agree that clustering (i.e., the number of local cliques in the network) and average path length (number of steps required to get from one agent to any other agent) are important factors. The former study found that inefficient networks outperformed efficient networks, whereas the latter came to the opposite conclusion.

Here we show that both results can be obtained depending on the social learning strategies that agents use. The underlying explanation is that strategy and network efficiency have similar effects on group-level performance: therefore, their interaction can counteract the individual effect of each. For example, an inefficient strategy in an inefficient network can increase the level of inefficiency to a level where it is no longer beneficial. Similarly, an efficient strategy in an efficient network can result in too much efficiency. Therefore, the concepts of strategy and network efficiency must be studied together.

We compare the performances of the *best member* and *conformity* strategies (an efficient and inefficient strategy, respectively) in a fully connected network (as above) with a locally connected lattice ($N = 100$, $d = 4$)[7]. Since the locally connected lattice only has a degree of 3 we restrict attention to the small-sample strategies, which have also performed best in our main study. Figure 3.4 shows strategy performance on these two different networks over time.

These results show that both effects can be obtained depending on the underlying social learning strategy. When individuals rely on the *best member* strategy, inefficient networks outperform efficient ones. When individuals rely on the *conformity* strategy, inefficient networks are better. As a result we are able to reconcile the contradictory findings from the literature and highlight the need to study the interaction between social

[7]We chose a network with a degree of 3 to be as close to the original networks studied by Lazer and Friedman (2007) and Mason and Watts (2012) as possible.

learning heuristics and network structure.

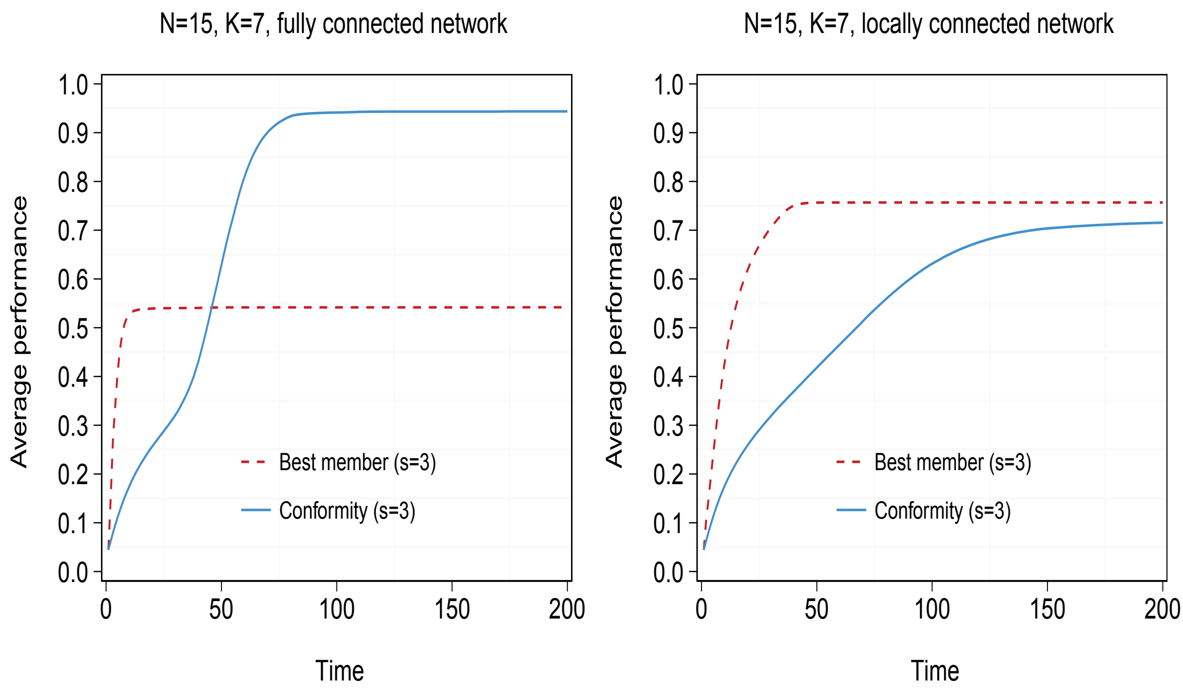

Figure 3.4: **Performance on efficient (LEFT) and inefficient (RIGHT) networks.** Inefficient networks can outperform efficient ones when agents rely on the *best member* strategy. The opposite result holds when agents rely on the *conformity strategy*.

3.3.3 Changing environments

So far we have assumed that the environment is stable. Would any of our conclusions change in a turbulent environment? We study two environments: a slightly turbulent environment where change occurs only once halfway through the simulation, and a highly turbulent environment where change occurs on every 20th time step. Following Levinthal (1997), we model environmental change by redrawing the fitness contribution of a randomly selected digit in the space. Our results (shown in Figure 3.5) remain the same in slightly turbulent environments, however, when the environment is highly turbulent the *best member* strategy initially performs better, because it is best strategy in the short run.

Given that the landscape changes frequently, there is insufficient time for the long-run advantage of the *conformity* strategy to show up. However, over time, agents using the *conformity* strategy will also get closer to better solutions, and will need to modify fewer digits after environmental change to identify good solutions. As a result, over time, the small sample *conformity* strategy takes over the *best member* strategy.

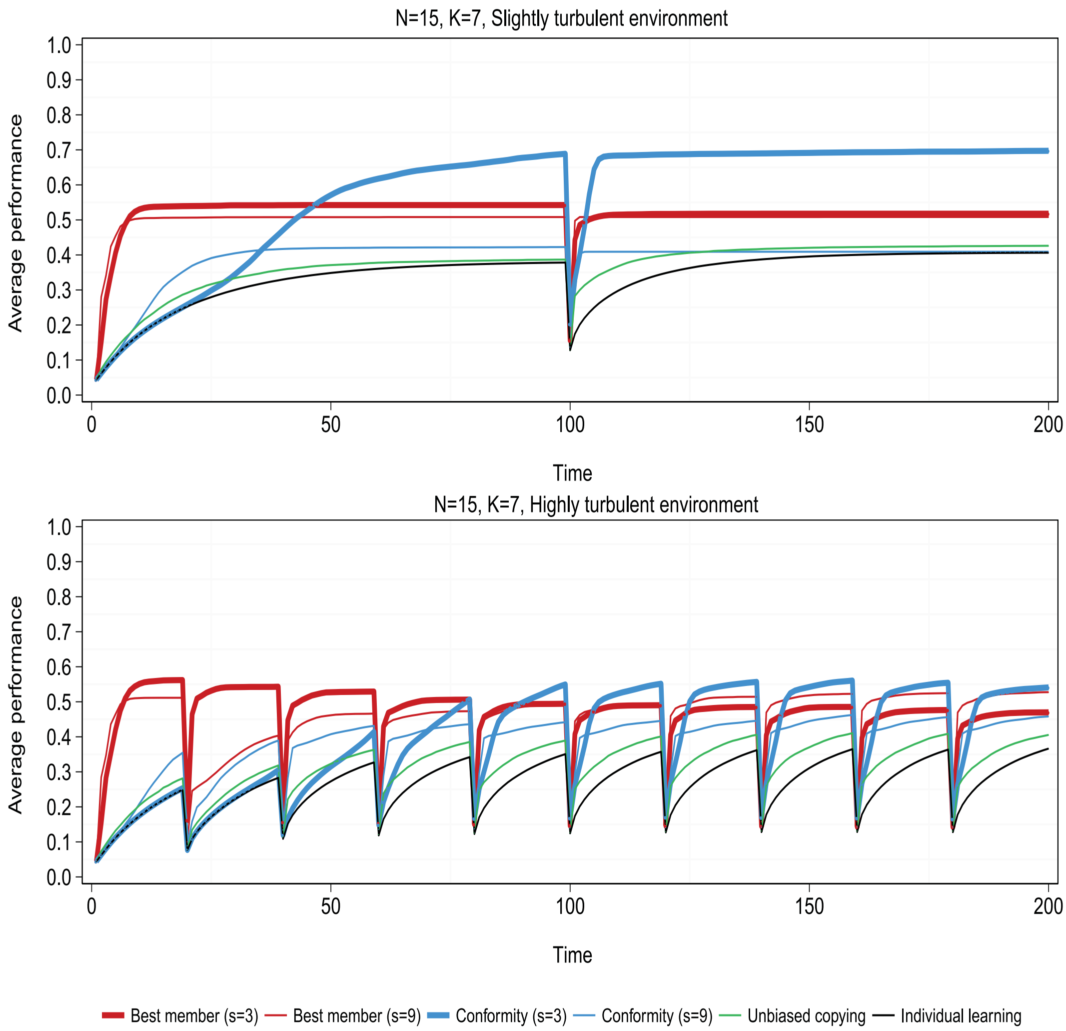

Figure 3.5: **Performance of strategies in slightly turbulent (change occurs halfway through) and highly turbulent environments (change occurs every 20th time step).**

3.3.4 Best sample size.

As noted above, sample size has no effect on *random copying*, therefore, we focus on identifying the best sample size for the *best member* and *conformity* strategies. In case of the *best member* strategy the best sample size turns out to be 2, however, the difference between different sample sizes is relatively small [8]. Therefore we choose to keep sample size of 3 for our main analyses to make it directly comparable to the *conformity* strategy that also uses a sample size of 3 [9]. In contrast, for *conformity* the best sample size is 3 and if it increases to the next odd group size (i.e., 5) the advantage of *conformity* is lost and performance drops to the level of the large sample *conformity* strategy reported in the main text.

3.4 Discussion

We studied how different social learning strategies composed of different building blocks naturally trade off exploration and exploitation and how this trade-off leads to different levels of performance in complex environments.

We introduced the concept of strategy efficiency and related it to the concept of network efficiency (Lazer & Friedman, 2007; Mason & Watts, 2012). We classified strategies on a continuum from more efficient to less efficient, which allowed us to suggest a rationale for why they produce different patterns of exploration and exploitation. We decomposed strategies into three basic building blocks - that is, rules that guide search, stopping search and making a decision - and studied how these rules affect strategy efficiency and how they interact with the structure of the task environment in two different

[8] Note that the best member strategy with a sample size of 1 would correspond to the *random copying strategy*.

[9] Note that the difference between the performance of the *best member* strategy with sample size 2 and sample size 3 is very small, so using a sample size of 2 in the main analysis would not change any of the results. Therefore, to allow for direct comparison with the *conformity* strategy we stick to a sample size of 3.

social networks. Our results indicate that strategy performance depends on both how it trades off exploration and exploitation and how its building blocks interact with the task environment. Our main result is that *best member* strategies reach the best performance in the short run, but a small amount of *conformity* (achieved by relying on small samples) ensured the highest long-run outcomes whenever task environments were complex. We also found that strategies with different levels of efficiency could achieve extremely different levels of performance.

This insight led us to study the interaction between network and strategy efficiency and enabled us to reconcile contradictory findings from the literature (Fang et al., 2010; Lazer & Friedman, 2007; Mason et al., 2008; Mason & Watts, 2012).

The importance of balancing exploration and exploitation has long been recognized in the behavioral sciences (Mehlhorn et al., 2015; Rendell, Boyd, et al., 2010; Voss & Voss, 2013). Gupta et al. (2006) discussed different mechanisms through which this balance can be achieved by, namely, punctuated equilibrium and ambidexterity. In punctuated equilibrium, organizations balance exploration and exploitation in a sequential way focusing exclusively on one or the other at any given point in time. In contrast, in ambidexterity the balance is achieved simultaneously through different organizational structures. It is interesting to note that the way in which different social learning strategies naturally trade off exploration and exploitation leads to patterns that are consistent with these different concepts. More efficient strategies such as *best member* and *random copying* lead to patterns reflecting punctuated equilibrium, where the whole population engages exclusively in either exploration or exploitation for short periods of time. In contrast, the conformist strategies balance exploration and exploitation in the population for longer periods of time, reflecting some form of ambidexterity with some agent focusing on exploitation while other focus on exploration.

We assumed in Chapter 2 that agents have a fixed probability of engaging in individual learning and otherwise rely on social learning. This differs from the assumption in the present chapter that agents switch between the two behaviors depending on their success. We believe that the simplified assumption was sufficient in the previous chapter to demonstrate our main points, however, we let the relative reliance on social versus individual learning evolve in this chapter to rely on fewer arbitrary parameters.

We are not the first to study exploration and exploitation in the context of social learning (e.g., Hanaki & Owan, 2013; Rendell, Fogarty, & Laland, 2010), but we believe our study has several novel aspects. First, as mentioned above, rather than modeling the relative reliance on exploration and exploitation with a parameter or by modeling the differential costs associated with these two behaviors (Hanaki & Owan, 2013; Kameda & Nakanishi, 2002; Rendell, Boyd, et al., 2010), we let it naturally evolve depending on the success of an social learning strategy in a given environment. In other words, we studied how the interaction between strategy and environment determines the reliance on exploration and exploitation purely in terms of success. To achieve this in our model, different strategies started with exploitation (i.e., social learning) and switched to exploration if exploitation did not prove successful. This approach has parallels in the biological literature with a strategy called 'critical social learner' (Enquist, Eriksson, & Ghirlanda, 2007; Rendell, Fogarty, & Laland, 2010). This strategy has been found to be highly successful and to outperform pure individual or social learning strategies [10]. Second, we directly compared different strategies and their properties and modeled them in terms of building blocks (rules for search, stopping search and deciding), whereas most existing studies have focused on a single class of strategies and their decision rules (Csaszar & Siggelkow, 2010; Lazer & Friedman, 2007; Rivkin, 2000). By comparing different strategies we were able to show when and why they are more or less successful and by modeling their building blocks we showed how the same decision rule (e.g. majority/plurarlity rule) can lead to very different levels of performance depending on the strategy's other building blocks.

[10] One can also consider the opposite strategy, first attempt exploration and if unsuccessful turn to exploitation and it is an equally plausible model of organizational learning, however, it is not the focus of the present study.

The notion of building blocks in the context of strategies can be loosely related to organizational structure and its components. Siggelkow and Rivkin (2005) studied the extent to which different organizational forms are able to cope with complex and turbulent environments, finding that some organizational configurations are more suited to complex but stable environments while others are better in simple but turbulent settings. We believe that the building blocks of a strategy can affect its performance in a similar way, so modifying the building blocks of a strategy can make it suitable for different environments. However, we leave the exploration of this issue to future research.

Social learning is often thought to have a homogenizing effect on the number of solutions in a population (Boyd & Richerson, 1985; Hanaki & Owan, 2013; Henrich & Boyd, 1998; Lazer & Friedman, 2007). Yet, in our model, exploitation sometimes promotes diversity, which arises because agents switch between exploration and exploitation depending on their success with these two behaviors. However, several other situations have been identified where social learning can promote diversity. Posen and Levinthal (2012) showed that when social learners copy parts of other agents' solutions and experiment with the rest, agents end up with heterogeneous solutions on rugged landscapes. Bala and Goyal (1998) and Rendell, Fogarty, and Laland (2010) showed that when agents are loosely connected in cliques, different cliques will end up with different solutions, but these solutions will not be able to spread to other cliques, thereby maintaining a multitude solutions in the population. Finally, when environments are turbulent and the most adaptive solution changes faster than the rate at with which the population can converge, previously adaptive information will be preserved in the population (Kandler & Laland, 2013).

Our study has broad implications for organizational learning, technological innovation and the diffusion of innovations. Most studies of exploration and exploitation in organizations focus on how to design the external environment to make firms more adaptive (Csaszar & Siggelkow, 2010; Fang et al., 2010; Lazer & Friedman, 2007; Siggelkow

& Rivkin, 2005). Our study highlights that it is also important to consider the social learning strategies used by agents and organizations. In addition our study on the relationship between strategies and social networks shows that changing the social environment without paying attention to the individual-level strategies might not produce the desired effect.

Research on technological innovation has highlighted the combinatorial nature of innovation with most new inventions being recombinations of existing innovations (Arthur, 2009; Solée et al., 2013). Much of this research has focused on how innovation occurs, whereas there has been very little attention devoted to the coevolution of innovation and imitation. Our study identifies situations where imitation can both help and hinder the development of technological innovation.

Several open questions remain to be addressed. In line with previous studies we focused on the NK landscape as a form of a tunably rugged landscape. The extent to which our results (and other results from the literature) would apply to other landscape problems is a question for future research. We also assumed for the sake of clarity that populations rely on a single social learning strategy. Future research should address the dynamics of exploration and exploitation in a population using multiple strategies at the same time. Our model could also be tested empirically. There are only a handful of studies on how people behave in combinatorial optimization problems that have a rugged structure and we know very little about how these results translate to other problems (Billinger, Stieglitz, & Schumacher, 2013; Garcia-Retamero et al., 2006; Mesoudi, 2008; Wisdom, Song, & Goldstone, 2013).

A surprising finding of the current and the previous chapter was that relying on small samples in the case of *conformity* (or *copy-the-majority*) leads to the best long-run outcomes. The next chapter explores in greater detail the reasons underlying this result.

Chapter 4

A sampling approach to conformist social learning

This chapter is based on Barkoczi, D & Galesic, M. (2015). A sampling approach to conformist social learning. *Under review*

4.1 Introduction

In this chapter we analyse in greater detail the effect of sample size on the performance of *copy-the-majority*. *Copy-the-majority* is one of the most studied forms of social learning belonging to the class of frequency-dependent copying strategies. An individual following this strategy is disproportionately likely to adopt an option held by the majority of others (Boyd & Richerson, 1985; Claidière et al., 2012; Hoppitt & Laland, 2013). This tendency has been linked to phenomena such as the widely observed S-shaped adoption curves in the diffusion of innovations literature (Henrich, 2001; Young, 2009), complex contagion (Centola & Macy, 2007) or social influence (Asch, 1956). Conformity has several evolutionary benefits compared to individual learning and other forms of social learning (Henrich, 2001; Henrich & Boyd, 1998), although it has been shown that it is most useful in spatially rather than temporally varying environments (Nakahashi, 2007; Nakahashi, Wakano, & Henrich, 2012; Wakano & Aoki, 2007).

