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Why We Live in Hierarchies?

A Quantitative Treatise

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A Quantitative Treatise

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Foreword

Much of our life is driven by a deep contradiction: We all dream of working in flat organizations, where we have uninhibited access to our peers, status does not impede the flow of ideas, and communication is effective, allowing our creativity to flourish. Yet, we spend much of our life—from childhood to retirement—in hierarchical systems, like schools, universities, and corporations.

Touting the benefits of flat organizations is in fashion these days. Reducing hierarchy can lead to more satisfied employees and speedier decision-making. Zappos, a major Internet start-up aimed at revolutionizing how we shop for shoes, eliminated its organizational hierarchy altogether, encouraging each employee to act like an entrepreneur. Other companies have simply fired their managers after realizing that they stand in the way of innovation.

But building a truly flat organization is excruciatingly difficult in practice. The reason is not incompetence. Rather, as Anna Zafeiris and Tamás Vicsek explain in this short book, we are challenging our own biology and culture every time we fight hierarchies.

Indeed, hierarchies precede us as humans. They are common in groups of animals, and they are organizational forms deeply ingrained in our biology. Most importantly, hierarchies are a common outcome of self-organization in complex systems.

The reason why animal and social systems both converge toward this form of organization is simple: Hierarchy has merits. If we try to optimize any complex system's activity toward a desired outcome, hierarchy emerges each time, particularly if there are limits pertaining to costs and available resources. For example, humans have a limited ability to process all of the information hitting us. We are unable to keep track of all of the functions our company must address. By offering a chance to specialize, hierarchies shield us—allowing us to deal only with the information relevant to our expertise. In hierarchies, as a researcher, I can focus on research, leaving the university's accountant to handle the financial and accounting issues. Beyond efficiency, hierarchies satisfy our psychological need for responsibility and order.

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Despite the prevalence of hierarchies, knowledge about hierarchical systems is scattered through the multiple literatures. Animal researchers have accumulated a great deal of insight into the role of hierarchies in animal societies; since Taylor, organizational researchers have written extensively about the benefits of hierarchical organizations in manufacturing. In the past decade, the emergence of network science has fostered a new ability. We can now capture the detailed interactions between a system's components—be that a network of pigeons in a flock or employees in an organization. These interactions have offered a fresh, big-data-driven quantitative perspective on hierarchy.

This book accomplishes an amazing feat—it integrates all of this knowledge and presents it in a brief, easy-to-understand treatise. It is the first text to offer a data-driven quantitative look at hierarchies, and it is more than a monograph. It is how to material, answering the practical questions everyone encounters in the face of a hierarchical system: How do I map it out? How do I measure the degree of hierarchy in the system? How do I uncover its origins? How do I visualize it? It offers a precise language through which we can converse about a wide range of characteristics of hierarchical systems, understanding their origins, benefits, and drawbacks.

The fact is that hierarchies both enable and restrain. When, how, and why they do these things are the million dollar questions. This short book opens the door to the answers and gives us the tools to find them.

Boston, USA   Albert-László Barabási
                                                      Northeastern University

Preface

Hierarchy is a fundamental concept regarding the structure and organization of complex systems in nature. It possesses several basic aspects, such as self-similarity, dominance, directed (top-to-bottom) sets of interactions. In addition to its various types of manifestation, hierarchy is present in almost all kinds of situation surrounding us, from the building blocks of matter (ranging from the elementary particles through atoms and solar systems to the universe) to large organizations (such as, universities or entire societies). Indeed, a large number of articles and books have been devoted to interpreting hierarchy, although apart from a very few exceptions, these works have approached the topic from the point of view of its qualitative features, instead of presenting quantitative results originating from models and/or calculations.

Networks associated with the complex set of connections among the units of a system have successfully addressed the structure of interactions of entities as parts of a living system. A few important new concepts involving the scale-free and small world nature of these networks have been proposed and extensively investigated over the past two decades. Networks have also been useful for shedding light on the intimate relationship between complexity and the widely varying roles the units of life (from proteins to people) can assume.

In this book, we aim to connect the above two essential aspects of life and treat the related phenomena in a quantitative manner. Establishing the relation of the two concepts (hierarchy and real-life networks) can be achieved by considering networks with predominantly directed edges, resulting in a globally directed and hierarchical structure with a number of distinct levels. To make the studies quantitative, we extensively discuss the possible definitions for the measures of hierarchy and then go on to present models and experiments that serve as interpretations/explanations of why and how hierarchy emerges and functions in a large class of phenomena.

One of the main conclusions of the studies of hierarchical systems we present—and it answers the question raised in the title of our book—is that *systems with a hierarchical structure perform better*, or in other words, are more efficient. In a way, they result in more benefit for less cost. This is true for the entire system, but in almost all cases, it also holds that *even the individual units gain benefit from this sort of cooperation*: They gain advantage (as compared to acting in isolation or being members of a fully egalitarian group) by voluntarily or forcefully becoming a member of a hierarchically organized structure.

In summary, we believe that having quantitative tools is helpful for getting a deeper insight into the origins of hierarchy and will be useful for those who are dealing with or planning to design complex systems that perform efficiently.

Tamás Vicsek, in addition to having the overall backing and inspiration of his family, enjoyed being involved in joint research on networks with his daughter Lilla and son András. His wife, Mária, helped a lot as well, in many different ways, including her excellent managing of the growing and supportive family and proofreading the text.

Budapest, Hungary   Anna Zafeiris
                                                                                                        Tamás Vicsek

The original version of the book was revised:
Author name and affiliation have been changed.
The erratum to the book is available at
https://doi.org/10.1007/978-3-319-70483-8_7

Contents

Chapter 1
Introduction

This book is concerned with the various aspects of hierarchical collective beha-viour, which is manifested by most complex systems in nature. From the many possible topics, we plan to present a selection of those that we think are useful in regard to shedding light onto our quite general subject from a number of very different directions. Our intention is both to present the essential contributions by the existing approaches and to go significantly beyond the results obtained through traditional methods by applying a more *quantitative* approach than the common ones (there are many books on qualitative interpretations). In addition to consid-ering hierarchy in systems made up of similar kinds of unit, we shall concentrate on problems involving either dominance relations or the process of collective decision-making from various viewpoints. In short, our book *is not a monograph* about hierarchy in general: it is, rather, an (at places subjective) overview of recent exciting developments concerning quantitative approaches to the evergreen ques-tion of hierarchies.

1.1 General Considerations

Since hierarchy is abundant in nature and society, although many of its quantitative aspects are still unexplored, the main goal we intend to achieve is the systematic interpretation and documentation of new unifying principles and basic laws describing the most relevant aspects of hierarchy (being, perhaps, the most wide-spread organizing principle in the Universe). To do so, we shall discuss recent experiments and models that are both simple and realistic enough to reproduce their observations and develop concepts for a better understanding of the complexity of systems consisting of many organisms. We shall cover systems ranging from flocks of birds to groups of people.

The related research goes beyond being interdisciplinary, and can rather be described as multidisciplinary, since it involves many kinds of system (both living
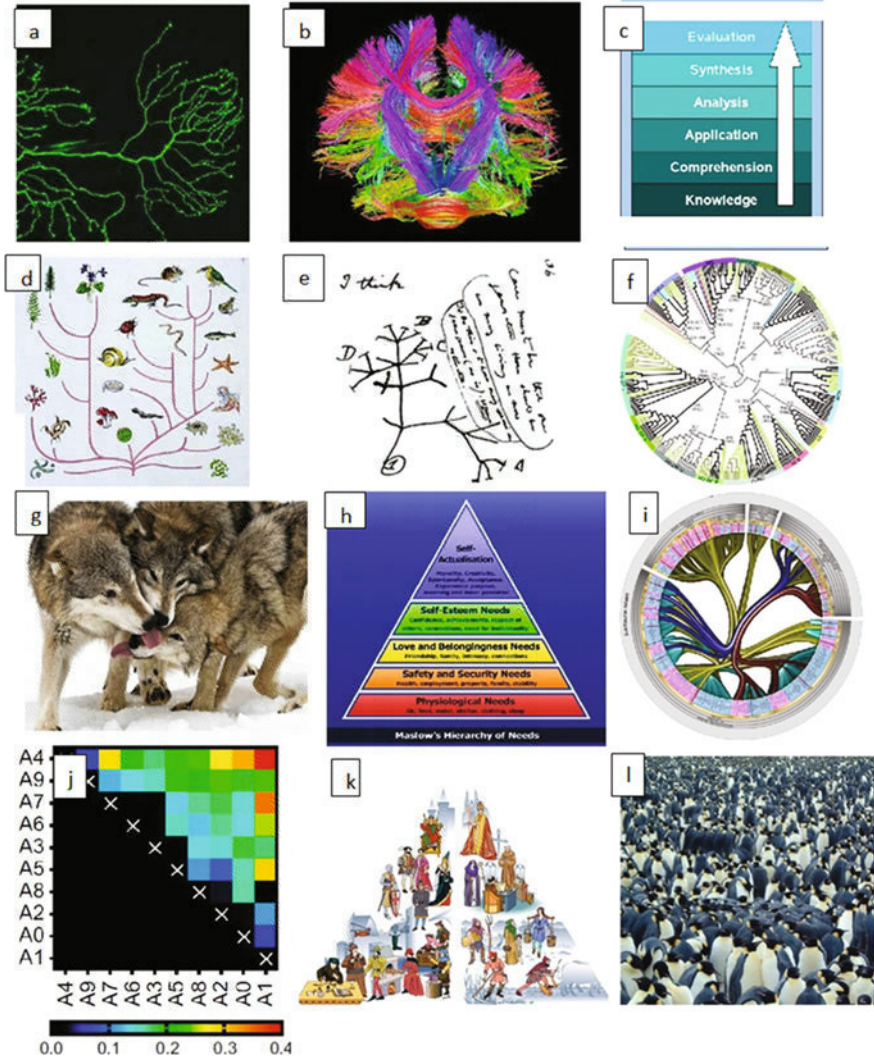
and non-living), various techniques, and technologies typically used in different branches of science and engineering. The topics we address might look overly diverse. However, one can always think of these research directions as facets of a single, to-be-explored idea.