How should one apply this strategy to ensure the best performance in terms of accuracy? We have seen in the previous two chapters that relying on smaller samples often leads to better performance. In addition, it has been suggested that in order to be adaptive, conformity should be relatively weak (Claidière et al., 2012; Eriksson & Coultas, 2009; Henrich, 2001; Kandler & Laland, 2009, 2013), where strength of conformity is typically defined by the probability of an individual adopting an option relative to the frequency of the option in the population; the smaller the probability relative to the population frequency, the weaker the level of conformity [1]. Strength of conformity is typically modeled by means of a theoretical parameter that moderates the importance of reliance on frequency-dependent learning. For example a parameter value of 0.6 would mean that an individual chooses the most frequent option 60% of the time and the less frequent option 40% of the time, reflecting a weak to moderate level of conformity. This abstract level of modeling strength of conformity is suitable for population genetic models used in

[1] Other definitions of strength of conformity also exist see e.g., Claidière et al. (2012)

most previous studies as it simplifies the calculations of evolutionary equilibrium steady states, and is in principle applicable to a wide range of organisms. However, in order to understand the consequences of using different social learning strategies, it is important to understand how they are implemented on a process-level. Or, as aptly put by Henrich (2001), models of social learning should in general aim to be based on plausible assumptions about underlying cognitive processes rather than "merely having equations with the symbols arranged in a particular fashion" (p. 1007).

Here we propose a sampling-based process model of conformist social learning and demonstrate that different forms of conformity can results from the size of the information samples on which individuals base their judgments, with weak conformity resulting from taking small samples. Importantly, our model can reproduce the conformity patterns reported in existing theoretical models and empirical observations (Boyd & Richerson, 1985; Henrich & Boyd, 1998; Nakahashi, 2007; Nakahashi et al., 2012). However, in contrast to existing studies which assume a motivational tendency to disregard individual over social information, we show that the relative reliance on the most frequent option can result from a simple statistical fact that smaller samples provide weaker evidence about the frequency of a behavior in the population, because of their inherently higher variability compared to larger samples. As a result, individuals with the same internal propensity to copy the most frequent option can exhibit different forms of conformity not because of any internal preferences for social or non-social information, but purely because of this byproduct of information sampling. This account also allows us to draw novel insights regarding the cognitive mechanisms underlying different patterns of behavior, with some patterns being consistent with a pure sampling-based social learning model, while others indicating a mixture of individual and social learning.

We further show that when choosing between options with different payoffs, counterintuitively, relying on small samples (a form of weak conformity) can lead to superior performance in terms of both individual accuracy (i.e., likelihood of choosing the superior behavior) and the speed of diffusion of an innovation in unstructured and structured populations. When one is uncertain about frequency of the superior option in the population, as it is typically the case in the real world, on average, relying on smaller samples leads to better performance compared to larger samples. This is because smaller samples provide large advantage when the superior behavior is in minority, but only a small disadvantage when it is in majority. We intuit these results mathematically, illustrate them by practical examples and discuss the implications of our approach.

4.2 Process based model of conformist learning

To build a sampling-based process model of conformity, we model the conformity strategy as being composed of the three basic building blocks (search, stopping, and decision rules).

Focusing on the simplest and most studied version of a frequency-dependent social learning strategy: *copy-the-majority* [2], we first ask: How many individuals do people "sample" from their social environments when making decisions about adopting new options, such as innovations or novel beliefs? While humans might be able to maintain social contact with more than 100 individuals (Dunbar, 1993; Hill & Dunbar, 2003), data from diverse studies converge to suggest that the number of people one discusses important issues with, or consider as close friends or support clique, typically does not exceed about five individuals (Fu, 2005; Galesic, Olsson, & Rieskamp, 2012; Marin & Hampton, 2007; Marsden, 1987). This core network size has likely emerged for reasons unrelated to accuracy of social learning discussed here, for example because of the limited number of relationships one can afford to maintain by making costly investments now in order to gain support in the future. Nevertheless, this number represents the typical size of a sample that individuals take from their social environments when making important decisions.

[2] An individual following this strategy decides between two available options by following the choice of the simple majority of others observed (Boyd & Richerson, 1985; Henrich & Boyd, 1998; Laland, 2004)

In line with these considerations, we propose that the sample sizes used in the previous two chapters (n=3 and n=9) seem reasonable with respect to everyday social decision making in humans.

To systematically study the effect of sample size on *copy-the-majority* we use the Condorcet Jury Theorem (hereafter simply *CJT*) (Efferson et al., 2008; King & Cowlishaw, 2007; Perreault, Moya, & Boyd, 2012). CJT models the probability that the simple majority of a group of *n* individuals is correct by the cumulative binomial distribution:

$$CJT(ps, n) = \sum_{i=m}^{n} \binom{n}{i} ps^{i} (1 - ps)^{n-i} \tag{4.1}$$

...where *ps* is the proportion of individuals with the superior solution, *n* is the sample size, *m* is $(n+1)/2$ for odd *n* and $n/2+1$ for even *n* (Condorcet, 1972; Grofman et al., 1983). Equation 4.1 shows that the probability that the majority is correct depends on the number of other individuals, or models, that one considers when making a decision. While this has been recognized (Boyd & Richerson, 1985; Efferson et al., 2008; King & Cowlishaw, 2007; Perreault et al., 2012), the problem of sample size has been ignored by previous studies, which have either not modeled sampling, studied a single sample size or averaged across all sample sizes and compositions and in general assumed that larger samples sizes are better (Perreault et al., 2012).

As shown in Figure 4.1 Panel A, when the proportion of the population with the superior solution (or individual probability of choosing correctly) is above 0.5, individuals relying on larger samples will be more likely to pick the superior option than individuals relying on smaller samples, asymptotically reaching perfect accuracy with an infinite sample size. In contrast, when this proportion is below 0.5, *CJT* predicts that smaller samples will outperform larger samples. Importantly, *CJT* predicts that an average individual copying the majority will never find the superior solution if the proportion of the population using that solution is lower than 0.5. The predictions of *CJT* apply to one-shot decisions, however, the context of innovation diffusion differs in several ways. First, during the diffusion of innovations, individuals repeatedly interact with the same group and adopt or consider adopting novel options as they appear. Second, the choices of individuals at one time step will influence the information available for sampling on the next time step. As a consequence, as the number of individuals adopting the superior option increases, one will be more likely to sample such individuals over time. In turn, an initially rare but superior option can increase in frequency by individuals selectively retaining it over time.

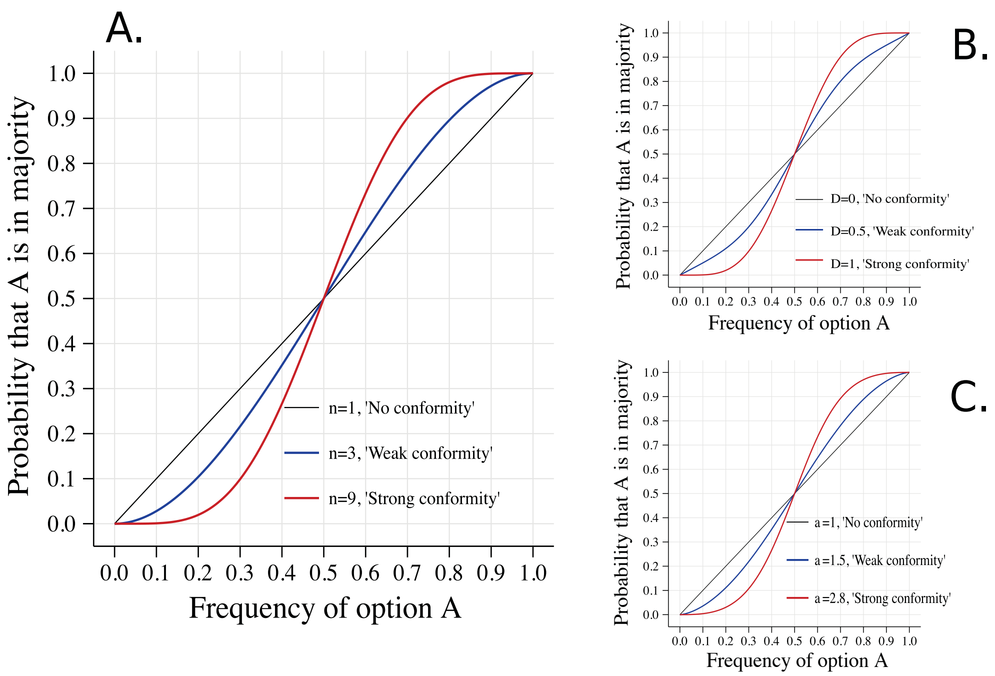

Figure 4.1: **Panel A:** Condorcet Jury Theorem. Probability that option A is in majority as a function of option A's frequency in the population and sample size (n; see Equation 4.1). **Panels B and C:** Demonstration of the equivalence of sample size and strength of conformity modeled by parameter D (Panel B; see Equation 4.3) and *a* (Panel C, see Equation 4.4). See text for detailed explanation.

To account for these characteristics, we first recognize that when individuals update their choices over *t* time steps, on each time step, the probability of sampling an individual holding a superior option will be equal to the proportion of such individuals on the previous time step. Therefore, we can embed Equation 4.1 in a recursive process described by the following equation:

$$ps_{t+1} = CJT(n, ps_t) \tag{4.2}$$

The same process can be modeled with the more abstract parameter specifying strength of conformity as used in previous studies. For instance, Boyd and Richerson (1985); Eriksson and Coultas (2009); Henrich and Boyd (1998); Nakahashi (2007) fixed sample size to an arbitrary level [3] but used parameter D to determine how much an individual would rely on the majority opinion. To allow for the comparison of our model with models in the literature we implementing this parameter by calculating CJT as:

$$SC = ps_t * (1 - D) + D * (CJT(fixed_n, ps_t)) \tag{4.3}$$

We explore three values of parameter D[4]: 0 (no conformity), 0.5 (weak conformity), and 1 (strong conformity) and assume that the sample size n is 9.

Another common way of modeling conformity is by the parameter a (Nakahashi, 2007; Nakahashi et al., 2012) using the following equation:

$$ps_{t+1,a} = ps_t^a / (ps_t^a + (1 - ps_t)^a) \tag{4.4}$$

We find values of a that match the sample sizes and parameter values of D studied above.

Several other implementations of strength of conformity exist in the literature, how-

[3] Often to n=3 or n=10.
[4] As in Henrich and Boyd (1998).

ever, differences typically stem from efforts to simplify mathematical calculations rather than to model different phenomena. Therefore, we restrict attention to two of the most widely studied implementations.

By calculating the expected accuracy of copy-the-majority under the sampling assumption (Equation 4.1) and the conformity parameter implementations (Equation 4.3 and 4.4), it is easy to show that sample size can mimic different levels of strength of conformity modeled by the parameter D (Henrich & Boyd, 1998). More specifically, assuming a fixed sample size of 9 in the conformity parameter implementation, it turns out that a parameter of $D = 0$ corresponds to taking a sample of size 1, a value of $D = 0.5$ to a sample of size 3 and a value of $D = 1$ to a sample of size 9 [5].

Specifying the sampling processes underlying social learning provides further insights into other phenomena related to conformism. For instance, one can model anti-conformity (i.e., contrarian behavior) as a social learning strategy that consists of the same search and stop rules but instead of copying the majority, it selects the minority option. In other words, anti-conformity (i.e., $a < 0$ or parameter M (see appendix in Efferson et al. (2008))) would correspond to the copy-the-minority strategy using the same sample sizes (see Appendix C for further details).

Our sampling account also shows that unlike conformity and anti-conformity, non-conformity (i.e., a tendency to copy the most frequent option with a probability less than the option's frequency but still higher than the frequency of the alternative option) cannot be explained purely by social learning strategies relying on samples of different sizes. Instead, as shown in Appendix B, curves produced with $D[-1,0)$ or $1 > a > 0$ (i.e., non-conformity) suggest a behavior that is a combination of social and individual learning. A parameter-based implementation of conformity would not have allowed us to draw this insight. It is also important to note that majority rules with higher or lower thresholds can produce curves that are in some regions consistent with anti-conformity and in other

[5] Negative values of D in the region [-1,0) imply anti-conformity and would correspond to the *copy-the-minority* strategy using the same sample sizes.

regions with non-conformity (see Appendix B). This means that it is difficult to draw clear conclusions about the type of conformity observed from data points alone, since the same strategy can be consistent with different forms of conformity (see also Efferson et al. (2008) who showed that data points from Asch (1956), which were originally interpreted as conformity, can be consistent with multiple behaviors).

Having demonstrated that sample size (as determined by the stopping rule) leads to different strengths of conformity, we first proceed to analyzing the performance of *copy-the-majority* using different sample sizes and second, provide intuition for the results both analytically and by using practical examples.

4.3 Study 1: Small Samples Increase the Likelihood of Identifying the Superior Option

We consider a population of individuals repeatedly choosing between two options A and B, where option A has a better long-run payoff than B. To illustrate, farmers might decide whether to plant hybrid corn or traditional corn or villagers might decide whether or not to boil drinking water (E. M. Rogers, 2010; Ryan & Gross, 1943; Wellin, 1955). While option A may be superior to B in the long-run, due to environmental fluctuation, A might produce positive outcomes for some individuals but negative outcomes for some others. Therefore, different individuals might experience different levels of success with an innovation. In our model individuals take a random sample from the population, observe the previous choices, but not the payoffs of others in their sample, and try out the option used by the majority in their sample. The payoff experienced by trying out an option is independently determined for each individual to capture individual differences in success with an innovation. If the selected option produces a higher payoff than the one they were using before, they switch to the novel option, otherwise they keep the option they were using previously. If the two options produce equal (indistinguishable) payoffs, the decision is made randomly. Therefore, learning in this context takes place by selective retention of options that produce good outcomes. In this framework, repeated social learning can be represented by a recursive function that involves iterating copy-the-majority for t time steps and updating the proportion of the population with the superior option after each time step (see Appendix for how to derive Equation 4.4):

$$ps_{t+1} = ps_t * (f + (1-f) * CJT(ps_t, n, i)) + (1 - ps_t) * f * CJT(ps_t, n, i) \tag{4.5}$$

...where CJT is the formula from Equation 4.1 and f is the level of environmental fluctuation, controlling the level of noise in feedback about payoffs. The parameter f determines how often the inferior option produces better payoffs than the superior option and vice-versa. When $f = 1$, the payoffs of the two options are constant, making them perfectly distinguishable (identical to the setting in Chapter 2). As f decreases towards 0.5 payoffs become more noisy, eventually making the two options indistinguishable when $f = 0.5$.

Before proceeding, two clarifications are in order. Majority is typically defined using a threshold of 50% of the population (simple majority), although empirical studies have shown that people often require higher thresholds to conform (T. J. H. Morgan & Laland, 2012). Using higher thresholds do not change any of the results, therefore, we do not report them here. Furthermore, note that the use of the binomial distribution to model sampling assumes an infinitely large population. However, in reality the population is bounded and is often small (e.g. a small community). This is important for the following reason: in social learning the sampling of models takes place without replacement, however, the binomial distribution assumes sampling without replacement. This assumption does not matter when the population is infinitely large, however, it does when the population is small. A more appropriate distribution for modeling the probability of the majority choice being correct in small populations is the hyper-geometric distribution (Tideman & Plassmann, 2013). However, the binomial distribution is often used in theoretical treatment of voting issues, because of simplified computations (Grofman et al., 1983; King & Cowlishaw, 2007). All our results hold when we assume small population sizes (e.g. $n = 100$). We very this by implementing our model as an agent-based simulation. Result are identical to the analytical calculations reported in this chapter.

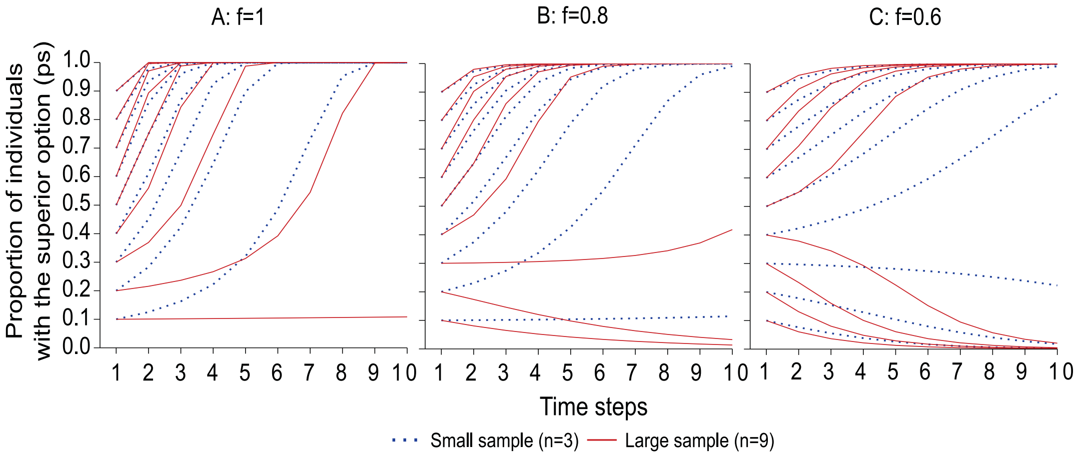

Figure 4.2: **Proportion of individuals with the superior option in the population (ps)** on each time step (x axis), for different initial levels of ps (y axis), for small and large samples (blue dotted and solid red lines), for different levels of environmental fluctuation f, panel **A**: f=1; panel **B**: f=0.8; panel **C**: f=0.6. In this cumulative social learning setting, individuals using copy-the-majority can find the superior option even if initial ps is smaller than 0.5. Small samples perform much better than large samples when ps is smaller than 0.5, but have only a small disadvantage when ps is larger than 0.5.

In separate scenarios we varied the proportion of individuals with the superior option (ps) on the first time step and iterated the social learning process for $t = 10$ time steps. These scenarios correspond to cases where an innovation appears in the population and a certain proportion of individuals have already adopted it. We investigated how the size of samples that individuals take randomly from the population on each time step affects the performance of copy-the-majority in these different scenarios. We focused on two sample sizes: small ($n = 3$) and large ($n = 9$), but other sample sizes (both odd and even) produce the same pattern of results. Results show that in this setting the prevalence of the superior option in a population can increase even when its initial proportion is lower than 0.5 on the first time step (Figure 4.2). In addition, small samples have a great advantage over large samples when the proportion of agents with the superior option is in the range below 0.5, but have only a minor disadvantage over large samples when this proportion is above 0.5, regardless of the level of environmental fluctuation f (panels A-C).