Although we shall concentrate on hierarchical collective behaviour in general, there will be two aspects of it that will pop up in the majority of cases: collective motion and dynamically changing partially-directed networks (and the natural relation between the two). A few of the many possible examples are visualized in Fig. 1.1.

◄**Fig. 1.1 a** Axon arborisation (the end part of a major kind of neuronal cell) shows a typical hierarchical tree-like structure in space. **b** The wiring of a human brain. Hierarchy is not obvious, but closer inspection and additional MRI images indicate hierarchical functional operation. **c** And this is a possible interpretation of how we think (thoughts being one of the end products of a functioning brain). **d** The visualization (of the now commonplace) idea of the evolutionary tree. **e** The famous first drawing of the branching of the phylogenetic tree with the "I think" note by Darwin. **f** This complex tree with its hundreds of branches shows the birth of new variants (associated with new plant species) of a single protein! **g** The well-known hierarchy of wolves, indicated by who is licking who (subordinates do this to those above them). The same behaviour can be observed between a dog and her owner. **h** Perhaps the only hierarchy named after a person. This pyramid is called "Maslov's hierarchy of needs". **i** Visualization of the connections (call relations) between the various parts of a C+ software system (containing many thousands of entities and relations; the more closely related parts are colour-coded and bundled). **j** The strength of the directional correlations between pairs of pigeons in a flock (individuals being denoted by A0,…,A9). The asymmetric structure of the dominant part of the matrix (the entire matrix minus its symmetric components) indicates strictly hierarchical leader-follower relations. **k** The picturesque representation of the two pyramids of medieval relations among the member s of a society: the left side corresponding to social organization, the right side corresponding to the religious organization. **l** And finally: we show a huge community of relatively simple animals. Where is the hierarchy here? Nowhere: groups of many thousands of animals (large flocks of birds, schools of fish) typically do not display the signs of hierarchy (and, indeed, are assumed not to be hierarchically organized). (All pictures are freely available from the internet except **j** which is from one of our papers.)

In addition, we give a brief description of the most relevant concepts to which hierarchy is related.

1.1.1   Organisms Versus Agents, Entities or "Particles"

Throughout this book, we shall consider systems made of many organisms, i.e., living entities (from a few dozen to several thousands). Of course, hierarchy is present in the non-living world as well, starting from elementary particles through the solar system all the way up to the entire universe, but that is a beautiful and long story that is not the subject of the present work.

Hierarchy in life can be understood in several ways. For example, one may rank one type of quality as being more important than another type of quality. However, in most cases, hierarchy involves many "units," which are related to each other in relatively simple ways. The stress is on "many" and "simple." Perhaps the best way to demonstrate this point is to consider a group of people. The interactions (relations) among them can be extremely complicated (just think of two people being in love with each other). Instead of considering such interactions, we assume that two people, let us say, in a large organisation are either working in the same kind of unit or one of them has the job of a leader (of a group, a department, a division, etc.). In this case, we assume that there is a directed link between the two that is pointing from the leader to the regular member of the company. When accounting for their relationship, this will be the aspect that we shall consider, with all of the other,

extremely complex features of the two persons (they are made of cells, they can detect the smell of the other person, etc.) being discounted.

This is how "particles" can be defined, even for a system of people: particles are units whose interactions can be—in the given context (!)—assumed to be very simple.

"Agents" are a bit more complicated than particles. Although their interactions are also assumed to be relatively simple, these units have a "purpose." The purpose is usually also simple and can be interpreted as optimizing/maximizing some sort of advantageous quantity. In its most typical form, this quantity is the difference between the "benefit" and the "cost," usually called fitness. Fitness can be defined for a whole group of agents as well.

To summarize the above: *hierarchy is typically defined for systems of agents and can be advantageous to a varying degree*. One of the primary messages of our text is that the *main reason for the hierarchical structure of the relations among organisms is that such a structure is more advantageous* than a fully regular or random or any other arrangement.

1.1.2 Collective Behaviour

Collective behaviour applies to a great variety of phenomena in nature, which makes it an extremely useful notion in many contexts. Examples include collectively migrating bacteria, insects or birds; or phenomena in which groups of organisms or non-living objects synchronize their signals—think of fireflies flashing in unison or people clapping in phase during rhythmic applause. The main features of collective behaviour are that an individual unit's action is dominated by the influence of its neighbours—the unit behaves differently from the way it would behave on its own. On one hand, such systems show interesting ordering phenomena, as the units simultaneously change their behaviour to a common pattern (Camazine et al. 2001; Sumpter 2010), and on the other hand, they can form structures that are capable of exhibiting much more complex functions than a single unit (consider, e.g., a single neuron versus a complete brain).

The world is made of many highly interconnected parts over many scales, whose interactions result in a complex behaviour requiring separate interpretation for each level. This realization forces us to appreciate that new features emerge as one goes from one scale to another, so it follows that the science of complexity and the closely related hierarchy—following a classification based on major analogies - is expected to reveal the principles governing the ways by which these new properties appear.

Over recent decades, one of the major successes of statistical physics has been the explanation of how certain patterns can arise through the interaction of a large number of similar units. Interestingly, the units themselves can be very complex entities, too, and their internal structure has little influence on the patterns they produce. It is much more the way they interact that determines the large-scale

behaviour of the system. It has been found that it is not only interacting spins or atoms, but also assemblies of molecules or granular particles, and even large groups of complex biological structures (bacteria, ants, birds, etc.) that can be examined through models of statistical physics (Vicsek 2001). It has been demonstrated that the collective behaviour of units has a number of features typical for many different systems. From the point of view of statistical physics, these could be considered as "universality classes" or major types of behavioural pattern.

It is, however, very important to note that in the above context, the hierarchical nature of interactions has been largely neglected, especially for the directed (or asymmetric) case (except for a few network theory papers). Our basic assumption is that observing and *quantitatively* interpreting the patterns of behaviour in hierarchically organized systems is likely to lead to a unified picture of hierarchical collective behaviour, and, in an ideal case, to the discovery of a number of basic relations or "laws" describing them.

1.1.3 Collective Motion

The actions of individual moving organisms come together into a whole, creating patterns of motion so complex that they seem to have been choreographed from "above." Flocks and schools have a distinctive style of behaviour—with fluidity and a seeming intelligence that far transcends the abilities of their members. Vast congregations of birds, for example, are capable of turning sharply and suddenly en masse, always avoiding collisions within the flock. Over the last two decades, computer models and sophisticated techniques for collecting data about a large number of animals have turned out to be very useful for establishing a significantly better understanding of such systems than we have ever had before (Vicsek and Zafeiris 2012).

1.1.4 Networks

When "generating" life as we perceive it today, nature "made use of" the existence of the above-mentioned hierarchical levels by spontaneously separating them into molecules, macromolecules, cells, organisms, species and societies. The big question is whether there is a unified theory for the ways in which elements of a system organize themselves so as to produce such a highly hierarchical structure of behaviour typical of wide classes of systems. Interesting principles have been proposed, including self-organization, simultaneous existence of many degrees of freedom, self-adaptation, rugged energy/fitness landscapes and scaling, etc. Physicists are learning how to build relatively simple models that produce complicated behaviour. At the same time, researchers working on inherently very complex systems (e.g., biologists or economists) are uncovering the ways in which

their infinitely complicated subjects can be interpreted in terms of interacting, well-defined (i.e., simpler) units (such as proteins) with the interactions corresponding to links. These connections can also be directed and/or weighted, and the units or nodes may have attributes within a complex network (Albert and Barabási 2002; Newman 2010; Barabási 2016).

Most of the networks in life and technology are dynamically changing and highly structured. For example, a dynamically changing network can be associated with a flock of collectively moving organisms or robots interacting as a function of their positions.

1.2   Motivation

It is widely accepted that we do not have a deep enough understanding of the reasons behind the abundance of multi-level hierarchies. However, there must be an advantage to such organization, because of the permanent evolution of the corresponding systems, preferring more efficient variants. But where is this advantage? Better adaptability? A more efficient, robust or stable structure? The faster spread of relevant information? Or, perhaps, better controllability (think of, e.g., an army)? On a more abstract level: What are the conditions for a hierarchical organization to emerge? Are there any general (valid for many systems) necessary and/or sufficient conditions for this emergence?

These are challenging questions, and if we can answer them, it could allow us to design and produce far more efficient devices or, perhaps more importantly, create far more functional organizations, be they industrial, educational or one of many other kinds.

Motivated by the above reasons, this book will be centered on topics and answers related to questions like:

1.2.1   What is Our Subject?

We shall primarily consider systems (structures, processes, phenomena) that are common in the living world. The related, practical questions are: what are the conditions under which hierarchy emerges? What kinds of mathematical tool are appropriate for describing the various aspects of hierarchy?

1.2.2   Why Do We Study?

We use a quantitative approach to interpreting realistic situations in life; because most of the presently available experimental and theoretical treatments of

hierarchical organization are predominantly qualitative, a need arises to present results involving numerics. On the other hand, interest in the topic seems to be increasing quickly. Understanding leadership and further aspects of hierarchy are expected to be very useful from the point of view of optimizing economy-related structures. On a less applied level, a deeper insight into the collective behaviour of groups has also been attracting growing interest.

1.2.3 How Do We Study?

As mentioned above (and explored here in a bit more detail), there can be several methods for treating the various quantitative aspects of hierarchy. First, it is possible—but far from trivial—to design experiments for studying how a hierarchical set of leader-follower relationships emerges from an originally disordered set of living entities. Second, one can design models and study them either analytically or using computer simulations. The two major quantitative approaches have been: game theory and agent-based modelling. In this book, we address the second alternative, since the game theoretical works we know of allow for a less straightforward comparison with actual, real life observations and experiments. A rare but important exception is the very recent book by Boix (2015), which delivers an impressive mixture of calculations, facts and ideas for treating large scale (political) hierarchy. Our work, concerned with hierarchies on a smaller scale of groups or collectives, can be looked at as complementing Boix's book.