To assess how much these results depend on the range of initial ps values, we plotted the average performance of populations using small and large samples for different ranges of initial ps and different levels of f (Figure 4.3). It is an empirical question which of these scenarios individuals encounter most frequently in reality. However, whenever the environment changes (e.g., a previously high-payoff option loses its value) or a novel option is introduced, a population will find itself in a situation where the superior alternative is in the minority (as in the examples of foraging and farming mentioned above or as in the previous chapters, (see also E. M. Rogers, 2010; Ryan & Gross, 1943; Wellin, 1955). Overall, when averaged over all time steps and across a broad range of values of initial ps ($0.1 - 0.9$), small samples have an advantage over large ones. However, even when the range of ps values is restricted to only those that favor large samples ($ps > 0.5$), there is no disadvantage of using small samples or the disadvantage is much smaller compared to their advantage in situations where ranges favoring small samples ($ps < 0.5$) are also included. This result implies that if a social learner is uncertain about the number of other individuals using the superior option (ps), taking smaller samples will increase the likelihood of identifying a majority that is using the superior option and, as a results, will more often lead to the option with the higher payoff.

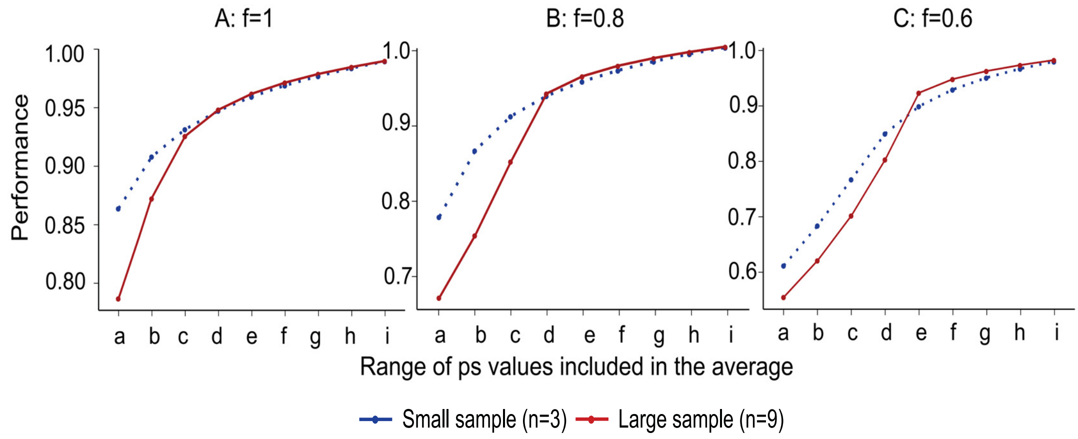

Figure 4.3: **Average performance of copy-the-majority (y axis) using small and large samples**, for different ranges of initial proportion of individuals with the superior option (ps) values (x axis) (a=[0.1-0.9], b=[0.2- 0.9], c=[0.3-0.9], d=[0.4-0.9], e=[0.5-0.9], f=[0.6-0.9], g=[0.7-0.9], h=[0.8-0.9], i=[0.9]). for different levels of environmental fluctuation f, panel **A**: f=1; panel **B**: f=0.8; panel **C**: f=0.6. When the full range of initial ps values is considered, average performance using small samples is much better than the performance using large samples. When only the range of initial ps values that favor large samples is considered (from ps>0.5), large samples perform better, but the relative difference between the two sample sizes is much smaller than when the full range of ps values is considered.

The basic intuition underlying our result is the following. Small samples have an advantage over large samples for three reasons, in particular when the superior option is used by only a minority in the population. First, when the superior option is in the minority (e.g., a new innovation was introduced or the environment has changed), smaller samples will include it as a majority more often than larger samples, due to sampling variability. This result can be derived from CJT. To illustrate, consider a situation in Figure 4.1 where *ps* is only 0.3. Taking a smaller sample and choosing the majority option in the sample will more often lead to the inference that this option is in the majority compared to taking larger samples. In Equation 4.1, this is reflected by the cumulative probability of sampling a majority of superior instances. This probability is larger for smaller samples as long as ps_t is smaller than 0.5. Consequently, ps_{t+1} will grow faster for smaller samples when the superior option is rare.

Second, compared to large samples, small samples require fewer agents with the superior option in order to reach a majority decision in favor of the superior option. Therefore, in a finite population, smaller samples can reach a decision in favor of a novel option sooner compared to larger samples. To illustrate, note that a sample size of three requires only two instances of the superior option to reach a majority decision in favor of the superior option, whereas a sample size of nine requires five such instances. As a consequence, if only two individuals in the population have the superior option, an individual using a sample size of three might be able by chance to have both of those individuals in her sample and make a decision in favor of the superior option. Yet an individual using a sample size of nine will have to wait for a few time steps until there are at least five individuals using the superior option. In Equation 4.2, this means that the term ps_t will not increase at all for individuals using large samples until a sufficient number of individuals have adopted the innovation in the population and they reach the majority in at least one of the samples. During the same time, ps_t will have a chance to grow for individuals using small samples.

Third, the benefit provided by large samples when the superior option is in the majority is smaller than the benefit provided by small samples when the superior option is in the minority (Figures 4.2 and 4.3). This is because the proportion of group members who still do not have the superior option is smaller when the superior option is in the majority than when the superior option is in the minority. In Equation 4.1, this is reflected in the second term $(1 - ps_t)$, which is larger for $ps_t < 0.5$, when smaller samples have an advantage, than for $ps_t > 0.5$, when larger samples have an advantage. To illustrate, when the proportion of individuals with the superior option is 0.2, the remaining 0.8 can still learn the superior option and improvement in the overall ps can be substantial. In contrast, when the proportion of individuals with the superior option is 0.8, only 0.2 of the population can learn the superior option. This provides an overall advantage for small samples across different initial proportions of individuals with the superior option. So far we have been assuming that all individuals are equally likely to sample all other individuals in the population. This assumption corresponds to an unstructured population where each individual is equally likely to communicate with all others. In most real-life social environments, however, individuals tend to form clusters and communicate within those clusters. Individuals within the same cluster tend to share similar information (making their beliefs correlated) and hold similar beliefs (e.g., due to homophily). In these environments, individuals do not sample randomly from the population; their samples are biased toward those in their immediate social environment. The next section explores the generality of our findings in more realistic social environments.

4.4 Study 2: Small Samples Perform Better Even in Clustered Environments

In a simple agent-based model, we simulated a population of N=100 agents facing the same task as described in Study 1 (implementing Study 1 as an agent-based model produces identical results to the analytical calculations described above), but instead of assuming an unstructured group (i.e. a fully connected network, as before), we modeled the connections between agents with a linear network characterized by a large number of clusters (clustering coefficient=0.67) and long distances between agents from different clusters (average path length=5.5). Other network structures such as small-world networks (Watts & Strogatz, 1998) produce the same pattern of results. In our model each agent is connected to 10 other agents, from which they sample either $n = 3$ (small) or $n = 9$ (large) agents. We iterate the process for $t = 10$ time steps and record the frequency of the superior option in the population after the agents had made their decisions on each time step. Figure 4.4 shows the proportion of agents with the superior option on each time step for different conditions of ps, and f averaged over $1,000$ replications. The main results from Study 1 are replicated. The relative difference between small and large samples is even more pronounced in clustered environments, where small samples reach a higher accuracy even when $ps = 0.5$.

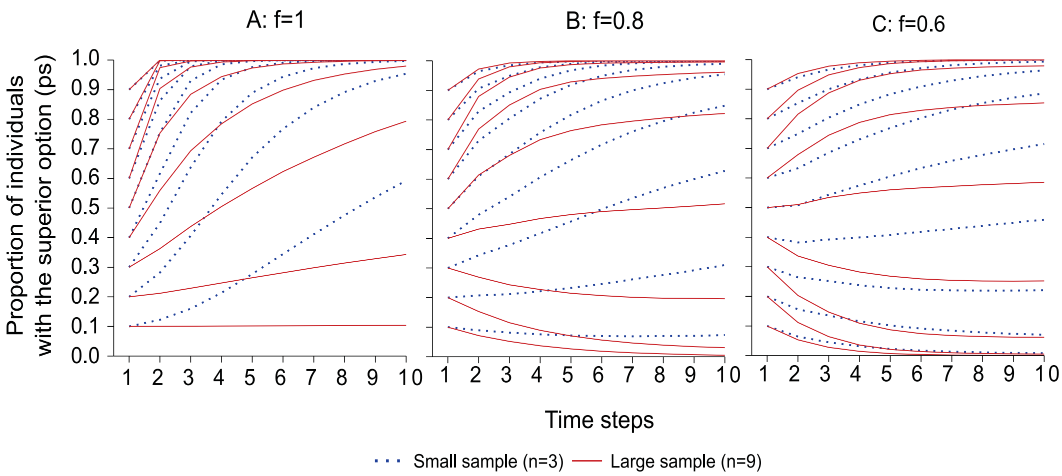

Figure 4.4: **Proportion of individuals with the superior option in the population (ps)** on each time step, for different initial levels of ps, for small and large samples, for different levels of environmental fluctuation f, panel **A**: f=1; panel **B**: f=0.8; panel **C**: f=0.6, assuming a clustered population. The pattern of results is similar to that of the unstructured population shown in Figure 4.2., except that small samples are better than large samples even for ps=.5.

The intuition underlying this result is that information within clusters might not be representative of the whole population. To illustrate, consider a population where the overall proportion of a superior option is $ps = 0.5$, but some clusters have $ps = 0.4$, while other clusters have $ps = 0.6$. Agents using smaller samples in clusters where $ps = 0.4$ will be more likely to infer that the less frequent (but superior) option is in the majority and will spread this option within the cluster. This in turn will promote spread of this option throughout the population (see also Kreindler & Young, 2014, for other contexts where clusters have been found to spread rare information). In contrast, agents using larger samples will be less likely to detect this novel useful option in clusters where it is in the minority.

4.5 Summary and Discussion

4.5.1 Summary

In this chapter we systematically investigated the influence of sample size on the spread of a novel option in a population over time. We focused on cases where a novel option requires reinforcement from a majority of peers in order to spread, a form of complex contagion (Centola & Macy, 2007). We showed that contrary to what might be expected based on the prevailing wisdom that more is better, relying on the majority option in smaller as opposed to larger samples improves both individual and population-level performance. This pattern of results holds under different levels of noise in feedback and in different social structures.

Our sampling account of strength of conformity allowed us to explain these results both analytically as well as by using simple intuitive examples. First, due to sampling variability, smaller samples are more likely to include a majority of superior options in the sample when the superior option is in the minority overall in the population. Second, smaller samples need fewer instances of the superior option in order for the superior option to be in the majority. Third, smaller samples lead to larger improvements when the proportion of individuals with the superior option is small and, therefore, leads to larger population level gains compared to when most individuals are using the superior solution.

4.5.2 Exploration vs. exploitation

The trade-off between exploration and exploitation is central to most adaptive problems (Hills et al., 2015; March, 1991). In the context of social learning, a key barrier to adaptation in changing environments in the lack of exploration (i.e., innovation) in the population (Whitehead & Richerson, 2009). Our results demonstrate a novel source through which innovation can be introduced in the population: sampling variability highlighting rare, but useful information. We believe this effect has not been studied previously and has potential implications for understanding the sources through which novelty is introduced in social groups.

4.5.3 Threshold models

In the study of innovation diffusion, an agentâĂŹs propensity to adopt (or not) an innovation has been linked to a threshold value that specifies how many other individuals the agent should observe exhibiting the innovation before deciding to adopt (Granovetter, 1978; Henrich, 2001). For example, an agent might adopt an innovation after observing one other individual, or might require 50 out of a total of 100 other individuals. We point out that sampling variability can significantly alter the results obtained from pure threshold models. Specifically, an individual with a high threshold value (e.g., not adopting until 50% of the population has adopted) will adopt earlier, given that variability in small samples will more often indicate 50% adoption rate in one's sample compared to its true population frequency.

4.5.4 Bet hedging

We showed that small samples can be robust in situations where individuals face varying circumstances or are uncertain about the frequency of the superior option in the population. One can argue that the optimal sample size still depends on whether this frequency is above or below 0.5. This would require that individuals accurately identify each situation they face and then apply the optimal behavior. However, in uncertain environments where the optimal behavior is difficult or impossible to determine, evolution should favor decision rules that perform well in most situations (McNamara & Houston, 2009). We showed that using small samples when they are not optimal results in much less harm than using large samples when they are not optimal, therefore, small samples minimize variance in payoffs. This is often referred to as bet hedging (Olofsson, Ripa, & Jonzén, 2009).

4.5.5 Why people conform

Several explanations exist for why people tend to conform to the behavior of others. Some suggest that conformity is an important element of human nature and have demonstrated people's tendency to conform in experimental settings (Asch, 1956; Bond, 2005; Cialdini & Goldstein, 2004). Here conformity is interpreted as a motivational goal to be like others and is often referred to as normative conformity. Individuals might also conform to others in order to coordinate or maintain cohesion within a group (Conradt & Roper, 2005). Other explanations, focusing on whether conformity can lead to accurate decisions have shown that it can be adaptive and can evolve in a wide range of situations (Claidière & Whiten, 2012; Henrich & Boyd, 1998; Wakano & Aoki, 2007). This is often referred to as informational conformity. Note that some of these explanations imply that people might also conform in situations where it is not the most adaptive strategy.

4.5.6 Conformity versus other strategies

In our study a *copy-the-successful* or a *random copying* strategy both have regions where they can perform better than *copy-the-majority*. In situations where innovations are treated as discrete options and are adopted in exactly the same way by each individual, copying a single random individual will lead to even better overall performance than copy-the-majority. However, in real life situations, innovations are unlikely to be adopted in exactly the same way. Consider adopting a novel crop. Even if the same seeds were planted, the soil and the weather conditions might differ, resulting in different payoffs (Diamond, 2005). In the present study we modeled this as environmental fluctuation, however, a more realistic way would be to model the success of adopting the innovation as being a function of several interacting aspects (e.g., crop, soil, weather, farming method). For the sake of simplicity and transparency we did not model this in the present study.

Another reason why copying the most successful individuals might perform worse than copy the majority is that it requires the ability to observe payoffs of other agents with sufficient accuracy. Even if payoffs were observable, such a copy-the-successful strategy could loose its advantage over copy-the-majority, whenever the payoff generating mechanism is dominated by noise, luck, context or other factors that make inferring success from behaviour difficult (Denrell & Liu, 2012; McElreath et al., 2013).

4.5.7 Sample size, conformity parameters and other strategies

Our results imply that the smaller the sample, the better an individual using the majority rule will perform, with the smallest possible sample being three individuals for an individual following the majority. It is useful to ask how this sample size corresponds to the best conformity parameter values found in the literature. Given that the best parameter values depend on the exact modeling details, we do not survey all studies here but only provide an illustration. For example, Henrich (2001) finds that the best conformity parameter (implemented similarly to D in this paper) should be smaller or equal to 0.5. As we have seen a value of 0.5 would correspond to a sample size of 3. In another study, McElreath et al. (2008) using an implementation similar to a in this paper find that a value of 1.953 provides the best fit to experimental data. In our sampling account this would correspond to a sample size of approximately 5. Finally, a recent experimental study found evidence for larger group sizes leading to stronger levels of conformity (Muthukrishna, Morgan, & Henrich, in press). This is in line with our predictions, however, note that our model implies that stronger levels of conformity in larger groups does not have to be a result of a stable individual trait or a situation specific decision. Instead, stronger levels of conformity can simply be a result of the sample size (or group size) individuals are exposed to. T. Morgan, Rendell, Ehn, Hoppitt, and Laland (2011) found that participants were more likely to choose social over asocial information when social information was presented by larger number of demonstrators. However, when social and asocial information were presented simultaneously, number of demonstrators did not affect participants' willingness to follow social information. In the latter condition, social information was revealed while in the former it was not. As these experiments manipulated several variables simultaneously, including visibility of social information at the time of choice, task difficulty, participants' experience and confidence, further research is needed to determine how number of demonstrators affect people's willingness to copy the majority.

A recent study by Perreault et al. (2012) investigated how different sample sizes impact the performance of social learning. As expected by the present account, the authors found that small samples sometimes have an advantage over larger samples, but they interpreted such situations as an artifact of their particular model specification. Their model differs in several ways from the present demonstration, in particular because they investigated a combination of odd and even sample sizes (1, 3, 8, and 16). As even sample sizes can include ties (i.e., situations when both options are equally frequent in the sample), the final results will depend on the frequency of ties and the way they are resolved. We believe that the advantage of small samples would be even stronger in that study if the sample sizes were either all odd or all even.

Note that small sample sizes do not have the same beneficial effect for other strategies. The success of copying a single random person from oneâĂŹs (random) sample will not be affected by the sample size, any sample size will produce the same accuracy. In the case of copying the most successful individual, however, larger samples would be beneficial because they would maximize the chance of spotting the best individual, assuming that the payoffs can be observed without error.

4.5.8 Positive versus negative outcomes

Our analysis focused on situations where the adoption of an alternative option was more likely to lead to positive than negative outcomes ($f > 0.5$), making that option superior. What if instead the alternative (initially minority) option could produce severe negative outcomes, for example in the case of adopting a dangerous novel practice? This would be the mirror image of the situation we modeled, with the superior option replacing the inferior option and vice versa. As a consequence all of reported results would remain the same.

We do not, however, model extreme environments where feedback is non-existent or extremely delayed and misleading (Hogarth, 2001). In such settings, social learning in general is not adaptive and can lead to the spread of inferior options (Tanaka, Kendal, & Laland, 2009). However, small samples would help a population recover faster from such a state whenever new, beneficial information enters the population.

4.5.9 More than two choice options

We assumed that populations choose between two available alternatives favored by different proportions of individuals and make simultaneous decisions on each time step (in order to avoid possible sequence effects that might lead to information cascades (Bikhchandani et al., 1992)). This scenario corresponds to the diffusion of innovations and standard population-genetic models of cultural evolution (Boyd & Richerson, 1985; Cavalli-Sforza & Feldman, 1981; E. M. Rogers, 2010). There are good reasons to believe that this task reflects many real-life situations. First, ranking of several options can be represented as a series of pairwise comparisons. Also, since the majority rule has the property of creating homogeneous groups (Boyd & Richerson, 1985; Henrich & Boyd, 1998), it is likely that over time most of the alternatives will be selected out of the population, leading to a competition between two of the most popular alternatives. The competition of relatively few choice options is reflected in the power-law distribution of various cultural products such as first names, baby names, dog breeds or scientific citations (Bentley et al., 2004; H. A. Herzog, Bentley, & Hahn, 2004; Mesoudi & Lycett, 2009; Price, 1976; Simkin & Roychowdhury, 2007; Simon, 1955). Even when there are several options available, most will be used by a small fraction of the population, having little impact on collective dynamics. However, our model can be straightforwardly extended to more than two choice options by using the multinomial distribution (see (List & Goodin, 2001)). As we have seen *CJT* predicts better performance for large samples for $ps > 0.5$ and worse performance for $ps < 0.5$. The predictions would also hold for an n option case where $n > 2$, where one would simply need to change the cut-off point. To illustrate, in the $n = 2$ option case the cut-off point is $1/n = 0.5$, similarly for an $n = 3$ option case it would be $1/n = 0.3$.

4.5.10 Small samples in other domains

Small samples have also been found to be beneficial both in the assessment of the expected values and prevalence of risks (Hertwig & Pleskac, 2010; Pachur, Hertwig, & Rieskamp, 2013), as well as in the early detection of correlations in the environment (Fiedler & Kareev, 2006). A common criticism against the latter studies is that when one considers not only the number of hits but also the false alarms in a signal detection analysis, the advantage of small samples largely disappears (R. B. Anderson, Doherty, Berg, & Friedrich, 2005; Juslin & Olsson, 2005). These criticisms do not apply to our study since our accuracy criterion (proportion of individuals with the superior option) does not map onto a criterion used for detection tasks. However, the table in the Appendix B allows us to categorize each scenario as hit (choosing the superior option), miss (selecting but not choosing the superior option), correct rejection (not choosing the inferior option) and false alarm (choosing the inferior option). Calculating each reveals that small samples score better on all four criteria (calculations are available from the authors).

4.5.11 Wisdom of crowds

We build onto the growing body of work within the wisdom of the crowds demonstrating the advantage of small group sizes on decision accuracy (Goldstein, McAfee, & Suri, 2014; Kao & Couzin, 2014; Mannes, Soll, & Larrick, 2014; Spiekermann & Goodin, 2012), however, our model is different from these studies in a number of respects. First we assume repeated social learning and track the frequency of adaptive behavior in the population over time rather than focusing on average performance from one-shot decisions. Second we model social learning of individual level decisions rather than the social aggregation of individual estimates. These are important differences, because repeated social learning creates a feedback loop in the learning process which is not present in these other studies, and because our performance measure is not affected by the benefit of error cancellation gained from pooling estimates as in these other studies. As a consequence, our findings are driven by different underlying mechanisms. To the best of our knowledge, our study is the first to demonstrate the advantage of small samples in repeated social learning settings. We believe that exploring the similarities and differences between the wisdom of crowds in one-shot and repeated social learning tasks is a fruitful direction for future work.

4.5.12 Heterogeneous populations

We assumed that all agents in the population have the same tendency to conform. Populations, however, consist of both conformist and anti-conformists (Efferson et al., 2008; Kendal, Giraldeau, & Laland, 2009). Further simulations (see Appendix C for details) revealed that assuming a mixed population of conformists and anti-conformists does not change our main results and, in fact, can be beneficial for *copy-the-majority* using small samples but harmful for large samples.

4.5.13 Conclusion

Our goal in this chapter was to systematically investigate how sample size affects the performance of the *copy-the-majority* strategy and to explain more precisely why we found an advantage for small samples in the previous chapters.

Our results suggest that individuals can vary in their level of conformity purely as a result of the samples they take from their social environments. In addition, small samples can be robust to varying environmental scenarios and, therefore, individuals who are uncertain about the payoff of an option and use the majority rule to decide will fare best by consulting only a few others. The sampling variability resulting from taking small samples can be beneficial by highlighting information that is not salient in the population. Our model also demonstrates how strikingly different behavioral patterns can emerge from individuals using the same strategy but only differing in the amount of information they sample. Overall, our results echo the findings in the literature about the benefit of weak conformity, however, following the suggestion of Henrich (2001) of building psychologically plausible models of social learning strategies, we show how strength of conformity can arise as a byproduct of information sampling without invoking an abstract parameter. These findings have practical implications for understanding the time-course and circumstances under which novel behaviors spread in social groups and the strategies underlying individual decisions to adopt novel practices in human societies.

So far we have been focusing on repeated social learning settings, where individuals constantly learn from their environment and make decisions, thus creating a feedback loop between information available for sampling and the decisions they make. Another set of representative environments in which social learning takes place are one-shot decision environments, where individuals or groups make a single decision by using the information available at a single time point. The following two chapters focus on social learning in one-shot as opposed to repeated settings.

Chapter 5

Wisdom of Randomly Assembled Small Crowds

This chapter is based on Galesic, M., Barkoczi, D. & Katsikopoulos, K. (2015). Wisdom of randomly assembled small crowds. *Under review*

5.1 Introduction

The previous chapter analyzed the dynamics of *copy-the-majority* in repeated settings such as in the case of innovation diffusion. In this chapter we recognize that this same strategy (i.e., majority voting) is also used in many one-shot decision situations, including political voting, committee decisions and group meetings. In a wide range of context the groups in which people rely on majority voting are relatively small. For example, jury sizes in many countries range from six to 15 people who most often decide by simple majority (Leib, 2007). Local town and parish councils such as those in the United Kingdom and Australia consist of five to around 30 members (Electoral Council of Australia and New Zealand, 2013; UK Department of Communities and Local Government, 2008), governing bodies of most German labor unions have from three to 35 members (Dejure.org, 2013), parliamentary committees in the United States, the European Union, Australia, and other countries have on average 20 to 40 members (European Parliament, 2014; Parliament of Australia, 2014; Peterson, 2013), subcommittees in the U.S. House and Senate consist of on average 10 to 15 people (Peterson, 2013), and policy boards of most central banks have up to 12 members (Lybek & Morris, 2004). Similarly, individuals considering a variety of decisions typically rely on six or fewer close friends (Galesic et al., 2012) and read about five and rarely more than 30 online reviews before deciding whether to trust a business (M. Anderson, 2014). Deciding in moderately-sized groups can be observed in other species throughout the animal kingdom (Krause & Ruxton, 2002).

In many cases, deciding by group vote rather than relying on a single decision maker can in many cases boost overall decision accuracy. It is typically argued that group wisdom increases with its size (Condorcet, 1972; Galton, 1907; Surowiecki, 2005), and technological advances make meeting and communication in larger groups easier than ever before (e.g., various social networking sites; LiquidFeedback (2014)). Why, then, do most committees remain moderately sized, and why do most people consult only a limited number of others' opinions? Existing explanations focus on time and coordination costs or on cognitive limitations that prevent stable relationships with a large number of individuals (Dunbar, 1993). We complement these explanations with an argument for the superiority of moderate group sizes based solely on group decision accuracy. We show that in many realistic decision environments, where groups occasionally face situations with unexpected outcomes, average decision accuracy peaks when voting is done by moderately sized groups. This does not occur because of selective sampling of group members based on expertise (Budescu & Chen, 2014; Goldstein et al., 2014; Mannes et al., 2014) but solely because the accuracy of groups deciding by simple majority or plurality rules increases with their size for relatively easy tasks but decreases for tasks for which most individuals make the wrong prediction. Thus, averaged across the range of difficulties often encountered in real life, accuracy is highest for moderately sized groups. These results challenge the basic prediction of Condorcet Jury Theorem (see Figure 4.1) that claims that whenever individuals are more accurate than chance ($ps > 0.5$) larger groups should perform better.

For examples of tasks with unexpected outcomes, consider election forecasts. Forecasters on average often show better-than-chance prediction accuracy, but a few election years have been difficult to predict. Such as the U.K. 2015 general election, where all but one polling company erroneously predicted that Tories would not win a majority of seats in the Parliament (Bialik, 2015). Similarly, majority of forecasters in the U.S. 2000 presidential elections predicted Gore's victory over Bush in Florida (Graefe, 2014; Whitson, 2014). As illustrated in more detail later on, tasks with unexpected outcomes that are difficult to predict can be found in many other domains, including economic forecasts, medical diagnoses, and general knowledge items. Consider the knowledge question "Which city if further north, New York or Rome?", which most people answer incorrectly. Temperature, the cue that is valid for most other comparisons of city latitudes, points to the wrong answer for this pair of cities (Gigerenzer, Hoffrage, & Kleinbölting, 1991). Note that in all of the above examples the majority of individuals can be wrong, resulting in average individual accuracy below 50% on those particular tasks. This can happen because these tasks are characterized by the so called Brunswikian uncertainty Juslin and Olsson (1997) that occurs because of imperfect correlations of environmental cues and the actual states of the world they are used to predict.

If most people rely on the sames cues to make inferences, cases where a cue is misleading can create situations where a majority of people are incorrect. However, even when individuals rely on different cues, these cues could all fail to predict the correct outcome for some specific tasks; either because the usual cues are not suited for predicting some particular cases or because the environment has changed between the moment of prediction and the moment when the outcome was observed. For instance, most diseases might be accurately diagnosed based on their symptoms, but some less well-known or rare diseases have symptoms that easily point to the wrong direction; similarly, forecasts of economic growth may prove to be wrong in some years because of unobservable underlying complexities affecting the financial markets. In what follows, we will call tasks with surprising outcomes that more people predict incorrectly "difficult", and those that most people predict correctly "easy".

5.2 Solving tasks of varying difficulty

Most committees will face a variety of task difficulties in the course of their existence, ranging from very easy to quite difficult. However, most past studies have assumed that groups always encounter tasks of the *same* and *known* difficulty (but see Grofman, Feld, & Owen, 1984, for an exception). Once task difficulty is known, it is easy to tell what the best group size should be to maximize accuracy. In principle, for easy tasks, in which average individual accuracy of group members (average individual probability of being correct) is larger than 0.5, majority vote in larger groups will be more accurate than in smaller groups, and vice versa for difficult tasks (Condorcet, 1972). However, in most real-life situations we cannot know in advance how difficult any particular task will be.

All we might know is an approximate distribution of task difficulties, for instance, that some tasks might be difficult and some quite easy. We also may know an approximate ratio of easy and difficult tasks. With these assumptions in mind we proceed to analyzing how the assumed distribution of task difficulties affects accuracy of groups of different sizes.

To study how group accuracy depends on group size when a task involves making a choice between two options using a simple majority rule, we can use the Condorcet Jury Theorem (CJT), just as in the previous chapter, which can be represented as

$$P_n = \sum_{i=m}^{n} \binom{n}{i} \hat{p}^i (1-\hat{p})^{n-i} \tag{5.1}$$

where P_n is group accuracy at group size n, m is size of simple majority, and $\hat{p}$ is average individual accuracy. Without loss of generality, n is assumed to be always odd. Individual group members can have heterogeneous skills. As long as the distribution of individual skills is symmetrical, CJT predictions remain essentially the same as if all individuals had the same skill level (Grofman et al., 1983). Deviations occur in some exceptional cases, for instance, when some individuals consistently have accuracy 0 or 1 or when average accuracy is close to 0.5 and groups are very small. With increase in n, group accuracy P monotonically increases to 1 for tasks with average individual accuracies 0.5 and monotonically decreases to 0 for tasks with $\hat{p} < 0.5$. When average of individual accuracies $\hat{p} = 0.5$, P will converge to a value between 0.39 and 0.61 (Owen, Grofman, & Feld, 1989). In other words, CJT predictions generalize to a large range of asymmetrical distributions of individual skills (Grofman et al., 1983).

For simplicity, we first focus on tasks involving two options between which groups choose by simple majority rule. We then analyze group accuracy for different combinations of task difficulties. We assume that individual group members have symmetrically distributed or identical skills and that they vote independently and investigate the effects of correlated votes in the last section. We assume that groups encounter two types of task difficulties: With probability e they encounter easy (denoted E) tasks, for which average individual accuracy $\hat{p}_E > 0.5$; and with probability $1-e$ they encounter difficult (denoted D) tasks, for which average individual accuracy $\hat{p}_D < 0.5$. The reader might wonder how average individual accuracy can be lower than 0.5 on difficult tasks. To illustrate this, consider situations where individuals are misinformed, for example, when all cues point toward a candidate who is very likely to win an election, but it turns out that the other candidate won. Such situations can occur in many cases that involve prediction, including political and economic forecasts or sports predictions. We illustrate such situations in the section 5.3.

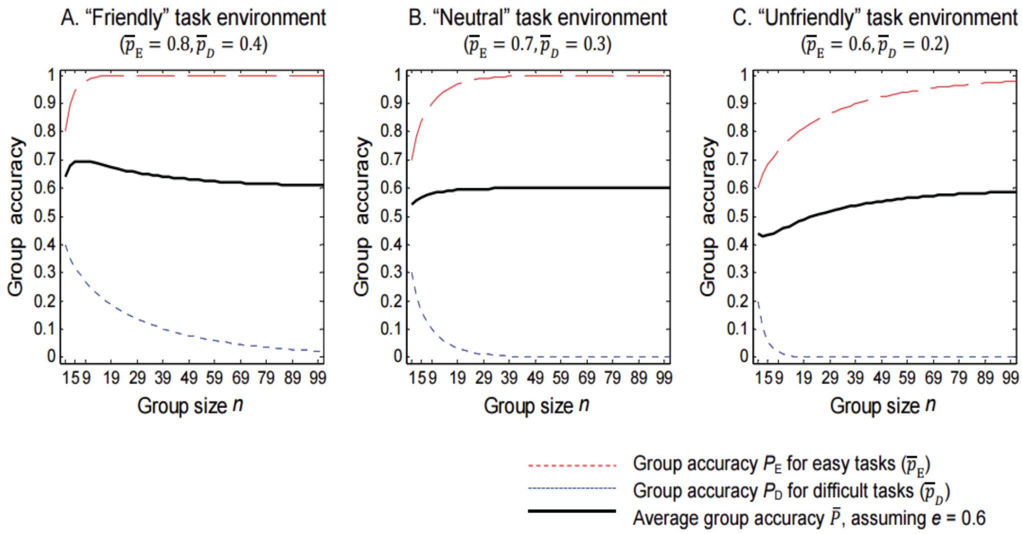

Figure 5.1: **Average group accuracy can peak at moderate group sizes.** Illustration of changes in group accuracy as a function of group size n and different combinations of task difficulties, assuming proportion of easy tasks $e = 0.6$. Note that as n increases, average group accuracy $\hat{P}$ converges to e. **A** In a "friendly" task environment ($\hat{p}_E + \hat{p}_D > 1$), $\hat{P}$ increases until $n = 7$, then decreases toward e. **B** In a "neutral" task environment ($\hat{p}_E + \hat{p}_D = 1$), $\hat{P}$ increases monotonically with n until it reaches e. **C** In an "unfriendly" task environment ($\hat{p}_E + \hat{p}_D < 1$), $\hat{P}$ decreases until $n = 3$, then increases toward $e = 0.6$ even though $\hat{P}_{n=1} < 0.5$.

Figure 5.1 shows how average group accuracy $\hat{P}$ across the two types of tasks changes with increase in group size n, assuming that the proportion of easy tasks is

$e = 0.6$. Following the Condorcet jury theorem (CJT), for easy tasks group accuracy P_E is larger than $\hat{p}_E$ and increases monotonically to 1 as groups get larger (red dashed lines in Figure 5.1). For difficult tasks, $P_D < \hat{p}_D$ and decreases monotonically to 0 with increase in group size (blue dotted lines). Importantly, simple CJT based on average individual accuracy $\hat{p}$ cannot be used to predict average group accuracy $\hat{P}$ across both types of tasks (black solid lines in Figure 5.1). Rather, the average group accuracy $\hat{P}$ (full black lines) must be calculated as the average of group accuracies on easy and difficulty tasks, weighted by the proportion of each type of task that the group encounters:

$$\hat{P}_n = eP_{E,n} + (1-e)P_{D,n} \tag{5.2}$$

where $\hat{P}_n$ is the average accuracy of a group of size n, e is the proportion of easy tasks it encounters, and $P_{E,n}(P_{D,n})$ is the accuracy of a group of size n on easy (difficult) tasks derived by the CJT. It follows that with an increase in group size, $\hat{P}$ converges to the proportion of easy tasks e, rather than to 0 or 1 as would be predicted by the simple CJT (see also Grofman et al., 1984). This happens because for large enough n, P_E reaches 1 and P_D reaches 0, so $\hat{P}$ converges to $e*1+(1-e)*0 = e$. Note that for $n = 1$, $\hat{P}_{n-1} = e\hat{p}_E + (1-e)\hat{p}_D$, which is the average individual accuracy across easy and difficult tasks.

As Figure 5.1 illustrates, changes in $\hat{P}$ with changes in n depend on the type of environment. We define a "friendly" environment as one in which $\hat{p}_E + \hat{p}_D > 1$, a "neutral" environment as one in which $\hat{p}_E + \hat{p}_D = 1$, and an "unfriendly" environment as one in which $\hat{p}_E + \hat{p}_D < 1$. These definitions express whether it is the accuracy in easy tasks or the accuracy in difficult tasks that is further away from chance. For example, $\hat{p}_E + \hat{p}_D > 1$ is equivalent to $\hat{p}_E - 0.5 > 0.5 - \hat{p}_D$,which means that in friendly environments, the accuracy in easy tasks is above chance more than the accuracy in difficult tasks is below chance.