1.3 Hierarchical Structures in Space and in Networks

There exist a few fields in the sciences that are closely related to the general notion of hierarchy, but they fall beyond the scope of our work (they represent the self-similar aspect of hierarchy). This is mainly so because these areas represent a research field of their own. In addition, in most of the present book, we consider hierarchy as a set of related entities, such that the relation between two connected entities is directed (one, in ways to be specified later, plays a role of being superior/leading/embedding, etc., in consideration of the other entity). Thus, here we only briefly touch upon the topic of spatially hierarchical objects (called fractals) and undirected (symmetric relations) but still hierarchical networks (called scale-free). For further details about such self-similar aspects of hierarchy, we suggest that the readers use the following books as a source: Falconer (2003), Feder (1988), and Vicsek (1992) for information about fractals, and Barabási (2009, 2016), Newman (2010), Newman et al. (2006), Dorogovtsev and Mendez (2003), and Pastor-Satorras and Vespignani (2007) for information about networks and scale-free networks.

Fractals are objects for which the topological dimension (the number of independent directions in which one can move from a given point of the fractal) is smaller than the dimension of the Euclidean space into which they can be embedded. They also possess a self-similar geometry, which means that a small part of a fractal has the same statistical features as the whole. Here, with the expression "same statistical features," we typically understand that the density correlations are the same. This is equivalent to saying that scaling up (blowing up) a small part of a fractal results in a structure that is statistically identical to the full fractal itself. This is a non-trivial feature and involves the fact that the dimension of the fractals is a non-integer number, as opposed to regular objects that have dimensions 1, 2 or 3.

Interestingly enough, a large variety of living systems involve fractal geometry in one way or another. As one proceeds from simpler to more complex manifestations of life, it is possible to encounter fractal bacteria colonies (Matsuyama and Matsushita 1993), ant trails (Jun et al. 2003) and networks of blood vessels in higher order organisms described by—among other important features—the so-called allometric scaling laws in biology in general (West et al. 1997) and, in particular, in mammalian metabolism (see, e.g., White and Seymour 2005). Perhaps the largest scale built by organisms is the cities in which we live, which display fractal-like features as well (Batty and Longley 1994).

The so-called *scale-free networks* can also be considered to be manifestations of a self-similar structure. Such a structure is not realized in space, but shows up in the specific way the entities of a system are connected to each other. Using the language of network theory, the degree of a node (entity) is the number of edges (connections) this node has leading to its neighbours in the network. The degrees may follow all sorts of distribution, but if this distribution is a power law, then the degree distribution is invariant under scaling: as the network grows in time, the exponent corresponding to the algebraic decay of its degree distribution remains the same.

The possible examples for systems that can be characterised in terms of scale-free networks are numerous. Most of these are not assumed to exist in real space. Going from the smaller scale to the larger, examples include networks corresponding to the interactions among proteins in a cell, then, taking a large jump, to many human-made systems (internet, web pages, airlines, etc.) or the various networks of social interaction (friendships, collaborations, industrial relations, etc.).

There are, however, some spatial structures that can best be interpreted in terms of undirected, topologically hierarchical networks. Louf et al. (2013) introduced a generic model for the growth of a spatial network based on a general concept of cost-benefit analysis. Their model leads to a wide variety of hierarchical spatial structures (trees) minimizing a condition-dependent fitness function. The work by Daqing et al. (2011) connects the fractal and the network aspects of structures by calculating the dimensions of spatially embedded networks. Motivated by the biological problem of allometry (how the body size of a living organism is related to its anatomy, shape and physiology), West et al. (1997) proposed a general model that describes how the vital materials are transported via space-filling fractal-like networks of branching tubes. From a similar point of view, Bejan connects many of

the corresponding phenomena (like arborescence, hierarchical networks in space, fractal-like objects, etc.) via the Constructal law (Bejan 1997).

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Chapter 2
Definitions and Basic Concepts

In this chapter we define the notion of hierarchy, more precisely, the dominant-subordinate relationship. Based on this concept, the hierarchical nature of the entire system can be measured and analyzed, for which several techniques and approaches are reviewed. We also discuss the main characteristics of hierarchical systems, such as their context and time dependency. Definitions and examples are also provided for various types of hierarchies. Finally, visualization techniques are overviewed, both for small and big graphs.

As we indicated in the introduction, the notion of hierarchy applies to a great variety of topics and contexts, be it the social structure of animal groups, human virtues, psychological needs or the structure of a computer program. Accordingly, it does not have a compact, precise, widely accepted definition that would be applicable to all cases. Available definitions usually bypass the problem of clarification by using synonymous words, which are, unfortunately, similarly unclear. For example, according to the Cambridge dictionary, hierarchy is "a system in which people or things are arranged according to their importance." Here, "importance" is the keyword, but importance is highly subjective: something that is important in a given context might not be important at all from another point of view. Here, we also find that hierarchy corresponds to "the people in the upper levels of an organization who control it." So, we learn that it is about *control*, but according to this definition, hierarchy is restricted to people in an organization, which is a very narrow interpretation. Checking a very popular site, Wikipedia, we find that "A hierarchy (from the Greek "hierarchia," "rule of a high priest," from "hierarches," "leader of sacred rites") is an arrangement of items (objects, names, values, categories, etc.) in which the items are represented as being "above," "below," or "at the same level as" one another." However, this interpretation does not inform us about the basic aspects of the arrangement, which represent, on the other hand, the heart of the problem.

As we shall see, it turns out from more strict investigations that we usually talk about hierarchy in situations in which the *entities of a system can be classified into levels in a way that elements of a higher level* **determine or constrain the**

Fig. 2.1 An example of flow hierarchy. The feeding-queuing hierarchical structure of a pigeon flock. Each square represents an individual. The edges point from the higher ranked bird towards the subordinate one, with edge widths corresponding to the ability to influence the behaviour of the lower-ranked individual. For the sake of better visibility, higher-ranked nodes are depicted higher in the picture. Reproduced from Nagy et al. (2013)
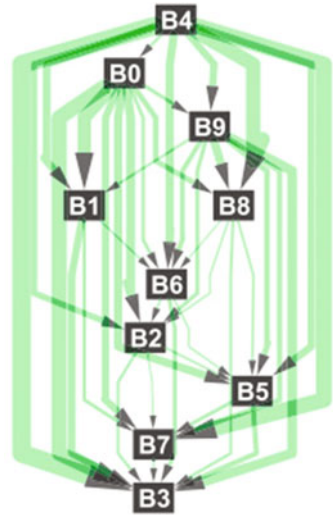
behaviour and/or characteristics of entities in a lower level. That is, at the heart of hierarchy, we find control of behaviour.

Definition A system is hierarchical if it has elements (or subsystems) that are in dominant-subordinate relation to each other. *A unit is **dominant** over another unit to the extent of its ability to influence the behaviour of the other. In this relationship, the latter unit is called **subordinate***.

A typical hierarchical structure can be seen in Fig. 2.1, depicting the ranks within a pigeon flock. The inner structure of the group has been established by observing and measuring the feeding-queuing behaviour of its members (Nagy et al. 2013).

Note that this definition does not tell us how hierarchical the *system* is. Instead, it expresses whether its elements (or subsystems) are in hierarchical relation or not (manifesting itself in a dominant-subordinate relationship). Furthermore, it tells the origin (reason) and extent of the dominant-subordinate relationship. Consider, for example, the rock–paper–scissors game. According to the rules,

- The rock blunts the scissors (and hence "disarms" it, beats it)
- The scissors cut the paper, and
- The paper covers the rock.

Figure 2.2 shows how the elements overpower each other. Based on the above definition, the hierarchical (dominant-subordinate) relationship among the units is clear, but the hierarchical nature of the whole system is not: is this network hierarchical at all?

In other words, from a graph-theoretical point of view, the above definition gives a lead regarding the *arrows* (where they should be and what their deeper meaning is) but it does not tell us how hierarchical the entire system is. At this point, we

Fig. 2.2 Graph representation of the rock-paper-scissors game. The dominant-subordinate relationship among the elements is clear, but the hierarchical nature of the entire system is not
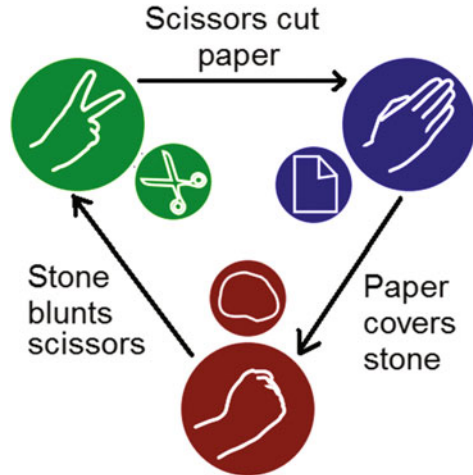
choose to keep it this way, mainly because the extent of hierarchy within a system has subjective aspects: for some, the rock-paper-scissors game is "fully" hierarchical, since its elements are clearly in hierarchical relation. For others, it is not, because no source (leader) can be determined.

Many approaches have been proposed to measure the hierarchy of a network, but none of them is "universal," or accepted by everyone for all cases. Section 2.1.2, "Measuring the level of hierarchy," gives an overview of these measures and algorithms..

A few comments related to the definition:

- During different group activities, the influence of the members might vary. In other words, *hierarchy is context/task-sensitive*, even within the same group! For example, as we shall see in Sect. 3.1.3, "Leadership versus dominance," the members of the same pigeon flock arrange themselves into different hierarchies according to the activity being undertaken: when they feed, the ranks are entirely different from those that can be observed during flight. This phenomenon is even more starkly expressed in human groups.
- Hierarchy might vary over time. As certain characteristics of the group members change (for example, the physical strength of the individuals in a pack of wolves), so do their ranks.
- This definition implies that the units *behave* somehow, or have some observable characteristics. In other words, entities without observable behaviour or characteristics cannot form a hierarchical structure.
- The influence can either be forced by the higher-ranked individual (e.g., when a higher-ranked pigeon does not let a lower-ranked one near the food source), or it can be voluntary (for example, leader-follower relationships during flight).
- A higher-ranked unit, by influencing the behaviour of other units more extensively, has a larger effect on the collective (emergent) group behaviour as well.

Hierarchical systems can be classified into the following subtypes:

1. **Order** hierarchy is basically an ordered set, in which a value is assigned to each element characterizing one of its arbitrarily chosen features. This assigned value defines the rank of the entity within the hierarchy. An example of this can be the ranking of artists, e.g., painters or sculptors, based on the average price of their artworks. In this example, the "set" is composed of the artists, and the feature is the average price of their artwork. Another example can be a hierarchy of firms, ordered by, say, their number of employees. In this type, the network behind the system is neglected or it does not exist. More formally, this type of hierarchy is "equivalent to an ordering induced by the values of a variable defined on some set of elements" (Lane 2006).