In all environments, $\hat{P}_n$ will start from $e\hat{p}_E + (1-e)\hat{p}_D$ for $n = 1$ and will eventually converge to e. In between these two extremes, $\hat{P}$ can be a monotonically increasing, monotonically decreasing, U-shaped, or inverted U-shaped function of n. Which of these shapes obtains is completely determined by three factors: the type of environment (friendly, neutral, or unfriendly) as defined precisely above, the value of the starting point of $\hat{P}_{n-1} = e\hat{p}_E + (1-e)\hat{p}_D$, and the relative frequency of easy and difficult tasks as measured by the ratio $\frac{1-e}{e}$. More precicely, the following holds as n increases to $n+2$ (the next odd group size):

$$\triangle \hat{P}_n \begin{cases} > 0 \; if \triangle P_{E,n} > \frac{1-e}{e} \triangle P_{D,n} \\ < 0 \; if \triangle P_{E,n} < \frac{1-e}{e} \triangle P_{D,n} \\ = 0 \; if \triangle P_{E,n} = \frac{1-e}{e} \triangle P_{D,n} \end{cases} \tag{5.3}$$

Where $\triangle\hat{P}_n = \hat{P}_{n+2} - \hat{P}_n$,$\triangle\hat{P}_E = P_{E,n+2} - P_{E,n}$, and $\triangle\hat{P}_D = P_{D,n+2} - P_{D,n}$.

This equation says that $\hat{P}$ increases as n increases to $n+2$ if the rate of change in accuracy on easy tasks $\triangle P_{E,n}$ is higher than the rate of change in accuracy on difficult tasks $\triangle P_{D,n}$, taking into account the relative prevalence of the tasks $\frac{1-e}{e}$. For example, if the environment is friendly, then the rate of change in accuracy on easy tasks is initially higher than the rate of change on difficult tasks because $\hat{p}_E - 0.5 > 0.5 - \hat{p}_D$. Now if additionally easy tasks are encountered more often, then $e > 0.5$ and thus $\frac{1-e}{e} < 1$, which means that this difference in rates of change is only magnified and $\hat{P}$ will definitely increase from n to $n+2$. On the other hand, if easy tasks are encountered less often, then $e < 0.5$ and thus $\frac{1-e}{e} > 1$, in which case it can be that $\hat{P}$ does not increase as n increases to $n+2$ even if the environment is friendly. But there is a catch. Notice that an initial increasing or decreasing trend in $\hat{P}$ may be reversed as n continues to increase exactly because the component $\hat{P}$,eP_E or $(1-e)P_D$, which initially changes faster, will also converge faster to its limiting value and then the other component will start changing faster. For example, if the environment is friendly then the component eP_E will initially increase faster than the component $(1-e)P_D$ decreases, but at some point, which depends on the value of e, this trend will be reversed, giving rise to an inverted-U-shaped curve. This is what happens in Figure 5.1A. In this friendly task environment, an increase in n initially leads to an increase in $\hat{P}$, here peaking at 0.7 for $n = 7$ before decreasing to e. Figure 5.1B shows a case of a neutral environment, where $\hat{P}$ increases monotonically with n until it reaches e. Finally, Figure5.1C shows a particularly interesting case that occurs in unfriendly environments. Here, a downward peak occurs, with $\hat{P}$ initially decreasing and then slowly increasing toward e. Note than in this case $\hat{P}$ will ultimately become larger than 0.5 (because $e = 0.6$) even though the average individual accuracy across the two types of tasks was lower than $0.5(\hat{P}_{n=1} = 0.44)$. This finding might be surprising, since the original CJT predicts that when $\hat{P}_{n=1} < 0.5$, with increase in n, group accuracy decreases to 0.

In sum, for $\hat{P}$ to profit from group size increase, the gain in group accuracy on easy tasks must be larger than the simultaneous loss in group accuracy on difficult tasks, weighted by the ratio of proportions of difficult and easy tasks. If an increase from n to $n+2$ leads to a gain in P_E that is larger than the weighted loss it produces in P_D, $\hat{P}$ will increase and otherwise decrease. It will reach its peak when the gains and weighted losses cancel each other. Solving Equation 5.3 analytically involves taking derivatives of the binomial cumulative distribution functions P_E and P_D with respect to n. This produces cumbersome solutions so approximations have been developed for large n (Grofman et al., 1983). To find solutions numerically and examine how group size relates to group accuracy for different combinations of easy ($0.6 \leq \hat{p}_E \leq 0.9$) and difficult ($0.1 \leq \hat{p}_D \leq 0.4$) tasks, separately for different proportions of easy tasks $0.1 \leq e \leq 0.9$, in increments of 0.1.

Figure 5.2 shows that non-monotonic changes in $\hat{P}$, such as those shown above in Figure 5.1, occur in half of all combinations of task difficulties we analyzed. Specifically, whenever the average individual accuracy across tasks starts from $\hat{P}_{n=1} > 0.5$ and the task environment is friendly (as defined above), $\hat{P}$ peaks at moderate group sizes from 3 to 43 members before it starts decreasing toward e. These results are reversed when $\hat{P}_{n=1} < 0.5$. Here, when the task environment is unfriendly, $\hat{P}$ reaches its minimum at moderate group sizes ($3 < n < 43$), and then increases toward e. An interesting implication of this result is that in unfriendly task environments, larger groups are often better, except in cases where $e < \hat{P}_{n=1}$, when relying on a single randomly selected group member might be best. This result adds to our understanding of the conditions under which it is better to increase group size or to follow the best individual in the group (Fifić & Gigerenzer, 2014; Katsikopoulos & King, 2010). Finally, when $\hat{P}_{n=1} = 0.5$, $\hat{P}$ will increase (decrease) monotonically to e in friendly (unfriendly) environments, and stay at 0.5 in neutral environments.

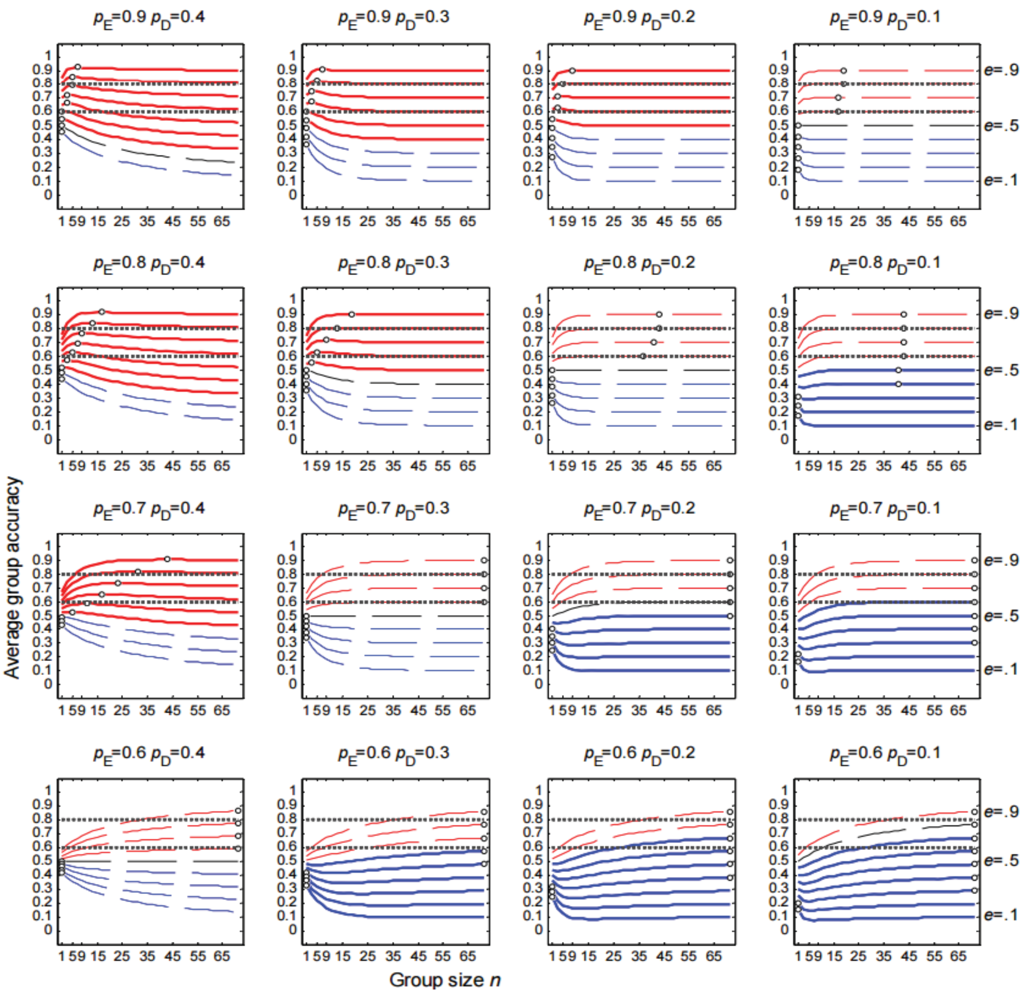

Figure 5.2: **Average group accuracy depends on combination of task difficulty and proportion of easy tasks.** Changes in average group accuracy $\hat{P}$ as a function of group size n, different combinations of easy ($0.6 \leq \hat{p}_E \leq 0.9$) and difficult ($0.1 \leq \hat{p}_D \leq 0.4$) tasks, and different proportions of easy tasks ($0.1 \leq e \leq 0.9$). Red lines represent cases in which average individual accuracy across tasks $\hat{P}_{n=1} > 0.5$, blue lines are for $\hat{P}_{n=1} < 0.5$, and black lines for $\hat{P}_{n=1} = 0.5$, where $\hat{P}_{n=1} = e\hat{p}_E + (1-e)\hat{p}_D$. Circles show maximum value of $\hat{P}$ for each case. Dashed lines denote cases where $\hat{P}$ changes monotonically with n until it reaches e, while solid lines denote cases where $\hat{P}$ changes nonmonotonically, that is, reaches an upward or a downward peak at moderate group size n before reaching e. In each panel, upper lines represent higher proportions of easy tasks e (see legend to the right of each row). Panels above the diagonal represent friendly task environments, those in the diagonal neutral, and those below the diagonal unfriendly task environments (see main text for details). Gray dotted lines denote region in which $0.6 \leq \hat{P}_{n=1} \leq 0.8$, as is commonly observed in real-world policy tasks (see section on real-world tasks)

This analysis can be extended to situations with more than two possible task difficulties and tasks with more than two options, as well as to groups whose members have correlated votes, say because of opinion leaders or shared information. In all of these cases it can be shown that groups with moderate sizes very often reach highest accuracy. We now turn to illustrating these situations.

5.2.1 Situations with more than two task difficulties

So far we have assumed, for simplicity, that a group faces only two types of tasks with difficulty $\hat{p}_E$ and $\hat{p}_D$. In real life, groups will face tasks of a wide range of difficulties. Average group accuracy across these tasks can be calculated by an extension of Equation 5.2:

$$\hat{P}_n = \frac{1}{T}\sum_{t=1}^{T} P_{t,n} \tag{5.4}$$

where T is the number of tasks, and P_t,n is group accuracy on a given task t at group size n, calculated using Equation 5.1.

5.2.2 Tasks with more than two options

What if tasks involve plurality choices between more than two options? CJT can be extended to these situations: Group accuracy will increase with n as long as the average individual is more likely to choose the correct option over any other option (List & Goodin, 2001). The probability that a group chooses the correct one of k options can be calculated as a multinomial probability of all k-tuples of individual votes for the k options for which the correct option is the plurality winner, given probabilities $p_1, p_2, ..., p_k$ that an average individual chooses each of the k options. Once group accuracies $P_{t,n}$ are calculated in this way for different tasks t and group sizes n, Equation 5.4 can be used to calculate average group accuracy. It is then easy to show that nonmonotonic changes in average group accuracy can occur in these situations, as well.

5.2.3 Effect of correlated votes

So far we have assumed that group members are independent in a sense that they rely on diverse (or uncorrelated) cues to make their judgments. Surprising outcomes can drive a majority of people in the wrong direction even when individuals vote independently. This can happen if the environment changes in a way that makes all cues incorrect or if by chance uncorrelated cues happen to be wrong on the same task. However, the assumption of perfect independence is unrealistic (see e.g., Broomell & Budescu, 2009). In real life people are often influenced by the same cues, such as the same pieces of information, media reports, or opinion leaders. It has been shown that the presence of opinion leaders or common information that introduces correlations between individuals' decisions can reduce or even reverse the positive effects of larger group size on group accuracy (Boland, Proschan, & Tong, 1989; Kao & Couzin, 2014; Spiekermann & Goodin, 2012). These findings can be parsimoniously explained within the present framework. Whenever the leader or the common information is correct, average individual accuracy improves and the task in effect becomes easier. Conversely, whenever the leader or the common cue is wrong, the average individual becomes less accurate and the task becomes more difficult. Hence, given stochastic accuracy of the leader or the common cue, the overall group accuracy can be represented as an average of its performance on easy and difficult tasks (see Equations 5.5 and 5.6 below). Accordingly, single peak functions of the kind presented above have been observed for groups with correlated votes (see references above) but to our knowledge the simple explanation in terms of a mixture of easy and difficult tasks has not been proposed before. To further explore effects of correlated votes on the results presented above, we introduce correlations between voters on each task, before averaging across tasks. Following Boland et al. (1989), we assume that on each task a proportion of r voters are following a leader or some other cue that is stochastically correct with probability l, and as a result their votes become correlated. Whenever the leader or cue is correct, all r voters are correct, and accuracy of the remaining voters depends on their individual skill (see Equation 5.7). We repeat the analyses above (presented in Figure 5.3) while increasing the assumed proportion of voters r who follow the leader from 0 to 1 in steps of 0.1. With increase in r, changes in group accuracy with its size become less and less prominent, and for high r there is almost no change in group accuracy with increase in its size (Hogarth, 1978). Because in the real world it is difficult or impossible to know what proportion of people will follow a leader in a particular task, we average the results over the whole range of values of r. The results, shown in Figure 5.3 demonstrate that, in all situations in which it was observed when we assumed independent votes, the superiority of moderate group sizes still holds under the assumption of correlated votes.

Following an opinion leader (who does not vote but influences some group members to decide in a certain way) or voting based on a common cue can be incorporated in the present framework and studied as a combination of easy tasks (when the leader or cue is correct) and difficult tasks (when the leader or cue is not correct). More precisely,

$$\hat{P}_n = l * P_n[p(1-r)+r] + (1-l) * P_n[p(1-r)] \tag{5.5}$$

where $\hat{P}_n$ is average accuracy of a group of size n, l is probability that an opinion leader is accurate on a certain task, P_n is group accuracy at group size n given individual accuracy specified within the square brackets, p is initial individual accuracy of group members, and r is the proportion of group members who are following the opinion leader. The higher r, the higher the correlation among group members, and in some cases the two values are identical (Spiekermann & Goodin, 2012). It is easy to see that when the leader is accurate the tasks will overall be easier (i.e., group accuracy will be higher) than when the leader is not accurate. A condition similar to Equation 5.3 must be satisfied for $\hat{P}$ to increase with group size n:

$$\hat{P}_{n+2}[p(1-r)+r] - P_n[p(1-r)+r] > \frac{1-l}{l}[\hat{P}_{n+2}[p(1-r)] - P_n[p(1-r)]] \tag{5.6}$$

A similar case can be made for situations in which correlations occur because individuals use the same sources of information.

5.2.4 Combining the effect of correlated votes and task difficulty

Eqs. 5.2 and 5.5 can be combined to account for both correlated votes and task difficulty:

$$\begin{aligned} \hat{P}_n = e[l_E * P_{E,n}[\hat{p}_E(1-r)+r] + (1-l_E) * P_{E,n} \\ [\hat{p}_E(1-r)]] + (1-e)[l_D * P_{D,n}[\hat{p}_D(1-r)+r] + (1-l_D) * P_{D,n}[\hat{p}_D(1-r)]] \end{aligned} \tag{5.7}$$

In simulations equivalent to those used to produce the main results (Figures 5.1 and 5.2), we vary r from 0 to 1 insteps of 0.1. We first assume that $l_E = \hat{P}_E$ and $l_D = \hat{P}_D$,that is, that the leader has the same skill as the average group member. Average results over all levels of r are shown in Figure 5.3. The results hold if we assume that the leader is 10 percentage points more or less likely to be accurate than the average member.

Having demonstrated the main findings and several extensions, we now illustrate these analyses with several real-world examples.