2. **Nested** (or **embedded, containment, inclusive**) hierarchy is a structure in which entities are embedded into each other. Higher level entities consist of and contain lower level entities, or, as Wimberley (2009) has formulated it, "larger and more complex systems consist of and are dependent upon simpler systems and essential system-component entities." (According to some categorizations, a *nested* hierarchy can contain only one entity at each lower level, a bit like the case of the Russian Matryoshka dolls, while a *generalized* nested hierarchy allows for multiple objects.) Uncovering a nested hierarchy structure within a system is closely related to community detection in graphs.
   Containment hierarchy has two sub-types:

   - A *subsumptive* **containment** hierarchy (a.k.a. *taxonomic hierarchy*) is a structure in which items are classified from specific to general. For example, domestic cats, lions, tigers and cheetahs (gepards) belong to the family of cats called "*Felidae*," dogs, foxes and wolves belong to the family of carnivorans, a.k.a. "*Canidae*," *Canidae* and *Felidae* both belong to the order of *Carnivora*, etc. (see Fig. 2.3a). Entities are containers, containing other containers. Mathematically, this arrangement can be formulated as:
     Foxes $\subset$ Canidae $\subset$ Carnivora (and Carnivora $\subset$ Mammals $\subset$ Animals, to go further on). Each entity on a lower level "is an" entity of a higher level: a fox "is a" Canidae, a Canidae "is a" Carnivora, a fox "is a" mammal, etc. It is assumed that entities on a lower level are proper (or strict) subsets of the entities on a higher level.
   - *Compositional* **containment** hierarchy (a.k.a. *level hierarchy*) describes how a system is composed of subsystems, which are also composed of subsystems, etc. The "hierarchy of life" is the best example of this structure, describing how organisms are composed of organ systems, which are composed of organs, which are composed of tissues, which are composed of cells, etc. (see Fig. 2.3b). Two important features often (although not always) appear in this type of hierarchy: firstly, there is a "scalar quality," meaning that entities on higher levels are often bigger than entities on lower levels (a cell is bigger than a molecule). Secondly, there are emergent properties—properties that are not present on lower levels, but due to interactions among the units, appear on higher levels—that also often accompany this structure. For example, consciousness appears on the level of the
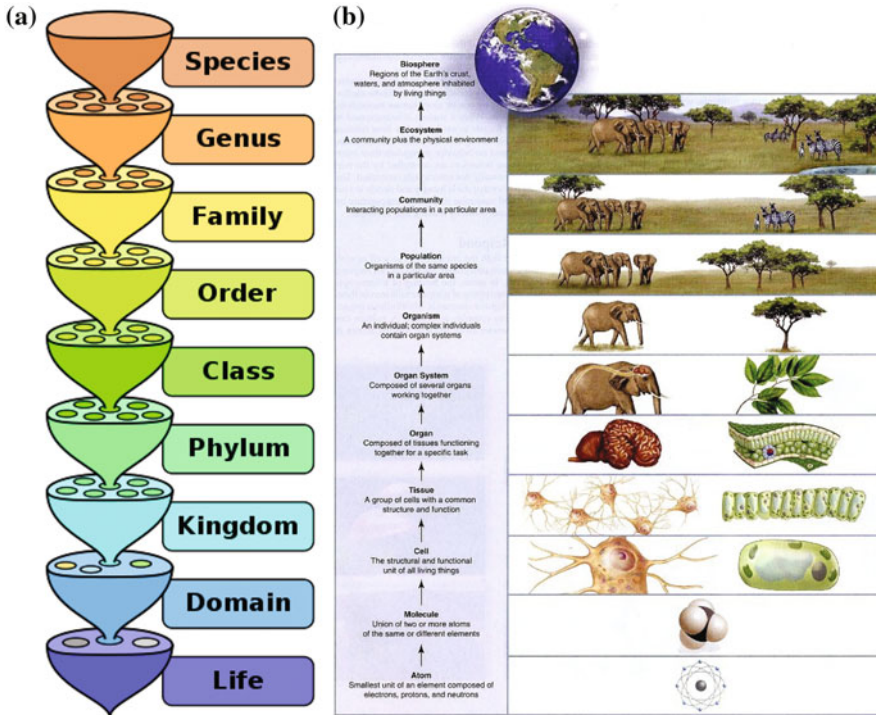
Fig. 2.3 The two types of containment hierarchy: "taxonomic" and "compositional". **a** In a *taxonomic* (or *subsumptive*) containment hierarchy, entities are containers, containing other containers. **b** A *compositional* containment (or *level*) hierarchy describes how a system is composed of subsystems, which are also composed of subsystems, etc. The best known example of this type of hierarchy is the "hierarchy of life." b is reproduced from Mader (2010)

brain (which is an organ), but it originates from the interactions of the neuron cells. Emergent properties are of prime importance, since they are a fundamental characteristic of "complex systems."

3. **Flow** (or **control**) hierarchy: "intuitively," this is an acyclic, directed graph. The nodes are layered into levels in such a way that nodes on higher levels influence nodes on lower levels, and the influence is represented by edges. Layers refer to power, that is, an entity on a higher level gives orders or passes on information to entities on lower levels. This is where the name comes from: such a structure represents the flow of orders, or, equivalently, how certain entities control other entities. Armies, churches, schools, political parties and institutions are typically organized in this way. Downwards orders flow along the edges; upwards pointing edges correspond to requests or the sending of information. Technological systems are also often organized in this way. In those cases, a central unit controls particular devices, which control lower level devices, etc. At the bottom-most level, sensors do not control anything directly, but they send

information upwards, which is used to refine the decision-making process enacted by devices on higher levels (see Fig. 2.1).

Importantly, these hierarchy types are not independent of each other. On the one hand, many systems can be described by more than one type. For example, members of an army form control hierarchy in such a way that people having higher rank give orders to lower-rank soldiers, but, at the same time, the very same army forms a compositional containment hierarchy as well. This is because an army is composed of various divisions (infantry divisions, motorized divisions, airborne divisions, etc.) that are also composed of smaller contingents, all the way down to the soldiers, who are the "units" in this structure.

On the other hand, both order and nested hierarchies can be converted into a flow hierarchy. In an order hierarchy, a directed edge can be assigned to each pair of adjacent members in the hierarchy, producing a chain of directed edges. In a nested hierarchy, a virtual node is assigned to every sub-graph, and if a sub-graph contains another, then the two corresponding virtual nodes are connected by a directed link, which produces a flow hierarchy along the network of virtual nodes.

Thus, flow hierarchy is the most important variant, and we shall mainly concentrate on its manifestations.

2.1 Describing Hierarchical Structures

In this chapter, we shall briefly summarize the basic concepts related to *graphs*, the mathematical object most often used in relation to hierarchy. It is important to highlight that graphs and networks are only the *models* of the real-life systems, not the systems themselves. It is a mathematical representation of the system under investigation, utilized because, using graph theoretical methods and algorithms described in subsequent chapters, they can reveal many important characteristics. An important further comment is that—as is done in the literature—we shall use the term 'graphs' for abstract mathematical constructions, while the term 'networks' will be associated with the underlying interactions within a real-life structure. Readers familiar with graphs may skip this chapter.

2.1.1 Graphs and Networks

As mentioned above, the most commonly used mathematical tool for describing hierarchical systems is graphs. Primarily, but not exclusively, they are connected to systems embodying flow (or control) hierarchy. Such systems and their graph representations go hand in hand to such an extent that when trying to assign a "hierarchy value" to a system (describing "how hierarchical" the given structure is), it is usually the hierarchy level of the *graph* (representing the system) that is measured.

The concept behind this representation is rather straightforward: the entities of the systems are the nodes of the graph, and if a pair of entities is in a subordinate-dominant relationship, then there is a directed edge between them.

In the following, we give a short overview of the basic theoretical concepts of graphs:

- A *graph* is a mathematical tool that is appropriate for handling a set of *objects* with *connections* among them. The objects are represented by *nodes* and the connections between them by *edges*. Formally, $G = \{V, E\}$ with a function *f:* $E \rightarrow V \times V$. The elements of *V* are the nodes (or *vertices*, or *points*), and the elements of *E* are the *edges* of the graph. The nodes are usually denoted by small Latin letters (e.g. *i, j, k*) or by Arabic numbers (1, 2,…, *N*). Formally, *f* sends edges to pairs of vertices (which are the "endpoints" of the edge), but in practice, we usually forget about the function *f* and simply think of *E* (the set of edges) as a subset of $V \times V$. Accordingly, edges are usually given by the starting and nodes, such as $e = (i, j)$, for any $e \in E$. The word *network* is often used as a synonym for graph in cases in which it stands for data that is actually observed.
- A graph can be either *directed* or *undirected*. In the case of a directed graph (or *digraph*), the relation has a special direction as well. For example, in the case of a hierarchy network, the direction can show which element dominates which other. In contrast, in an undirected graph, the connections do not have special directions, as in the network representing the flight connections among cities. Informally speaking, in the case of an undirected graph, the edges are just "lines," and in the case of digraphs, they are "arrows."
- A simple *loop* is an edge that connects a node to itself. (An edge whose starting and endpoints are the same vertex.)
- A *path* in a graph is a sequence of connected vertices. (Most definitions specify that the nodes within a path have to be distinct from each other.)
- A *cycle* is a closed path, that is, a path whose starting and endpoints are the same vertex. Many time cycles are also referred to as loops.
- A *tree* is a graph in which there are no loops, cycles or multiple edges. In other words, it is a graph in which any two nodes are connected by exactly one path. There are two special kinds of vertex: (i) the root node, which does not have parents, and the leaves (or end-nodes), which do not have children. Accordingly, in a tree, nodes can be layered into levels.
- A *cluster* (a.k.a. *module*, *community* or *cohesive group*) is a part of the graph in which the units are more densely connected to each other than to the rest of the graph. We will use this elastic description, since the concept does not have a well-defined, widely accepted definition. Importantly, in real-life networks, the presence of such modules is a signature of the hierarchical nature of the structure (see, e.g., Vicsek 2002; Ravasz et al. 2002; Palla et al. 2005).
- A *directed* community is simply a community in a directed graph. Here, the nodes can be related to each other based on the number of incoming and outgoing links connecting them to other nodes within the same module. A node

having more outgoing edges towards other members of the module is more like a "source"-node, whereas a node with mostly incoming links from these members is more like a "drain" (Palla et al. 2007).