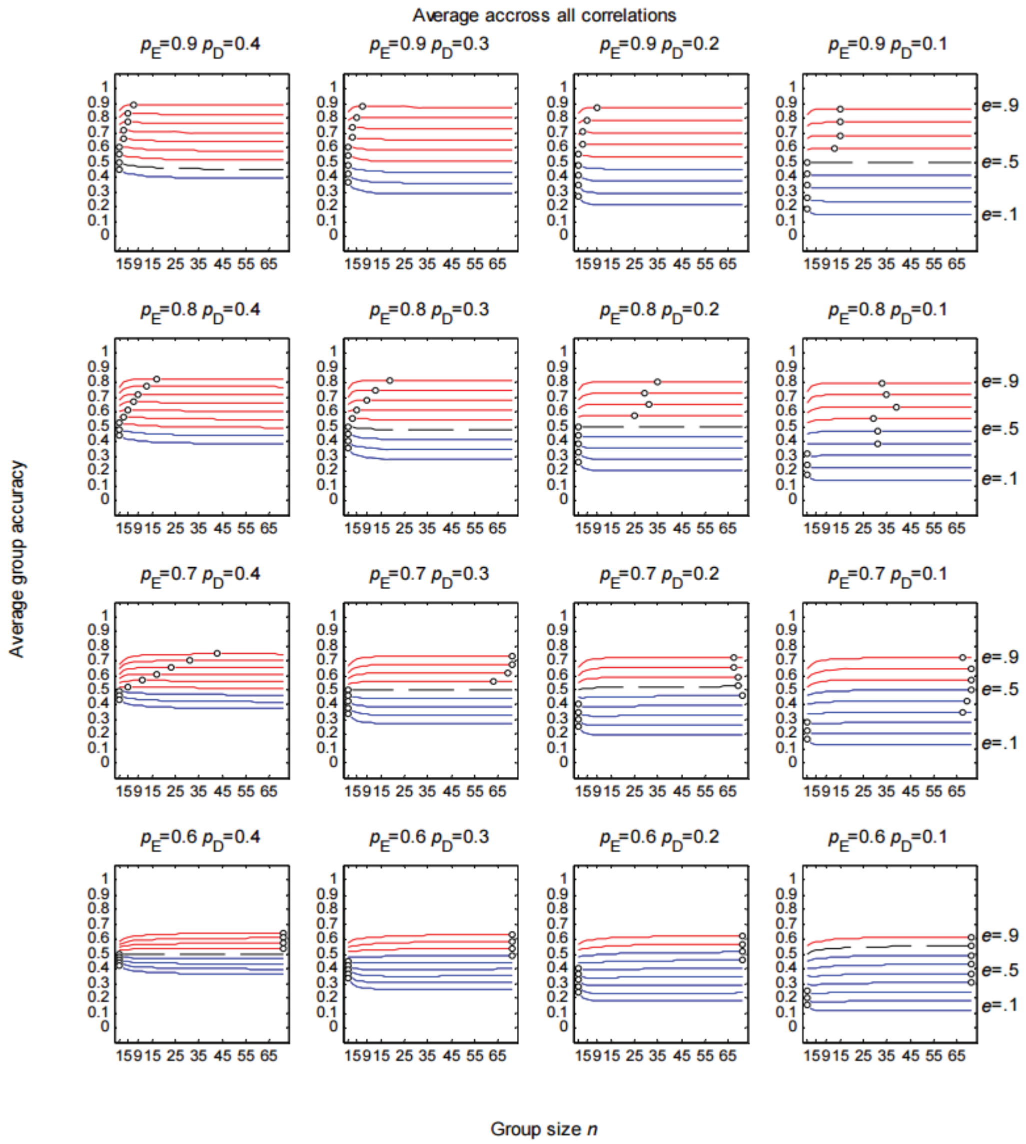

Figure 5.3: **Group accuracy after repeating the analysis in Figure 5.2 for correlation levels r ranging from 0 to 1 in steps of 0.1 and averaging over them.** Leader accuracy l is assumed to be equal to the average individual accuracy (see main text for more details). Figures for each level of r and different values of l are available from the authors.

5.3 Real-world illustrations

What is the best committee size in typical real-world environments? To answer this question, we need to have a rough idea of the distribution of task difficulties a committee might encounter in the real world. Given that committees are typically composed of people who are experts in the relevant area, we could expect that their accuracy in easy tasks is above chance more than their accuracy in difficult tasks is below chance. In other words, a typical task environment in which committees need to make decisions might more often be friendly than unfriendly. For the same reason, we could expect that the average individual accuracy across tasks is $\hat{P}_{n=1} > 0.5$; that is, on their own, committee members are more often right than wrong. Studies documenting expert accuracies across a range of tasks in the fields of politics, health, and economics support these expectations. To illustrate, in a longitudinal study of expert forecasts of five U.S. presidential elections, average individual accuracy across years $\hat{P}_{n=1} = 0.66$. Average individual accuracy in most years was above 0.8 while it was as low as 0.2 in only one year, 2000 (Bush vs. Gore; see (Graefe, 2014), and gray lines in Figure 5.4A). Similarly, a review of accuracy of medical diagnoses for 11 diseases showed that the average individual accuracy for most diseases is above 0.8, and it is rarely lower than around 0.4, for $\hat{P}_{n=1} = 0.7$ across diseases (Schiff et al., 2009); gray lines in Figure 5.4B). Finally, a review of accuracy of predictions given by the top officials of the U.S. Federal Reserve Bank about future economic trends showed that their average individual accuracy when predicting whether unemployment, economic growth, and inflation would increase or decrease was rather high for two of these domains, and it was never lower than 0.4, with $\hat{P}_{n=1} = 0.71$ (Hilsenrath & Peterson, 2013). Finally, in a study including 120 general knowledge tasks such as which of two randomly selected cities is farther north, or which of two randomly selected countries is larger or more populated, Juslin (1994) found that participants were more often right than wrong on average ($\hat{P}_{n=1} = 0.76$, but tended to be incorrect on a subset of tasks in which otherwise useful cues pointed to the wrong answers (Figure 5.4D). Under these conditions, groups of moderate sizes are likely to reach the most accurate decisions. Of all such conditions presented in Figure 5.2 in 71% (17/24) average group accuracy peaks at moderate group sizes ranging from $n = 3$ to $n = 31$.

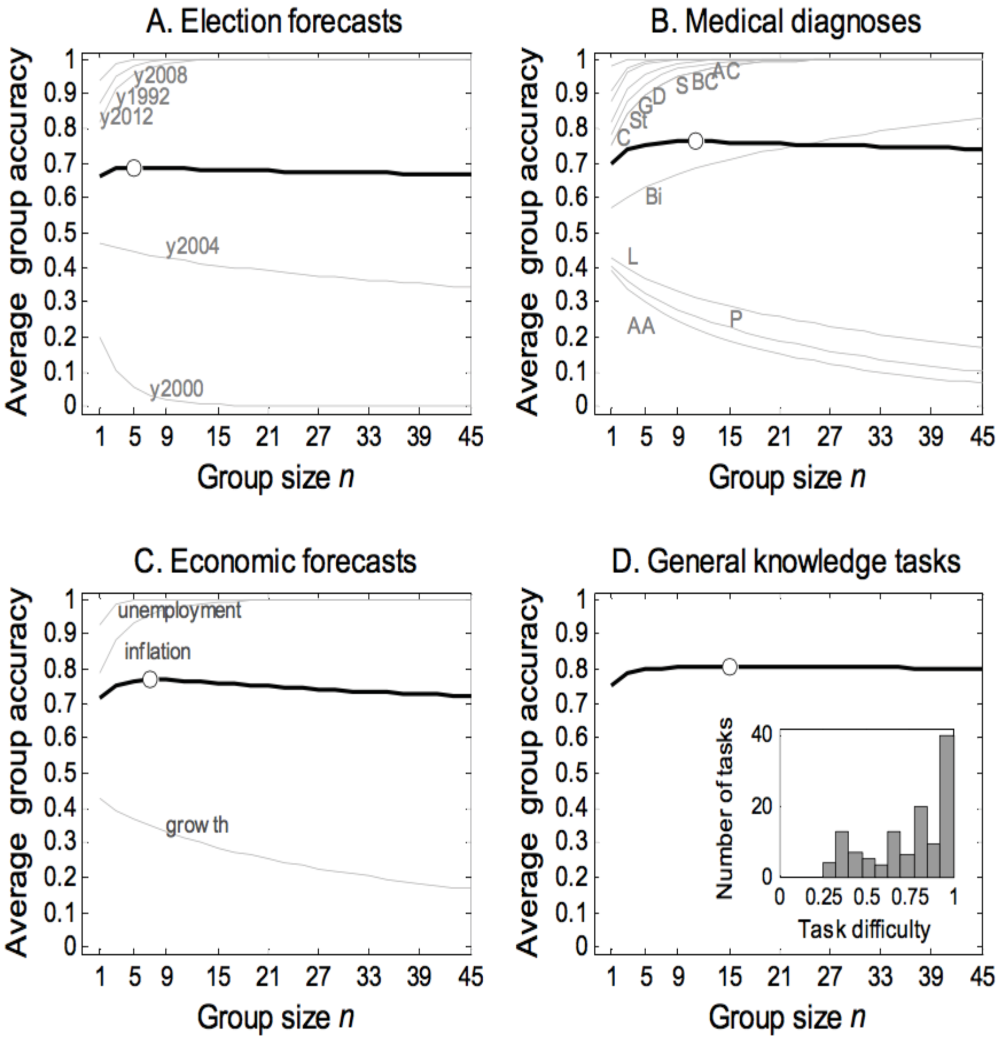

Figure 5.4: **Real-world environments are often friendly and group accuracy peaks at moderate group sizes.** Gray lines: Group accuracy for different group sizes and different tasks, assuming task difficulties corresponding to those faced by **A** experts predicting U.S. political elections in years 1992, 2000, 2004, 2008, and 2012 (Graefe, 2014), **B** doctors giving medical diagnoses for a range of diseases (AC=acute cardiac ischemia, BC=breast cancer, S=subarachnoid hemorrhage, D=diabetes, G=glaucoma, St=Soft tissue pathology, C=cerebral aneurysm, Bi=brain and spinal cord biopsies, L=Lyme disease, P=pyrogenic spinal infections, AA=abdominal aortic aneurysm; (Schiff et al., 2009)), and **C**U.S. Federal Reserve Bank officials giving economic forecasts about future economic trends in unemployment (unempl), inflation, and economic growth (Hilsenrath & Peterson, 2013), and **D** individuals answering 120 general knowledge items about sizes, latitudes, and populations of cities and countries (Juslin, 1994). In panels (A-C) each gray line represents one task; in (D) each gray line depicts several tasks and the frequency of different tasks at each level of task difficulty ($\hat{p}$) is shown in the inset. Note that in all domains easy tasks prevail, accompanied with a few surprising tasks that were difficult for most people. Thick black lines: average group accuracy across different tasks. For all four examples, average group accuracy peaks at moderate group sizes (as indicated by circles): in **A** at $n = 5$; in **B** at $n = 11$; in **C** at $n = 7$; in **D** at $n = 15$.

If we assume that a policy maker or an individual needs to decide on the best group size to solve a range of tasks such as those above, what group size would reach the highest accuracy? How many political experts should a journalist consult to improve election forecasts, how many doctors should a patient consult to improve the accuracy of her medical diagnosis, and how many economists should a government consult to make a good guess about the future course of the economy? To answer this, we combine group accuracies for different tasks to get average group accuracy in each of the three domains illustrated above (see Equation 5.4). As Figure 5.4 shows, the best group size for improving election forecasts by political experts in this particular illustration is $n = 5$. For diagnosing a variety of health problems, the best size of a panel of medical experts in this example would be $n = 11$. Finally, for economic tasks such as those faced by Federal Reserve officials, the best group size seems to be $n = 7$. Perhaps coincidentally, this is the designated number of seats on the Federal Reserve's Board of Governors, although at the moment of writing this paper two of those seven seats are empty (Federal Reserve, 2014). Finally, for answering general knowledge items correctly, the best group size for participants of Juslin's (1994) study is $n = 15$.

5.4 Conclusions

Our results suggest that the highest accuracy across a diverse set of tasks may be achieved by moderately sized rather than large groups. These results hold even if we assume that individuals have diverse skills, that their votes are correlated, that tasks have more than two options, or that groups encounter more than two task difficulties. Note that we modeled tasks in which groups use simple majority or plurality rules to choose between discrete options, rather than using averaging to predict a quantitative property. Wisdom-of-crowds effects are typically studied in the latter type of task (Galton, 1907; Surowiecki, 2005), although it has been shown theoretically that the performance of majority and plurality rules often compares to that of a computationally more demanding averaging rule (Surowiecki, 2005). Note also that we do not assume any selective sampling of group members, for example, based on expertise (Budescu & Chen, 2014; Goldstein et al., 2014; Mannes et al., 2014). A smaller group that would produce more accurate decisions in our model can simply be selected randomly out of a larger group of experts. Overall the study highlights an important characteristic of the environment that has been neglected before: the distribution of different task difficulties over time. This opens a novel perspective in the study of group judgment and decision making and serves as an important factor in analyzing the ecological rationality of social learning in one-shot decision environments.

So far in all chapters we have been assuming that individuals are trying to maximize a universal, objective criterion (i.e., accuracy), that is the same for each individual. In many real-life environments, however, the best option varies between individuals. Such settings involve making decisions about matters of taste as in the case of deciding between books, movies, music and other cultural products. In the next chapter we study how and when the building blocks of the three strategies we studied so far (and some new variants) could be modified to make them applicable to situations involving matters of taste.

Chapter 6

Social learning about matters of taste

This chapter is based on Analytis, P.P., Barkoczi, D., & Herzog, S.M. (2015). You're special but it doesn't matter if you're a greenhorn: social recommender strategies for mere mortals. *Proceedings of the 37th Annual Conference of the Cognitive Science Society*. Pasadena, CA: Cognitive Science Society.

6.1 Introduction

Where should I go for my next vacation? Which car should I buy? Many choices people encounter are about "matters of taste" and thus no universal, objective criterion about the options' exists. How can people increase their chances of selecting options that they will enjoy?

One promising approach is to tap into the knowledge of other individuals who have already experienced and evaluated options. In the area of recommender systems this source of knowledge has been used to develop *collaborative filtering methods*, which estimate the subjective quality of options that people have not yet experienced (Adomavicius & Tuzhilin, 2005; Resnick & Varian, 1997). One key insight from that literature is that building recommendations based only on the evaluations of individuals *similar* to the target individual often improves the quality of the recommendations (e.g., Herlocker, Konstan, Borchers, & Riedl, 1999)—where similarity between two people is typically defined as the correlation in their evaluations across options they have both evaluated.

Although the consumer industry enables people to benefit from recommender systems in some domains (e.g., choosing a movie on Netflix), for many everyday decisions there is neither an algorithm nor "big data" at hand. How can individuals leverage the experience of other people when they have no access to big data but access only to a relatively small community of other people with whom they share some prior experience about the available options?

In this chapter we make three contributions. First, we have undertaken an exercise in *theory integration* by mapping the striking conceptual similarities between seminal recommender system algorithms and both (i) models of judgment and categorization and (ii) models of social learning and social decision making (from psychology, cognitive science, judgment and decision making, anthropology, and biology). Models from recommender systems have been developed for problems involving matters of taste while the latter two classes of models have their origins in inference problems about matters of fact. Second, we have recast the latter two classes of models as *social recommender strategies* which can be thought of as social learning strategies with modified building blocks. Finally, based on this mapping, we have investigated how ordinary people can leverage the experience of other people to make better decisions about matters of taste. To this end we studied the inevitable trade-off between (i) harnessing the apparent (dis)similarity between people's tastes—to discriminate between more and less relevant advisers—and (ii) estimating those similarities accurately enough. We have investigated how this trade-off evolves with the amount of experience a decision maker has (i.e., the number of options previously evaluated).

Outside of the recommender systems literature, social recommender strategies remain an under-explored topic. Research on advice taking, social learning, and judgment aggregation in psychology, cognitive science, judgment and decision making, anthropology, and biology has focused almost exclusively on "matters of fact" where there is an objective criterion to be inferred ("wisdom of crowds"; e.g., Larrick, Mannes, and Soll (2012)). This is echoed in the last 4 chapters which also focused on making decisions about matters of fact. To the best of our knowledge, there are only a handful of studies on social recommender strategies (Müller-Trede, Choshen-Hillel, Barneron, & Yaniv, 2015; Van Swol, 2011; Yaniv, Choshen-Hillel, & Milyavsky, 2011). They show that people rely on the similarity between themselves and their advisers when making decisions about matters of taste and that this is a good strategy.

6.2 Mapping recommendation systems algorithms to *informational* and *social* cue-based strategies

Table 6.1 displays several social recommender strategies that predict one's own future evaluations based on the past evaluations provided by other people.

Table 6.1: Social recommender strategies conceptually similar to strategies using informational cues or social cues (i.e., people's opinions as cues). All strategies first estimate the expected utility $\hat{u}_i$ (i.e., enjoyment) of each option i and then select the option with the highest estimated utility; when several options have the same estimated utility, one of the tied options is chosen at random. Strategies incorporating similarity information are typeset in *italics* and those averaging across several individuals' evaluations are typeset in **bold**. All strategies are person based, except consider similar options, marked in *blue*.

(Dana & Dawes, 2004; Davis-Stober, Budescu, Dana, & Broomell, 2014; Dawes, 1979; Desrosiers & Karypis, 2011; Einhorn, Hogarth, & Klempner, 1977; Gigerenzer & Goldstein, 1996; Hammond, Hursch, & Todd, 1964; Hogarth & Karelaia, 2005; Juslin & Persson, 2002; Kruschke, 1992; Resnick, Iacovou, Suchak, Bergstrom, & Riedl, 1994; Richerson & Boyd, 2008; Shardanand & Maes, 1995)

We identified conceptual similarities between the proposed social recommender strategies (inspired by seminal algorithms from recommender systems research) and heuristics and strategies for predicting matters of fact, where people have access to either *informational cues* potentially related to an objective criterion (e.g., number of movie theaters in a city to predict its population size) or *social cues* (i.e., the opinions of other people concerning the same objective criterion).

This mapping emphasizes the close correspondence between recommendation algorithms on the one hand and informational and social cue-based strategies on the other.

Table 6.1 introduces the strategies we study and their parallels in the literature. Note that these strategies differ slightly from the strategies studied in the previous chapters. The previous chapters focused on copying of options with discreet payoffs, where the frequency of each option could be tallied and the majority rule could be applied. However, in the current setting individuals' preferences are on a continuous scale and, therefore, averaging becomes a more appropriate decision rule [1]. We also introduce a search rule based on similarity rather than random order. In addition, we introduce several hybrid strategies that combine averaging and similarity ordered search rules. These strategies can also be thought of as social learning strategies composed of different building blocks. To illustrate, the *Follow your clique* strategy can be modeled as: (1) Search among your peers in the order of similarity; (2) Stop after looking up the k most similar peers; (3) Average the evaluations of the people in your sample and choose the option with the highest evaluation.

These social recommender strategies can be placed on a continuum, on the boundaries of which strategies rely either only on similarity information (i.e., use a search rule based on similarity rather than random order as in the previous chapters) or only on aggregation of opinions (i.e., strategies that average the evaluations of all individuals in one's sample). As we move away from the boundaries the strategies rely increasingly on both

[1] Note that Hastie and Kameda (2005) have shown that the performance of averaging and the majority rule often correspond very closely.

of these two fundamental principles.

Below we illustrate some of the strategies using a fictional data set that has the same structure as the large-scale data sets used in recommender systems research and in our own simulation study below.

6.3 Example: Deciding which movie to watch based on other people's past experiences

Amit likes superhero movies and wants to watch *Batman* or *Fantastic Four*. His friends have already seen both movies. Furthermore, he and his friends have all watched and evaluated several other movies (see Table 6.2). In addition to any contextual information about the movies (e.g., director, cast, movie length), Amit can use his friends' evaluations to inform his movie choice.