- Vertices can be characterised by the number of links they have, reflecting how "strongly" they are connected to other nodes. Accordingly, the *degree* of a node in an undirected graph is simply the number of its edges. In a directed graph, vertices can be characterised by their *in-degree* and *out-degree* values: the *in-degree* value refers to the number of links pointing *towards* the given node, whereas the *out-degree* value refers the number of links going outwards from the vertex.

2.1.1.1   Centralities and Complexity Measures of Networks

Once a graph/network is defined, a number of interesting local and global quantities can be introduced for its characterization. Here, we first mention a few commonly used quantities of this kind, and next, we turn to measures that are essential from the point of view of hierarchy.

Centrality values are usually associated with a single node or edge, but typically depend on the global structure of the network. Perhaps the best known and most used quantity in this context is the so-called 'betweenness' centrality, which measures the centrality of a node in a connected graph based on the shortest paths. For every pair of nodes, there exists at least one shortest path between the nodes. Betweenness centrality for each node is then the number of these paths that pass through the node (Freeman 1977). Obviously, it measures the level of importance of a given node in the context of information transfer within the network.

While betweenness centrality has a unique definition, the situation is much less well defined when one considers the level of complexity of a network. The situation is similar to what holds for the definitions of hierarchy measures, and, indeed, although complexity and hierarchy are two different notions, they are intimately related. Several complexity measures have been defined in the literature, and we reproduce only a few of them here in order to illustrate their nature. The algorithmic complexity of a network is given by the shortest possible program that can be used to generate its structure. Complexity measures that involve hierarchy are typically specified for networks with an underlying tree-like structure. For example, the so-called cyclomatic number (Temperley 1981) measures the complexity of an expression, represented as a tree. Expressions with either identical nodes or with all different nodes are the extremes in an "entropy" scale, because they are either trivial or impossible to compress. The more complex ones in the cyclomatic sense are those whose branches are different, yet some subtrees are reused across branches. Bochev and Buck (2005) discuss this and further relevant measures of network complexity in detail.

2.1.2 *Measuring the Level of Hierarchy*

In this section, we shall focus on measures for *flow* hierarchies. More precisely, we consider measures *for graphs representing flow hierarchy*. We have two main reasons to do so: (i) observations and experiments, as well as results of computer simulations, are likely to return flow hierarchy; (ii) all other hierarchy types can be transformed into flow hierarchy in a rather straightforward way. For example, considering a containment hierarchy, its clusters can be identified with the nodes of a graph in which the directed edges will indicate the containment relation. That is, in the graph, there will be an edge pointing from node *A* to node *B*, if cluster *B* fully contains cluster *A* in the original structure (Nepusz 2013).

Most of the proposed measures take values on the [0, 1] interval, returning nearly 0 for a completely hierarchy-less structure, like a full graph or a circle, and returning a value close to 1 for "completely hierarchical" structures, like a directed tree. Values for transient structures rely on "intuition," and intuition differs from person to person. This is one of the main reasons why there is no "most appropriate" measure serving all needs. The measures reviewed in the present book have values on the [0, 1] interval, with higher values representing higher degrees of hierarchy.

This section of the book is relatively extensive for two reasons: (i) it is about an obviously central quantitative characteristic of a hierarchical structure; (ii) in spite of its essential importance, there is no unique definition of the level of hierarchy of a system.

This latter situation is analogous to that of the definition of a community in a network. The notion itself is so complex that, depending on the aspect that we are interested in, a suitable definition should be chosen. For example, a community (cluster) in a network can be defined as a sub-network of nodes that have a relatively greater number of connections among them than with the other nodes. However, we can require this "relatively more" to manifest itself in various ways. Directed, weighted and connections specified according to further criteria make the problem of defining clusters in a network an even more open problem.

To introduce this aspect of the problem of finding the best measure of hierarchy, the reader is asked to consider the following question: which structure is more hierarchical? A set of nodes arranged into layers connected by directed edges, all directing from an upper to a lower layer, or a "star" consisting of a central node from which a number of directed edges lead to the other nodes of the network? To us, the right answer is: it depends on the context, on the function, etc. Next, we account for a number of relevant possible angles from which such a question can be approached.

2.1.2.1   Global Reaching Centrality

The central idea of this approach is to give a rank to each node by measuring its "impact" on other nodes. Impact is defined by the ratio of vertices that can be reached from the focal node i. *Local reaching centrality*, $C_R(i)$ defines this quantity exactly: in a directed, un-weighted graph, $C_R(i)$ is the maximum number of vertices that can be reached from node i, divided by $N-1$. Then, the level of hierarchy is inferred from the distribution of the local reaching centralities: the more hetero-geneous the distribution, the more hierarchical the corresponding graph/network. In order to demonstrate this statement (namely, that the distributions of the local reaching centralities reveal the hierarchical nature of a network), three different graph types are compared in Fig. 2.4: an Erdős-Rényi (random) graph (which is not hierarchical), a tree (which is highly hierarchical), and a scale-free graph (which is "moderately" hierarchical). The most homogeneous $C_R(i)$ distribution belongs to the Erdős-Rényi (ER) graph: the $C_R(i)$ values are either 0 or close to 1, marked by the two narrow spikes at these values with a solid black line. In contrast, we find all kinds of $C_R(i)$ value in a tree, as indicated by the red line in Fig. 2.4 (note the log-log scale).
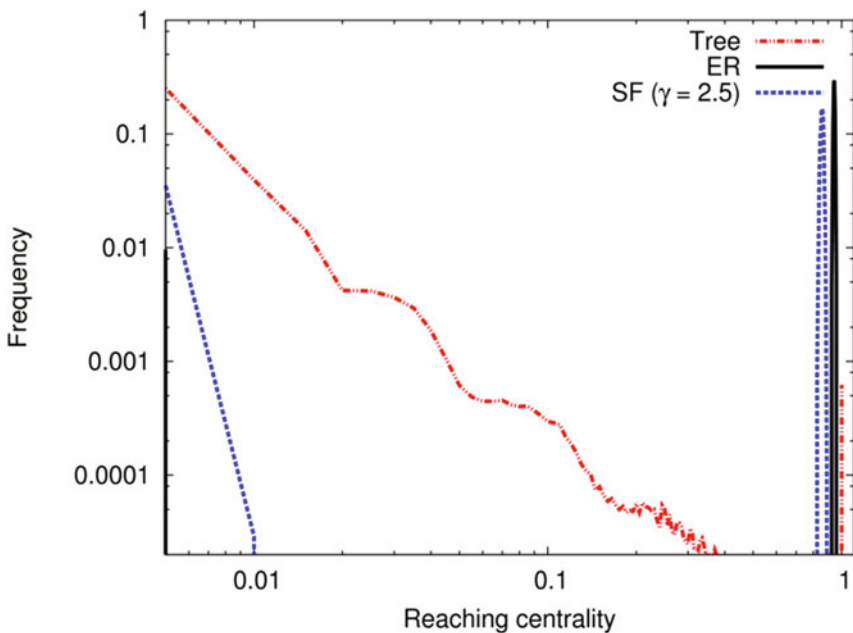
Fig. 2.4 Distributions of the local reaching centralities for three kinds of directed network: Tree, Erdős-Rényi (ER) and scale-free (SF). All the curves are averages of 1000 graphs with $N = 2000$, of the appropriate graph type. Reproduced from Mones et al. (2012)

This distribution follows a power law that is distorted due to the random branching numbers. The blue dashed line belongs to the "moderately hierarchical" scale-free graph, marking a "moderately heterogeneous" distribution.

These curves represent distributions, while for a measure, we expect a number. The definition proposed by Mones et al. (2012) grasps the heterogeneity of the $C_R(i)$ distribution as follows: Let $C_R^{\max}$ denote the highest local reaching centrality in a graph $G = (V, E)$. Then, the Global Reaching Centrality, *GRC*, is defined as:

$$\text{GRC} = \frac{\sum_{i \in V} \left[C_R^{\max} - C_R(i) \right]}{N - 1},\tag{2.1}$$

where V is the set of nodes and N is the number of nodes in G. The GRC values for our three example graphs (Tree, Scale-free and Erdős-Rényi), are as follows:

Tree: 0.997 ± 0.001, which is the highest.
Scale-free: 0.127 ± 0.008, that is, SF networks are slightly hierarchical.
Erdős-Rényi: 0.058 ± 0.005, that is, these are not hierarchical at all.

These values, the means and variances are calculated for an ensemble of 1000 graphs, and they demonstrate that the returned values are close to our "intuition." Equation (2.1) applies to directed, un-weighted graphs. Its generalized version is suitable for analysing weighted and/or undirected graphs by an appropriate modified definition of the local reaching centrality (Mones et al. 2012).

2.1.2.2 Random Walk Measure

The main motivation for this approach is the claim that—in contrast to the assumptions behind most of the proposed methods—it is not correct to treat all directed acyclic graphs as already being maximally hierarchical, independent of their inner structure. This observation is based on the common intuition that a hierarchical structure often corresponds to a multi-level pyramid in which the levels become more and more wide as one descends from the higher levels towards the lower ones.

The measure proposed by Czégel and Palla (2015) is based on properties of random walks within the graph, and, in accordance with the above-mentioned claim, directed trees corresponding to multi-level pyramidal structures obtain higher values of hierarchy than directed stars or chains.

Intuitively, the method is based on the assumption that there is information flow coming from the high-ranking nodes towards the ones at the bottom, similarly to the case of an army or company, in which the leaders send instructions downwards along the links. In order to track the sources of the instructions/information/etc., random walkers are dropped onto the nodes who then move *backwards* along the links. Once a steady state is reached, the density of such random walkers (the number of them visiting a given node) can be interpreted as being proportional to the rank of this node: high random walker density indicates that the vertex is a
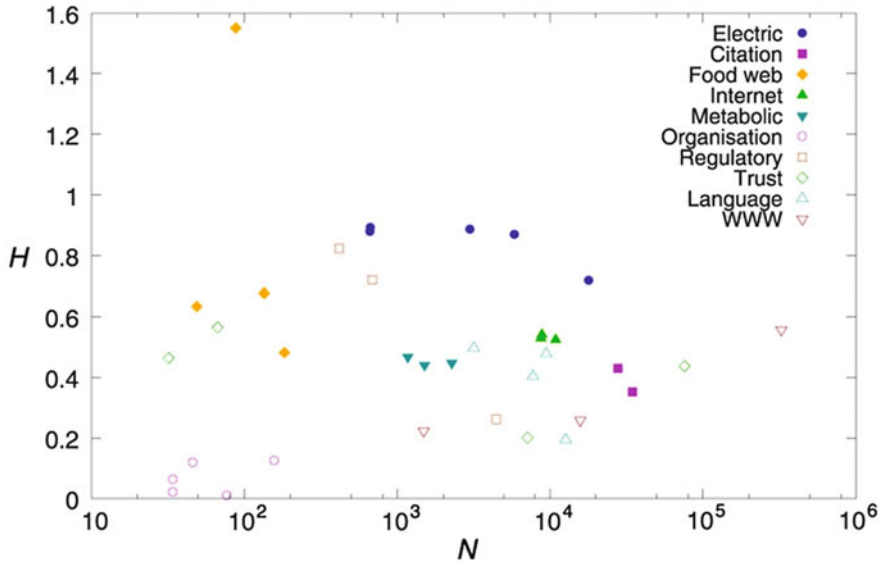
Fig. 2.5 Hierarchy scores as a function of the network size. The different symbols correspond to different networks. The x axis marks the size of the network (N, number of nodes) on a logarithmic scale, whereas the y coordinate shows the hierarchy value (H) of the graph. Reproduced from Czégel and Palla (2015)

source of information, low density indicates the vertex is more likely to be just a "receiver" of orders—that is, low in rank. The hierarchical nature of the network is then estimated based on the distribution of these random walker densities: if the distribution is homogeneous, the source of information/order cannot be pinpointed, thus, the network is not hierarchical. In contrast, inhomogeneous distribution indicates clear information sources: the network is hierarchical. This homogeneity/inhomogeneity is measured with a value called H, with higher values reflecting more hierarchical structures (bigger inhomogeneity) and lower values less hierarchical networks.

The largest H values belong to regulatory networks, electric circuits and food webs, whereas the lowest ones belong to the informal networks of acquaintances in different organizations (Fig. 2.5). Moderately hierarchical examples include the Internet and various citation-, metabolic-language and trust networks, the results of which are in good accordance with our intuitive expectations.

An even clearer picture regarding the hierarchical nature of a network can be obtained by "normalizing" the hierarchy measure H against the hierarchy measure of the same network, but under the assumption of random connections. This is the "z-score", defined as

$$z = \frac{H - \langle H \rangle}{\sigma(H)},$$

(2.2)

where H is the hierarchy score, $\langle H \rangle$ is the expected H value of the randomized graph, and $\sigma(H)$ is the standard deviation of H in the randomized ensemble.

In the rest of the section, we will give an overview of some further measures, focusing on the main ideas behind them. Here, our aim is not to give a detailed description of the techniques, but rather to flip through the type of concepts that have been proposed so far regarding the problem of measuring the hierarchy level of a graph.

2.1.2.3 A Measure for Undirected Networks

The measure proposed by Trusina et al. (2004) quantifies the flow hierarchy of undirected networks. It is based on the assumption that every vertex already has a rank associated with it by denoting its place in the global hierarchy. This estimate for the rank can be the degree of the node (originally proposed by the authors), but can be other conceivable measures as well, such as betweenness centrality or eigenvector centrality. With these assumptions, the hierarchy measure is given by the fraction of shortest directed paths going strictly upwards in the hierarchy.

More precisely, this method assumes that the shortest paths in the network consist of a part going upward along the hierarchy (towards more important nodes), followed by a part going downward along the hierarchy (towards less important nodes). Either part may be empty, of course, but one should not turn back upwards after the downward part again. Paths of this type are said to be hierarchical, and the measure simply calculates the fraction of vertex pairs that are connected by the shortest hierarchical path.

2.1.2.4 Determining the Levels of Organizations

One of the first methods was proposed by Krackhardt (1994), whose main motivation was to measure the levels of hierarchy of organizations. He defined four measures that can be used together as an estimate of the extent of flow hierarchy in networks. These measures are:

- *Hierarchy*: The fraction of unordered vertex pairs (i, j) such that vertex i is reachable from vertex j but vertex j is *not* reachable from vertex i, or vice versa. It works on directed graphs only.

- *Connectedness*: The fraction of unordered vertex pairs (i, j) such that vertex j is reachable from vertex i via a directed path *or* vertex i is reachable from vertex j.
- *Efficiency*: One minus the proportion of possible "extra" edges that are not needed to maintain connectedness of the components. It is assumed that each component should be an out-tree (as an archetype of perfect hierarchy), and thus a component of size N must have, at most, $N-1$ links; any more than that is a violation of efficiency. This measure obviously penalizes cases in which there are two separate paths leading upwards along the hierarchy from a node A to its superior B; one of the paths is not required to maintain connectedness, hence the structure is inefficient.
- *LUBness*: For each unordered pair of vertices (i, j), the lowest upper bound (LUB) is a vertex k such that both i and j are reachable from k. LUBness is the fraction of pairs having a LUB. This definition can be explained by Krackhardt's assumption that out-tree is the most perfect hierarchy one can achieve.

Each of these metrics may take values from zero to one, and each metric measures some kind of a "deviation" from the perfect hierarchy assumed by Krackhardt, i.e., a directed out-tree. (It also applies for in-trees if we reverse the edge directions in the definition of LUBness). However, these measures (with the exception of efficiency) can be calculated only for directed networks.

2.1.2.5   Concept for Containment Hierarchies

Unlike the measures presented so far, the concept by Ravasz and Barabási (2003) addresses the notion of containment hierarchies. They observed that log k and log C are correlated in many real-world networks (where k is the vertex degree and C is the local clustering coefficient).

They argue that this is due to a containment hierarchy in the network (although they have not used the word "containment"). In order to determinate this, they proposed a simple recursive generation process that creates graphs with a power-law degree distribution, a linear dependence between log k and log C, and multiple levels of hierarchies contained within each other. The bottom line of their argument is that hierarchy in undirected networks can be quantified by looking at the log k vs. log C plot and fitting a straight line to the data; the larger the slope of the line, the more hierarchical the network.

2.1.2.6   Layout-Motivated Measure

Carmel et al. (2002) proposed a layout-based metric for measuring the amount of hierarchy in a directed graph. They have conceived a layout algorithm that places the nodes of the graph in 2D space such that a set of constraints related to the target level differences are taken into account as much as possible. More formally, this means the following. For each $i-j$ edge, we assign a measure that describes the

desired difference between the y coordinates of vertex i and vertex j. The graph is then laid out using their algorithm, and the difference between the maximal ($\max Y$) and minimal y coordinates ($\min Y$) is compared to the diameter of the graph. A strictly hierarchical graph with no cycles can be laid out in such a way that the distance between levels is 1, thus the difference between $\max Y$ and $\min Y$ is equal to the diameter, while a cycle (i.e., a perfectly un-hierarchical graph) would be laid out with equal y coordinates, yielding a hierarchy measure of zero.

The disadvantages of this method are twofold:

- In the general case, it is not possible to assign desired target level differences to the edges. We could simply say that the desired difference is 1 for all of the edges, but this would work only if none of the edges span more than one layer. Edges skipping layers, but otherwise pointing in the right direction, would skew the layout and decrease the hierarchy measure
- This measure is not applicable to undirected graphs.

2.1.2.7 Measures for Structures "From Down to Top"

Next, in contrast to the situation we assumed above, we shall consider the edges of directed networks to be oriented *upwards* (i.e., from lower to higher levels), as in a *who-reports-to-whom* organizational diagram. We do so in order to follow the terminology of the related literature. It is usually a straightforward thing to apply the definitions to directed networks that use the opposite convention.

Sometimes, we will talk about layers or levels (sets of nodes with the same rank). Layers are indexed from 1 upwards, and a lower layer index corresponds to a higher rank.

Some of these measures will work on networks in which the ranks of individual nodes are not known in advance; others are defined for a network and a corresponding ranking of nodes, and therefore must be optimized through some optimization procedure when the ranks are unknown.

2.1.2.8 Fraction of Edges Participating in Cycles

Here, the main idea is to reveal somehow the possible asymmetry between nodes by assuming some sort of flow along the links, and then checking whether or not these flows exhibit any kind of overall directionality. One way to do so is to find all of the elementary cycles in the network, count the edges participating in them, and divide this number by the total number of edges. This approach works for both directed and undirected graphs; in directed graphs, only directed cycles matter. (A cycle is elementary if no vertex appears in it twice.)

All of the elementary cycles in a directed graph can be found simply by using Johnson's algorithm (Johnson 1975), which is $O((N + E)(c + 1))$, where N is the number of nodes, E is the number of edges and c is the number of elementary

cycles. The case of undirected graphs is a bit trickier, as the union of two elementary cycles with at least one shared edge is also an elementary cycle (after removing the shared edges from the union), and thus, we can expect a far greater number of cycles than that for directed graphs for which this condition does not hold. It is therefore common to search for a *cycle base* instead, i.e., a set of cycles such that every other cycle can be reproduced from selected base cycles by taking their disjoint unions. Since every edge that participates in a cycle must also participate in one of the base cycles, finding a cycle base is enough for our purposes.

Luo and Magee (2011) proposed the opposite of this measure (i.e., the fraction of edges not participating in cycles) as a hierarchy measure for directed networks. One big advantage of this approach is its simplicity.

2.1.2.9   Minimum Fraction of Edges to be Removed to Make the Graph Cycle-Free

This approach is slightly different from the one called "fraction of edges participating in cycles." For instance, consider a graph consisting of two interlocking directed links sharing an edge. In this graph, all of the edges participate in cycles (hence the previous measure would be 1.0), but removing the shared edge would make the graph entirely cycle-free. We call a set of edges whose removal makes the graph cycle-free a *feedback arc set*.