Movie	John	Bob	Linda	Mary	Lou	*Avg.*	**Amit**
Superman	3	4	2.5	4.5	3	*3.8*	**2.5**
Spiderman	4	4.5	3	2	3.5	*3.4*	**3**
Batman	5	5	2	1	3	*3.2*	**?**
Fantastic Four	2	3	2.5	3	2.5	*2.6*	**?**
X-Men	1	1.5	2	1.5	3	*1.8*	**2**

Table 6.2: A typical recommender system problem. The movies are rated on a scale of 1 to 5 (higher values indicate more positive ratings). *Avg. = average.*

From Amit's perspective, his own future evaluations are the criterion values he seeks to maximize and the evaluations of his friends are informational cues he can use to predict his own future evaluations. Based on his past evaluations of the other movies, Amit thinks that he and Linda have similar taste. If Linda truly were his "taste Doppelgänger" he could simply copy her evaluations and arrive at very accurate estimates of his own future enjoyment (*Follow your Doppelgänger*). However, it is unclear to what extent this seeming similarity—based on only a small set of joint past experiences—would generalize well to future cases. Amit may thus prefer to take the evaluations of others into account, as well. For example, he could assign equal weights to all individuals and simply use the average evaluation (i.e., the "mainstream" option; *Follow the whole crowd*). Yet by doing so he would also incorporate evaluations from individuals with possibly very different—or even antithetical—tastes. Alternatively, he could search for a movie that everybody rated similarly to the target movie and then use his own evaluation for that similar movie as a proxy (*Consider similar options*; e.g., *Spiderman* is similar to *Batman*).

6.4 Simulation study

We investigated the performance of the proposed social recommender strategies (see Table 6.1) by simulating their predictions for a large-scale, real-world data set. We varied the experience of the simulated decision makers (i.e., the number of options previously experienced in that domain; that is, the number of rows in Table 6.2). As experience increased, the strategies relying on similarity could thus base their similarity estimates on more data.[2]

The social network from which a person could leverage vicarious experience would likely be much smaller than the thousands of people available in typical recommender system data sets. The cognitive limit of the number of stable relationships that people can maintain is estimated to be around 250 (Dunbar, 2010). We therefore opted to simulate small "communities" of 250 members each to mirror this real-world feature (as opposed to letting decision makers have access to all other individuals in the population). However, within those small communities, we assumed a fully connected network.

[2]A similar challenge is faced by recommender system algorithms when recommending options to new users about whom they know nothing or only very little. This challenge is commonly referred to as the *user cold start problem* Ekstrand, Riedl, and Konstan (2011).

6.4.1 Method

Dataset

We used the funniness ratings of 100 jokes collected in the *Jester* data set. Jester[3] was created by an online recommender system that allows Internet users to read and rate jokes. Users evaluated jokes on a scale ranging from *not funny* (–10) to *funny* (+10). At the beginning of the recommendation process, a set of 10 jokes was presented to the user. Thereafter, Jester recommended jokes and continued to collect ratings for each of them. The data set contains 4.1 million evaluations of 100 jokes by 73,421 participants. In contrast to other data sets studied by the recommender system community, here a large number of participants evaluated all options. Since its publication, the Jester data set has been used extensively to study collaborative filtering algorithms.

Simulation procedure

For simplicity we worked only with participants who evaluated all jokes (reducing the number of participants from 73,421 to 14,116). We randomly selected 14,000 participants in order to partition them into evenly sized communities of 250 members each. In line with previous work in the recommender system literature, we used the Pearson correlation coefficient as a measure of similarity (Herlocker, Konstan, Terveen, & Riedl, 2004).[4]

In each simulation run, we followed the following steps: First, we randomly generated 56 communities with 250 members each (14,000/250). Second, we randomly divided the jokes into a training (x jokes) and a test (10 jokes) set; this assignment was the same for all individuals within all communities. The strategies were then fitted on the training set. Individuals could access only advisers within their own community. Third, for each

[3] http://eigentaste.berkeley.edu

[4] The Pearson similarity coefficient between two individuals or two items i and j is defined as $w(i,j) = \frac{\sum_{n=1}^{k}(u_{in}-\bar{u}_i)(u_{jn}-\bar{u}_j)}{\sum_{n=1}^{k}\sqrt{(u_{in}-\bar{u}_i)^2(u_{jn}-\bar{u}_j)^2}}$

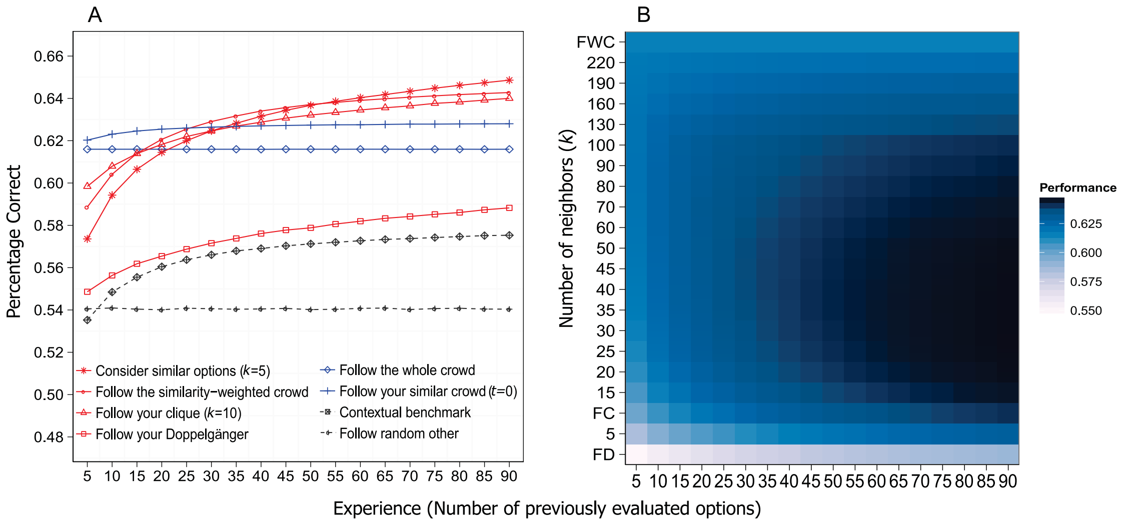

Figure 6.1: **Panel A**: The performance of strategies as a decision maker's experience with the domain of jokes (i.e., number of jokes previously experienced and evaluated) increases; the strategies are grouped by color to those that rely primarily on aggregation (blue), those that rely heavily on similarity information (red) and benchmark strategies (black) (see also Table 6.1). **Panel B**: Performance of the *Follow your clique* strategy as a function of the experience with the domain (i.e., number of options experienced; x axis) and the size of the clique (i.e., number of most similar people consulted; y axis). Note that *Follow your Doppelgänger* and *Follow the whole crowd* are special cases of this strategy when the number of similar people consulted equals 1 and N, respectively. **FD**: *Follow your Doppelgänger*. **FC**: *Follow your clique*. **FWC**: *Follow the whole crowd*.

individual (within all communities) we generated all 45 possible pair comparisons within the test set $[10 \times (10-1) \div 2]$ and examined the performance of the strategies in predicting which of the two jokes in a pair had a higher evaluation for that individual, resulting in 45 pair comparisons per individual, 11,250 per community (45×250), and 630,000 in total ($11,250 \times 56$). For each strategy we recorded the proportion of correct predictions. This procedure was repeated 100 times and results were averaged. We investigated how the performance of the strategies changed as a function of experience by repeating this procedure for different numbers (x) of jokes experienced in the training set (varying from 5 to 90 in increments of 5).

6.4.2 Results

How did the strategies perform?

Figure 6.1 shows the performance of each strategy as a function of the number of options evaluated. For the highest level of experience the strategy based on item similarity (*Consider similar options*) performed best (predicting 65% of the pair comparisons correctly). This was followed by the strategies that relied on both similarity information and aggregation: *Follow your clique* and *Follow the similarity-weighted crowd* predicted approximately 64% of the cases correctly and *Follow your similar crowd*—relying on similarity information more crudely—performed slightly worse at 63%. Strategies relying solely on either user similarity (*Follow your Doppelgänger*) or aggregation (*Follow the whole crowd*) performed worse than the other strategies, reaching 59% and 62%, respectively.

The usefulness of less similar advisers

These results provide a rationale for why people rely on similar advisers (Müller-Trede et al., 2015; Yaniv et al., 2011). However, relying purely on similarity (*Follow your Doppelgänger*) does not perform that well because of the difficulty of reliably estimating similarity in light of sampling error. Mirroring results from research on the wisdom of crowds (Goldstein et al., 2014; Mannes et al., 2014), taking into account additional—although less similar—advisers and averaging their recommendations markedly improves performance.

Experience within a domain

Strategies that rely heavily on similarity information have steep learning curves. For small amounts of experience, *Follow your similar crowd* is the best performing strategy. *Consider similar options*, *Follow your clique*, and *Follow the similarity-weighted crowd* start to outperform *Follow the whole crowd* once approximately 15 options have been added to the training set and *Follow your similar crowd* after approximately 25 options.

Thus, decision makers who have not yet experienced many options are well-advised simply to aggregate the evaluations of individuals who seem to have at least minimally similar (i.e., positively correlated) tastes (*Follow your similar crowd*) or even to unconditionally aggregate the evaluations of all individuals (*Follow the whole crowd*). Although the opinions of truly similar individuals are more informative than those of truly dissimilar individuals, this discrimination is only beneficial to the extent that it is accurate enough. For small training samples, estimates of similarity are apparently often not accurate enough to be of any use.

How large should your clique be?

When *following your clique*, the size of k (i.e., the number of neighbors whose evaluations are averaged) is a *hyperparameter* that needs to be chosen beforehand (in Figure 6.1A we fixed $k = 10$). The value of k determines the stopping rule used by the strategy. Figure 6.1B shows how performance changes as a function of k and experience (i.e., the number of options experienced). With little experience it is better to rely on large cliques (ca. 100), whereas for more extensive experience, performance peaks at moderately sized cliques (ca. 30).

The potential of one-reason decision making

Following a *random other* person correctly predicted 54% of the comparisons, which indicates a very modest, minimally shared sense of humor in the population (i.e., slightly better than chance). We also tested another benchmark strategy that simply used the length of a joke as a cue to predict its evaluation (i.e., some people may prefer long, story-like jokes while others may prefer short and witty linguistic puns). This one-cue strategy predicted 57% of cases correctly—it was almost as accurate as the *Follow your Doppelgänger* strategy (59%), which also relied on one cue, yet a social one.[5]

6.5 General discussion

Mapping out the striking conceptual similarities between seminal recommender system algorithms, on the one hand, and extant models of judgment and decision making (based on informational or social cues), on the other, allowed us to recast the latter models as social recommender strategies (see Table 6.2). This theory integration allowed us to analyze the performance of social recommender strategies for *mere mortals* who have access to only a small pool of potential advisers, rather than the "big data" available to recommender systems.

Two results stand out. First, the successful strategies all have one thing in common: They aggregate evaluations across several people (or items). Second, the amount of experience within a domain turns out to be a crucial determinant of the success of strategies using similarity-based search. Whereas *experienced* people can benefit from relying on only the opinions of seemingly similar people, *inexperienced* people are often well-advised to aggregate the evaluations of a large set of people (picking the option with the highest average evaluation either across all people or across at least minimally similar people) even if there are interindividual differences in taste, because reliable estimation of similarity requires considerable experience.

6.5.1 Experience and the bias–variance trade-off

With increasing experience with the domain, the performance of all top-notch strategies increased—except for the wisdom of crowds strategy (*Follow the whole crowd*), which

[5]This result conflicts with a relevant finding from a speed dating experiment Gilbert, Killingsworth, Eyre, and Wilson (2009), where the experience of a random other person (from the same population) predicted the actual dating enjoyment better than the same participants' predictions (based on an extensive set of informational cues available before the speed date started, namely, among other things, a picture and information about age, height, favorite movie, sport, book, song, and food).

unconditionally averages across all people and is thus—by design—unaffected by the increasing accuracy of the similarity estimates. Such an averaging strategy assumes that everybody has the same taste and performs well to the extent that the tastes in the population are indeed homogeneous. From a bias–variance trade-off perspective e.g. (Geurts, 2010; Gigerenzer & Brighton, 2009), this strategy suffers from potentially high bias to the extent that its homogeneity assumption is wrong, but exhibits zero variance in its prediction error because it does not estimate any free parameters.[6]

In contrast, the strategies relying on similarity have a comparatively low bias because they can adapt to the homogeneity or heterogeneity of tastes in the population. However, they potentially suffer from variance because their predictions depend on the similarity estimates—to differing degrees—and thus they lie on a bias–variance continuum. At one extreme, a strategy of adopting the evaluations of only the seemingly most similar person has the potential to profit from the vicarious experiences of one's taste Doppelgänger but is most reliant on an accurate estimation of similarity. At the other extreme, a strategy of relying on a large crowd of at least minimally similar people (i.e., with at least positively correlated tastes) is more biased but also more robust because it depends on only roughly discriminating between similar and dissimilar advisers (see also Goldstein et al., 2014; Mannes et al., 2014).

6.5.2 Theory integration: Reconnecting the cognitive sciences with recommender systems research

New statistical tools haven often served as an inspiration for the development of new psychological theories (Gigerenzer, 1991). In the case of recommender systems, however, the insights developed within the last two decades have not been much incorporated into cognitive science[7]—despite recommender systems being widely available and relevant

[6]Also from a Bayesian perspective, it is prudent to go with the crowd: An inexperienced decision maker—by statistical necessity—is a priori more likely than not to have "mainstream taste" unless there is diagnostic private information to the contrary (S. M. Herzog & Hertwig, 2013, p. 210).

[7]In a similar vein, Analytis, Kothiyal, and Katsikopoulos (2014) pointed out the overlooked analogy between ranking models from machine learning and human search behavior.

for everyday decision making and seminal recommender systems being inspired by the work of cognitive scientists (Rich, 1979). We hope that the current paper initiates a cross-fertilization between the two until now largely unconnected research streams.

Chapter 7

Conclusion

In the beginning of this thesis I proposed a general framework for the study of social learning that consists of:

(1) Modeling social learning as cognitively plausible process-level strategies.

(2) Studying important elements of the social and task environments in which social learning takes place.

(3) Building computational and analytical models to study the match between social learning strategies and different environments in order to explain why a given strategy is successful in a given environment.

This framework is grounded in the study of ecological rationality that has proven fruitful in the study of decision making in general (Gigerenzer et al., 1999). I tried to extend the scope of ecological rationality to the domain of social learning. To do so I studied three representative classes of social learning strategies and their combinations: frequency-dependent, payoff-biased and unbiased copying. In each chapter I focused on an important everyday setting in which social learning has been shown to play an important role and tried to identify the key environmental properties characterizing it.

The first three studies focused on what I called *repeated* social learning settings. *Repeated* social learning settings are characterized by feedback loops between the choices of individuals at a given time step and the information available for social learning on subsequent time steps. Such settings play an important role in everyday decision environments including organizational learning (Chapter 3) and innovation diffusion (Chapters 2 and 4). In Chapter 2 I showed that in *repeated* social learning settings, the speed with which different strategies are able to drive the populations toward the best solutions is crucial, thus favoring strategies such as *copy-the-best* and *random copying* that need to sample only a few individuals in order to make a decision. In Chapter 4 I showed that the distinction between *one-shot* and *repeated* social learning settings is an important one, given that predictions about strategy performance in *one-shot* decision environments do not translate to *repeated* settings. This finding can explain why, for example, Garcia-Retamero et al. (2006) and Hastie and Kameda (2005) came to opposite conclusions. In the discussion section of their cue-order learning study Garcia-Retamero et al. (2006) recognize that their findings are contradictory to a study by Hastie and Kameda (2005). The former study found that the *best member* strategy performs best while the latter found the *majority rule* to be better. From this thesis it becomes clear that the key difference between the two studies was that Garcia-Retamero et al. (2006) studied a *repeated* social learning setting, while Hastie and Kameda (2005) focused on *one-shot* decision tasks. In the *repeated* setting studied by Garcia-Retamero et al. (2006) the speed with which the best member strategy was able to diffuse good solutions outweighed the benefit gained from information pooling via the majority rule in the *one-shot* context studied by Hastie and Kameda (2005).

Within the context of *repeated* social learning I made a distinction between whether the environment *simple* (Chapters 2 and 4) or *complex* (Chapter 4), where complexity was characterized by the number of components and the interaction between the components of the option to be copied (Simon, 1965). I showed that different strategies are favored in *complex* environments than in *simple* environments. When the environment is *simple*, best member strategies perform better, however, when it is *complex*, some forms of conformity can be better because they promote more extensive search and ensure that the population does not get stuck with locally optimal solutions early-on. In addition I showed how the level of *clustering* in the social network in which agents are embedded in interacts with the social learning strategies they use, and pointed out, that identifying the best strategy depends on the social network and vice-versa.

A surprising result of these studies is that relying on small samples in the context of conformity can often lead to a very high level of performance, both relative to the same strategy relying on larger samples as well as to other strategies. This has been systematically investigated in Chapter 4 and provides a striking illustration of how the same decision strategy (copy-the-majority) can result in completely different aggregate behaviors depending on the other building blocks of the strategy (the stopping rule in this case).

Chapter 5 developed this finding further by moving to one-shot decision environments, where individuals aggregate information available at a single time step. Focusing on the context of group decision making or group voting, I showed that in many situations it is better to rely on a small sample (or small group) of individuals when using the majority rule to decide. A key environmental characteristic, that is, *varying task difficulty* across trials, has been shown to account for this finding.