Note that although Fig. 2.6 shows a directed graph, this measure works just as well for undirected graphs—but the number of edges to be removed may be different! For instance, the graph with the two rings on the left side of Fig. 2.6
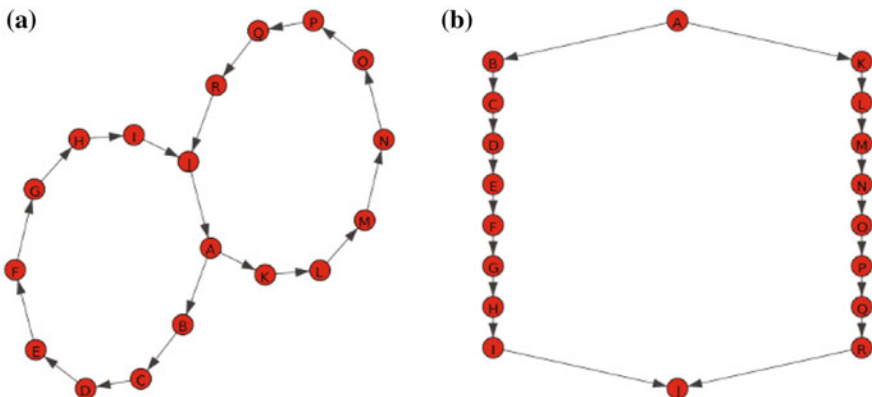
Fig. 2.6 Illustration of the difference between "the fraction of edges participating in cycles" and the "fraction of edges to be removed to make the graph cycle-free." Subfigure **a** shows a graph in which all of the edges participate in cycles. However, as can be seen in **b**, it is enough to remove a single edge (from *J* to *A*) to break both cycles and obtain a perfect hierarchy

becomes cycle-free through the removal of one single edge if the edges are directed, but one has to remove *two* edges to make it cycle-free in the undirected case.

This measure is very easy to calculate for connected undirected simple graphs. Since the graph is connected, the minimum number of edges required to connect N vertices is $N-1$. Adding any extra edge on top of these $N-1$ edges necessarily creates a cycle, thus the number of edges one has to remove from an undirected simple connected graph with N vertices and M edges is $M-N+1$, and the fraction of such edges is therefore $1-(N-1)/M$.

For directed graphs, finding a minimum feedback arc set is an NP-hard problem (Healy and Nikolov 2013), but heuristic procedures exist to find an approximation. One such procedure is the greedy cycle removal algorithm by Eades et al. (1993) Namely:

1. Create an empty "deque" (double-ended queue).
2. If the graph is empty, we are done.
3. If there are sink vertices in the graph, remove them one by one and add them to the *beginning* of the deque.
4. If there are source vertices in the graph, remove them one by one and append them to the deque (add them to the *end* of the deque).
5. If no sinks and sources remain, find a vertex where the difference between the out-degree and the in-degree is as large as possible, remove it from the graph, append it to the deque, and return to step 2.

At the end of the algorithm, the deque contains a possible ordering of vertices where ordinary edges point "forward" in the ordering and feedback arcs point "backward." The cardinality of the feedback arc set found by this heuristic is, at most, $M/2-N/6$, where M is the number of edges and N is the number of vertices.

Another heuristic is as follows. Scan each edge of the graph one by one and maintain two sets, S and T. At each step, check whether edge e forms a cycle with the edges already in S. If not, add e to S; otherwise add e to T. In the end, both S and T are acyclic, and the smaller of the two sets gives a feedback arc set with, at most, half of all of the edges. More sophisticated approximations are to be found in Even et al. (1995) and Saab (2001).

For graphs up to a couple of hundred nodes, one can use the following strategy as well:

1. If the graph is undirected, break it down into components and calculate the sum of $M-N+1$ for each component, where M is the number of edges in the component and N is the number of vertices. This is the total number of edges to be removed in order to make the graph cycle-free; the fraction follows from a straightforward division.
2. If the graph is directed, break it down into weakly connected components and estimate the number of edges to be removed from each of the components as follows:

- If the component is acyclic (i.e., it has a topological ordering), no edges have to be removed at all.
- If the component has less than 20 edges, use a brute-force search to find the minimum number of edges to be removed in order to make it cycle-free.
- Otherwise, find a minimum cut of the component, add the edges of the cut to the feedback edge set, and proceed recursively with each side of the cut.

2.1.2.10   Fraction of Hierarchy-Violating Edges

A hierarchy-violating edge is one that originates at a higher level and terminates at a lower level, meaning that someone higher up in the hierarchy "reports to" someone on the lower level. This is a clear violation. Naturally, this measure requires the ranks to be known in advance, as it is otherwise impossible to decide which edges violate the hierarchy.

Another, stricter definition of a hierarchy-violating edge is that it is an edge for which subtracting the rank of the origin from the rank of the target yields a result that is not zero and not one. This definition penalizes not only the edges that go "the wrong way" in a hierarchy, but also the edges that skip levels.

In the absence of ranks, one has to find the ranking that minimizes the fraction of hierarchy-violating edges, which leads to a problem that may be familiar from community detection. A trivial way to minimize the number of hierarchy-violating edges is to use the same rank for every node, assuming that edges between peers (i.e., nodes with the same rank) are allowed. A possible solution is to disallow edges between peers, which effectively reproduces the feedback arc set problem, since a directed graph minus a minimum feedback arc set is a directed acyclic graph that can then be decomposed into layers. Each feedback arc is then a hierarchy-violating edge.

2.1.2.11   Average Expected Downstream Path Length

This measure is based on random walks, more precisely, the expected length of a path a random walker is allowed to take on the graph with the following constraints:

1. The walker is only allowed to step downstream in the graph, i.e., towards lower layers. A path that goes downward in a layered hierarchy is called a *downstream path* (hence the name of the measure).
2. The transition matrix of the random walk is a usual right-stochastic matrix derived from the weighted adjacency matrix of the graph (loop edges are not allowed).
3. The random walk terminates as soon as the walker ends up in a sink node or in a node that has neighbours in higher layers only.

The measure also requires an a priori layer assignment, and it is an open problem to find the optimal assignment given the graph alone. When the layers are known, the measure can be calculated very easily: one has to proceed recursively from the lowermost layer towards the uppermost layer and make use of the following two equations:

1. If a vertex v is a sink, then the expected length of downstream paths from v is zero.
2. If v is not a sink, the expected length is one more than the expected length of downstream paths from its lower-level neighbours, weighted by the probabilities of reaching those neighbours from v in a single step. Note that only the expected length of downstream paths for vertices in layers lower than v has to be known, therefore, a single sweep from lower layers to the uppermost layer is enough.

To make graphs with different numbers of layers comparable, it is advised to normalize this measure as follows.

Suppose that vertex v is at layer $l(v)$ and there are k layers. The maximal value of the expected downstream path length originating from v (denoted by $h(v)$) is then $k - l(v)$. The normalized variant of the measure takes the average of $h(v)/(k-l(v))$ for all non-sink vertices, assuming that 0/0 is 0.

The above overview of the "further hierarchy measures" was composed using the working paper by Nepusz (2013).

2.1.3 Classification of Hierarchical Networks

The methods overviewed in Sect. (2.1.2) assign a value for each graph, reflecting the extent to which the input network is hierarchical. Now, we will reverse the direction and show an algorithm that creates a graph based on an input parameter p (taking values on the [0, 1] interval), indicating how hierarchical the output graph should be. $p = 0$ refers to non-hierarchical structures and p close to 1 refers to strongly hierarchical structures. The method was proposed by Mones et al. (2012).

The construction of a graph with tunable levels of hierarchy goes as follows (Fig. 2.7a):

- A level-value (ℓ) is assigned to every node in a directed tree in the following way:

  - The nodes at the "bottom-level" (that is, the leaves) are assigned $\ell = 1$.
  - The level-value of the root node is equal to the number of hierarchical levels in the tree (for example, $\ell = 5$ in Fig. 2.7a of the root node).
  - All children of a node with level-value ℓ will have $\ell - 1$ as their level-value.

- Next, a given number of randomly directed edges are added to the tree according to the following rules:
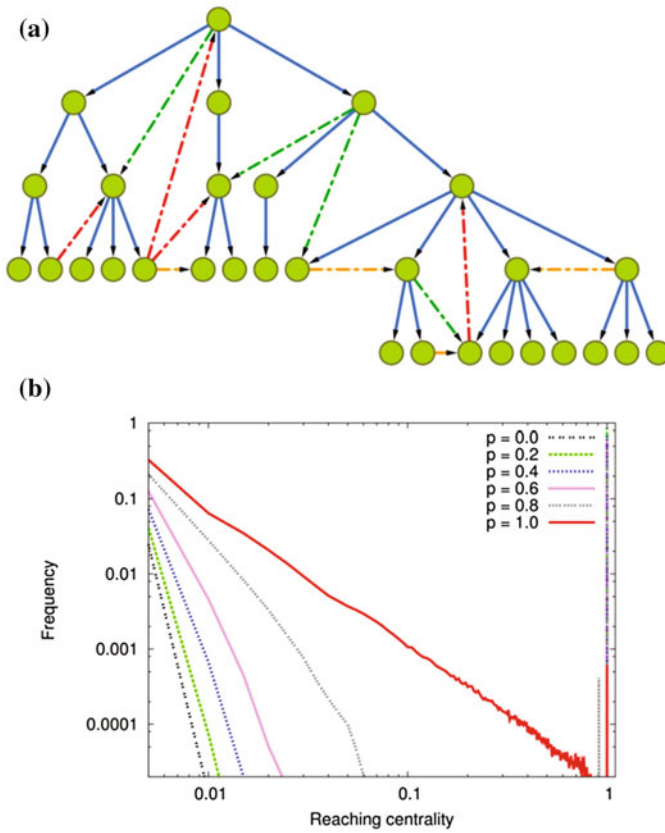
Fig. 2.7 a The different types of edges while constructing a hierarchical graph based on an input parameter *p*. Solid blue edges belong to the original tree used as the backbone of the output graph. Edges pointing downwards (green) conserve the hierarchy, horizontal edges (orange) have a slight influence, and finally, the ones directed upwards (marked with red) cause strong change within the structure. **b** Distribution of the local reaching centrality (see Sect. 2.1.2) values for adjustable hierarchical networks with various *p* values. Each curve is an average of 1000 networks with *N* = 2000 nodes for <*k*> = 3. Note that from the highly random (*p* = 0) to the highly hierarchical (*p* = 1) state, the distribution changes continuously and monotonously with *p*. Reproduced from Mones et al. (2012)

- 1−*p* proportions of these edges are added completely randomly by choosing their starting point (*A*) and end-node (*B*) with probability 1/*N* (*N* is the number of nodes in the graph). In a case in which there is no directed edge pointing from *A* to *B*, such an edge is added to the graph.
- Regarding the remaining edges (accounting for the *p* proportion of the "extra" edges), they are added only if $\ell_A > \ell_B$.