In the final chapter I presented results on social learning in *matters of taste* rather than *matters of fact*. *Matters of taste* are part of many decisions people make every day, including choosing books, movies, or holiday destinations. Models of social learning have seldom been applied to such settings which provide an ideal context for studying how different search rules might perform. The main question of this study was whether it pays to search based on similarity rather than randomly as in the previous chapters. To address this question recommender system algorithms where recast as cognitively plausible social learning strategies composed of different building blocks. The basic finding was that individuals who are experienced with a domain benefit from searching based on similarity rather than randomly, while individuals who have little experience are better off aggregating the opinions of other individuals. Taken together these studies identify several key environmental factors of social environments:

(1) Simple versus Complex environments

(2) One-shot versus Repeated settings

(3) Uniform versus Varying task difficulties

(4) Matters of Taste versus Matters of Fact

(5) Clustered versus Unclustered social environments

In each of these cases I showed how different building blocks (search, stopping, decision rules) might be suitable for different environments. This framework is admittedly a first step toward studying the ecological rationality of social learning. In what follows I briefly outline proposed future work within this framework.

I focused on three basic building blocks, search, stopping and decision rules. It is an important question for future research whether there are other building blocks in the context of social learning that could be modeled. If other building blocks can also be identified then the question of constructing new social learning strategies that might perform even better than those proposed here or in the literature in general could be addressed.

Another contribution to the literature would be to use the proposed ecological rationality framework to re-examine existing results in the diverse literature on social learning from different disciplines and synthesize them by reconciling contradictory or hard to compare findings. One example was given above regarding the contradictory findings of Garcia-Retamero et al. (2006) and Hastie and Kameda (2005). Another example was studied in Chapter 3, where I showed that determining the best communication network depends on the underlying strategy used. Two published studies found contradictory results regarding the best communication network for problem solving (Lazer & Friedman, 2007; Mason & Watts, 2012). The analysis presented in Chapter 3 suggests that these two studies ignored an important factor, namely the underlying strategies used.

In this thesis I focused on the goal of identifying the option with the highest (objective or subjective) payoff. However, many of our decisions are driven by other goals, such as to enhance cooperation, maintain group cohesion, make a decision that is transparent, or one that is good for the whole group and not just a single individual. A more comprehensive list of such goals could be assembled and the problem of social learning could be recast for each of these goals. I hypothesize that different building blocks might be suitable for problems motivated by different goals. For example, if the goal is to maintain group cohesion, then searching based on proximity and following the majority might be more appropriate than copying the most prestigious individual. A comprehensive list of goals could be assembled, for example, by drawing from Fiske's four elementary social relationships, which categorizes social relationships into four elementary goals, namely community sharing, authority ranking, equality matching and market pricing (Fiske, 1992).

It is well known that the performance of social learning strategies also depends on what strategies other individuals use (Rendell, Boyd, et al., 2010). In this thesis I studied social learning strategies in isolation (i.e., assuming that the whole population relies on a single strategy; see Appendix for Chapter 4 for an exception). This is admittedly a simplification, however, it allowed me to study in greater detail the properties of different strategies. I believe it is an important next step to study strategies in conjunction, however, the first step in this direction should be to come up with a theoretical justification or empirical evidence for which strategies should be studied in conjunction and why. Without such a theory, results obtained from studying strategies in conjunction can always be challenged by including or removing another set of strategies, therefore, the conclusions drawn from such studies are unlikely to be more realistic.

In a similar spirit, a more comprehensive list of everyday domains involving social learning could be assembled and further environmental factors could be identified. In the present thesis I focused on innovation diffusion, organizational learning and the wisdom of the crowds. It is an open question whether other decision tasks including medical, financial or environmental decisions have important properties that are unique to each.

Finally, while modeling social learning as building blocks assumes psychologically plausibility, the question whether people use these strategies is still unresolved. The studies reported here map out the environmental conditions in which different combinations of search, stopping and decision rules are ecologically rational. They provide strong, testable predictions about specific social learning strategies that we should expect to observe in empirical studies.

One possible direction would be to develop experimental paradigms where the full decision process involved in social learning can be observed. In such experiments the information about the frequency of different behaviors, the payoffs of agents, or the costs of social learning can be manipulated and the way in which individuals search, stop, and decide can be examined (see Mason & Watts, 2012; McElreath et al., 2008; Mesoudi, 2008; Wisdom et al., 2013, for examples of such paradigms). One can also conduct survey studies probing individuals about the ways in which they collect information from their social environments. Galesic et al. (2012) found that people typically consult around five other individuals about various important matters in life and Pachur et al. (2013) studied the number of people recalled from memory when judging the frequencies of different risks. Both of these studies can inform us about the way in which people search their social environments and when they tend to stop search.

Another possible way to test strategies empirically is to see whether they are consistent with aggregate patterns of collective behavior. Henrich (2001) studied the shape of the diffusion curve in populations using different forms of social and individual learning and showed that only some forms of social learning are consistent with the widely observed S-shaped adoption curves in the diffusion of innovations literature (E. M. Rogers, 2010). A similar approach was adopted by Bentley et al. (2004) who showed that random copying is likely to underlie change in cultural trends such as baby names or dog breeds. Finally, Todd, Billari, and Simao (2005) tried to distinguish between various individual mate search heuristics by testing whether they can reproduce aggregate age at marriage patterns.

I hope that the framework proposed in this thesis will further stimulate empirical research on social learning strategies in humans.

Appendices

Appendix for Chapter 4

A. How to obtain Equation 4.4

To obtain Equation 4.4 we list all possible situations faced by a hypothetical agent (summarized in the table below) and calculate the probability of choosing the superior option (option A) in each situation. I and S denote inferior and superior payoffs, respectively.

Current option	Option selected by majority	Payoff of current option	Payoff of selected option	Decision
A	with $CJT(ps_t)$, A	with f: S	with f: S	keep A
A	with $CJT(ps_t)$, A	with (1-f): I	with f: S	keep A
A	with $CJT(ps_t)$, A	with f: S	with (1-f): I	keep A
A	with $CJT(ps_t)$, A	with (1-f): I	with (1-f): I	keep A
A	with $CJT(1-ps_t)$, B	with f: S	with (1-f): S	flip a coin
A	with $CJT(1-ps_t)$, B	with (1-f): I	with (1-f): S	switch to B
A	with $CJT(1-ps_t)$, B	with f: S	with f: I	keep A
A	with $CJT(1-ps_t)$, B	with (1-f): I	with f: I	flip a coin
B	with $CJT(ps_t)$, A	with f: I	with f: S	switch to A
B	with $CJT(ps_t)$, A	with (1-f): S	with f: S	flip a coin
B	with $CJT(ps_t)$, A	with f: I	with (1-f): I	flip a coin
B	with $CJT(ps_t)$, A	with (1-f): S	with (1-f): I	switch to B
B	with $CJT(1-ps_t)$, B	with f: I	with (1-f): S	switch to B
B	with $CJT(1-ps_t)$, B	with (1-f): I	with (1-f): S	switch to B
B	with $CJT(1-ps_t)$, B	with f: I	with f: I	switch to B
B	with $CJT(1-ps_t)$, B	with (1-f): S	with f: I	switch to B

For each hypothetical situation we can calculate the probability of choosing the superior option. Combining each situation yields the following equation:

$$ps_{t+1} = ps_t * CJT(ps_t, n) + ps_t * (1 - CJT(ps_t, n)) * [f * (1-f) * 1/2 + f * f + (1-f) * f * 1/2] + (1 - ps_t) * CJT(ps_t, n) * [f * f + (1-f) * f * 1/2 + f * (1-f) * 1/2]$$

By simplifying this equation we obtain Equation 4.4 in the main text.

B. Conformity, anti-conformity and non-conformity

We have seen in the main text that conformity defined as $D(0,1]$ and $a > 1$ can be mimicked by the copy-the-majority strategy relying on different sample sizes. Here we show that 1) anti-conformity can be modeled using the same approach and 2) non-conformity cannot be obtained by sampling alone, indicating a combination of social and individual learning.

Panel A of Figure A1 shows anti-conformity as implemented by the copy-the-minority strategy relying on different sample sizes (row 1), parameter M[1] as implemented by Efferson et al. (2008) in their Appendix (row 2) and parameter a in the region $a < 0$ (row 3). As we can see all three implementations produce the same curves.

A more interesting situation is shown in Panel B of Figure A1. Here we model non-conformity (i.e., the tendency to adopt an option with a probability lower than the option's frequency in the population but still higher than 0.5). Non-conformity, as it is defined here, lies in the region between the horizontal dashed line and the 45 degree line. We can see that both parameter D (row 2) and a (row 3) can produce curves that exhibit non-conformity. However, one can not achieve such curves with pure social learning strategies relying on different sample sizes. However, we can produce curves that lie in the non-conformity region by setting the majority threshold higher (solid lines) or lower (dashed lines). In column 1 we focused on a sample size of 5 and 9 (note that one cannot increase the majority threshold for a sample size of 3), and set the thresholds higher (4 and 8) or lower (1 and 3) compared to the threshold of 3 and 5 as in the simple majority rule. Setting the thresholds higher or lower produces curves that are largely consistent with non-conformity, however, their shapes are substantially different from what the D and a produce. This indicates, that behaviors that look consistent with non-conformity as defined by D and a (Figure A1, Panel B, rows 2 and 3) are likely to be a result of a

[1] $C_{t+1,M} = \sum_{i=0}^{N/2} \binom{N}{i} ps^i (1-ps)^{n-i} + M \left\{ \sum_{i=N/2}^{N} \binom{N}{i} ps^i (1-ps)^{n-i} \right\} - Mi$

mixture of individual and social learning.

Also note that higher and lower threshold majority rules (Figure A1 top right panel) are consistent with non-conformity in the top right and bottom left quadrants of the figure, while the same strategies are consistent with anti-conformity in the top left and bottom right quadrants. This indicates that one cannot draw conclusions about the underlying behavior by observing data points in only one of the quadrants (e.g., see Efferson et al. (2008) and their critique of Asch (1956)).

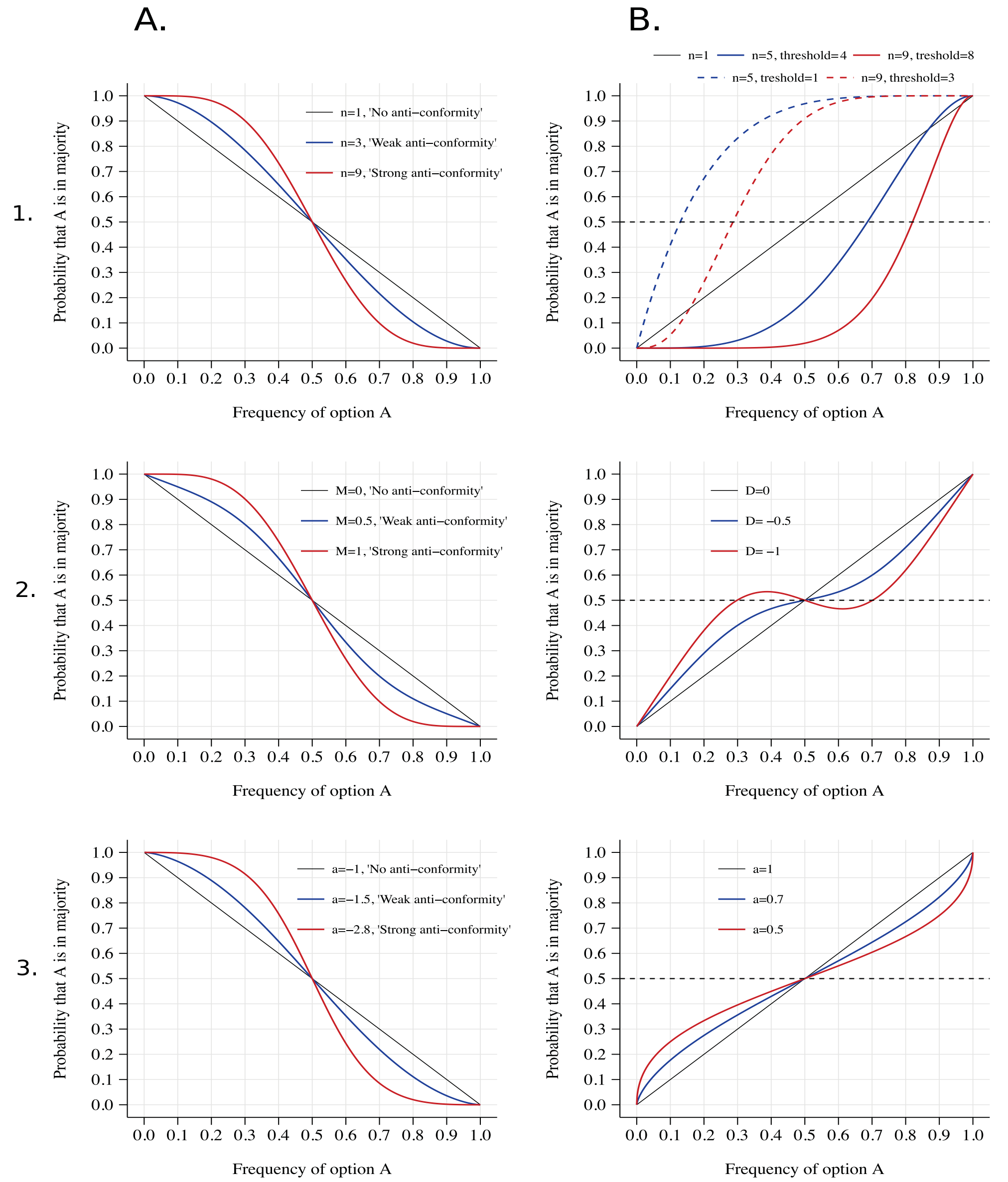

Figure A1: Anti-conformity (Panel A) and non-conformity (Panel B) as implemented by sampling (row 1), parameter *D* (also M)(Efferson et al., 2008) (row 2) and parameter *a* Nakahashi (2007) (row 3).

C. Heterogeneous populations

In the main text we considered the dynamics of *copy-the-majority* when this is the only strategy used in a population. However, the performance of social learning strategies depends largely on the other strategies in a population (Rendell, Boyd, et al., 2010), therefore, we tested whether our results hold when some percentage of the population copies the minority. *Copy-the-majority* and *copy-the-minority* have very different population-level dynamics, where the former creates behaviorally homogeneous groups while the latter fluctuates around 50% adoption rate in the case of 2 options (Efferson et al., 2008; Kendal et al., 2009). How the two strategies complement each other is, therefore, and interesting question to examine. Figure A2 shows the performance of *copy-the-majority* with small ($n = 3$) and large ($n = 9$) samples when some percentage of agents are using the *copy-the-minority* strategy. Adding multiple strategies does not change the pattern of results reported in the study, helps small samples but harms larger samples.

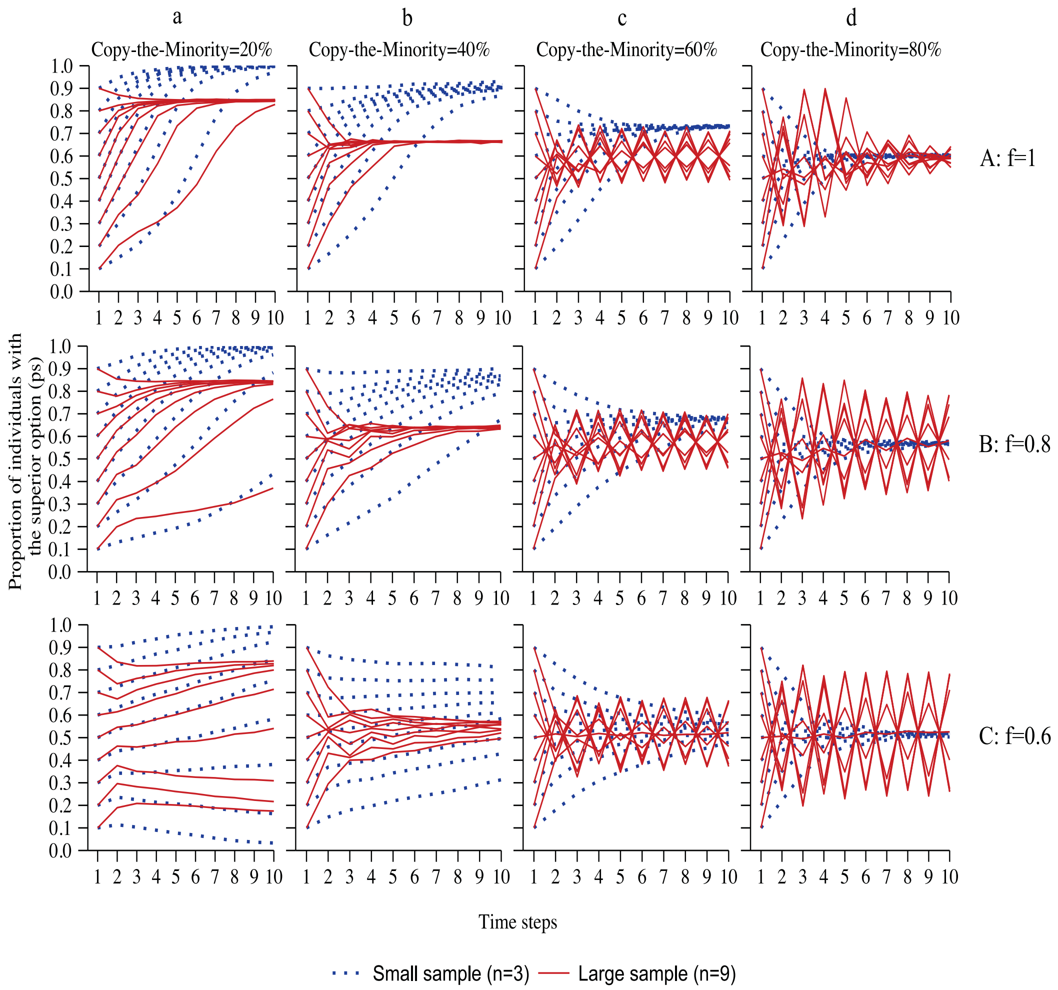

Figure A2: Proportion of agents with the correct option on each time step using *copy-the-majority* with small ($n = 3$) and large ($n = 9$) samples where some percentage of agents are using *copy-the-minority*. $a = 20\%$ copying the minority, $b = 40\%$ copying the minority, $c = 60\%$ copying the minority, $d = 80\%$ copying the minority. Based on 500 replications. Panel **A**: $f = 1$, **B**: $f = 0.8$, **C**: $f = 0.6$.

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