Figure 2.7b depicts the *GRC* values (see Sect. 2.1.2) for hierarchical graphs created with the above algorithm, for *p* = 0.0, 0.2, 0.4, 0.6, 0.8 and 1.0.

Similarly to the problem of *measuring* hierarchy, the problem of *classification of hierarchical structures* is not trivial either. Next, we will give an overview of a method proposed by Corominas-Murtra et al. (2013), which is based on three expectations towards hierarchical systems. These are: (i) treeness, (ii) feed-forwardness, and (iii) orderability. (See later for greater detail.)

Using the above three features, a 3D morphospace ("phenotype-space") can be defined in which the three axes are the tree's quantifiable features. Placing real-life hierarchical and random null-models into such a coordinate system, fundamental characteristics can be revealed. As it turns out, networks do not occupy the entire morphospace; instead, they accumulate in four major clusters within the large voids, which most probably results from the constraints under which they evolve.

Let us define the proper position of a network $G(V, E)$ within the morphospace.

First, $G(V, E) = G$ is transformed into its corresponding *node-weighted condensed graph* $G_C(V_C, E_C) = G_C$, which is an acyclic feed-forward structure in which the cyclic modules (strongly connected components) of G are replaced by single nodes. Accordingly, in a node-weighted condensed graph G_C, each node has a weight α_i indicating the number of nodes it includes from G, the original graph. For example, in Fig. 2.8, subfigure h depicts the node-weighted condensed graph G_C corresponding to G, the one depicted on subfigure d. In this, node S_2 includes 3 nodes from G, and S_1 includes 2. (This method, the localization of strongly connected components, is an often-used approach for identifying subsystems within a graph.)

Then, we calculate the three values using both G and G_C:

1. "Treeness", T: Taking values on the $[-1, 1]$ interval, this captures how unambiguous the "chain of command" is within G_C. In hierarchical networks, like the one in Fig. 2.8a and on its corresponding node-weighted graph depicted in **e**, the chain-of-command is unequivocal, characterized by positive T values. In a case in which the chain of command is ambiguous, the structure is said to be *anti-hierarchical*, marked by negative T values (Fig. 2.8b, f). Intuitively, this feature is calculated by comparing the diversity of choices one can make top-down vs. the uncertainty on the way bottom-up, captured by the concepts of *forward and backward entropies.*

2. "Feed-forwardness", F: Since the paths within cyclic modules (like S_1 and S_2 in Fig. 2.8h) violate the downstream order within the graph, they are penalized according to their *size* and *position*; larger modules closer to the top of G have greater influence on the overall structure of G than smaller ones close to the bottom. Accordingly, they introduce a larger penalty. F is defined on the $[0, 1]$ interval.

3. "Orderability", O: This is defined as the fraction of nodes that do not belong to any cycle. These nodes are orderable, and accordingly, a bigger ratio results in a higher value of orderability. O takes values from $[0, 1]$.
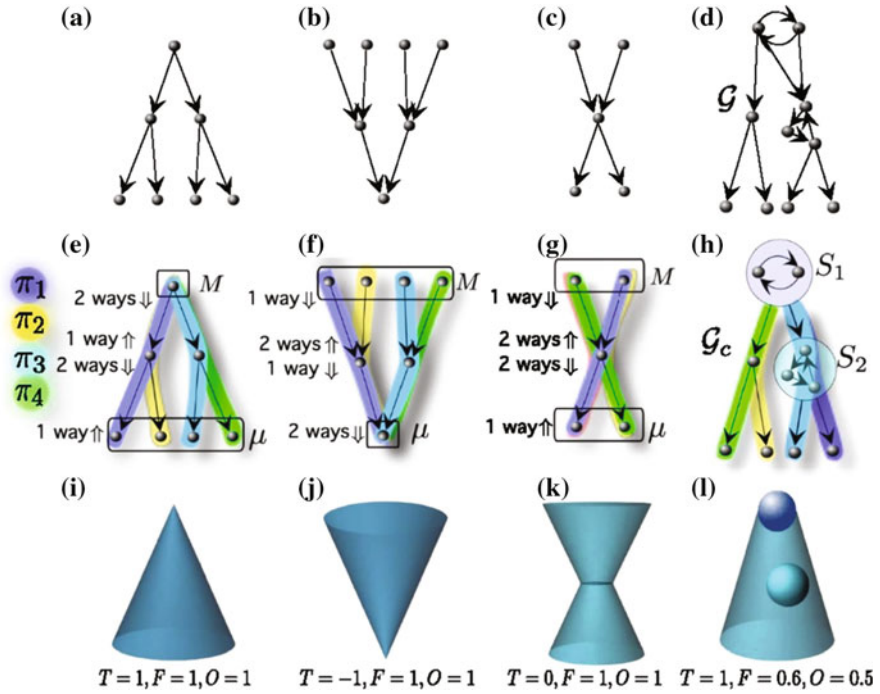
Fig. 2.8 A visualization of the tree concepts characterizing hierarchical networks: treeness (T), feed-forwardness (F) and orderability (O). Based on these tree features, a morphospace can be defined in which the similarities and differences (resulting from evolutionary constraints) can be analysed. **a** A perfectly hierarchical graph is tree-like (or pyramidal, $T = 1$) with feed-forward edges ($F = 1$) and orderable nodes ($O = 1$). **b** In anti-hierarchical networks (characterized by negative T values and head downwards pyramidal structures). The chain of command is ambiguous. **c** Non-hierarchical ($T = 0$). **d** A graph with cyclic modules, violating the orderability of the nodes. **e–h** The corresponding node-weighted condensed graphs of the networks in the first row, with paths top-down and bottom-up. **i–l** The icon representation of the graphs in the first row, along with their *TFO* values. Reproduced from Corominas-Murtra et al. (2013)

Figure 2.9 depicts the location of random null models (white circles) and 125 real networks within the morphospace. Since random networks are being built without any selection pressure, they are neither hierarchical nor anti-hierarchical, and accordingly, they occupy the $T \approx 0$ segment.

The main observation is that the vast majority of real networks fall into four clusters:

i. Gene regulatory networks (plus a protein kinase NW) occupy the first cluster at the top of the coordinate system (Fig. 2.9), marked as "GRN." These systems are characterized by very high orderability values (O) with variable F values. The broad range of F (feed-forwardness) is caused by various sized modules near the top of the networks, corresponding to a small fraction of genes, (transcription factors) participating in cycles.
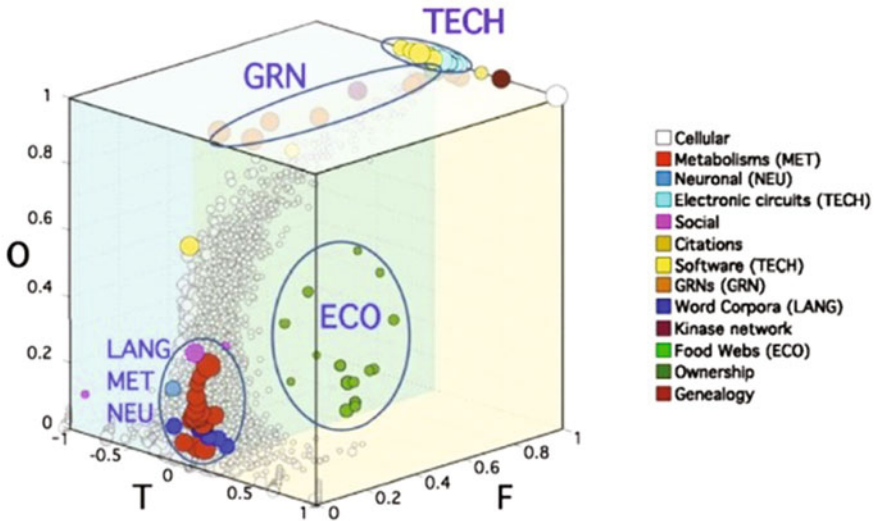
Fig. 2.9 The position of 125 real networks and various random null models within the morphospace defined by the coordinates T (treeness), F (feed-forwardness) and O (Orderability). The random networks are white, while the real networks are colour-coded according to their types listed in the key. The size of the circles is proportional to the number of nodes the corresponding graph includes. Reproduced from Corominas-Murtra et al. (2013)

ii. Electronic circuits and software graphs are strictly feed-forward ($F \approx 1$) with orderable nodes ($O \approx 1$), biased slightly towards negative T values. This cluster (marked as "TECH" in Fig. 2.9) is located on the top right edge of the morphospace.

iii. The third cluster is defined by the ecological flow graphs, marked as "ECO" in Fig. 2.9. Their positions within the morphospace reveal a certain degree of pyramidal structure combined with the important role played by loops. This special, separated position is consistent with the trophic pyramid mingled with recycling.

iv. And finally, the fourth cluster is composed of metabolic, neural, linguistic, and some social networks ("LANG, MET, NEU"), embedded within the cloud of random graphs. These networks display a large central cycle, much larger than their randomized counterparts, a feature that is most probably due to the advantage of reusing/recycling molecules.

Two of these clusters (LANG/MET/NEU and TECH) overlap with random networks with similar connectivity, suggesting that non-adaptive factors shape the topological nature of these graphs. In contrast, the position of the ECO and GRN clusters indicate that the topological features of the ecological and gene networks are the result of functional constraints.

2.2   Visualization Techniques

2.2.1   A General Overview

The aim of the various visualization techniques is the same: to illustrate the entire network as a single figure in an easily perceptible way, revealing as much information about its hierarchical nature/inner structure as possible. Since (real) hierarchical systems are often complex, with many characteristics, the extent to which a visualization technique reflects the main features of a network is limited. Different visualization tools highlight different characteristics and different hierarchy types require different visualization tools. There exists no "best method"; the appropriate technique depends on the specific characteristics we would like to highlight.

The most simple—and widespread—visualization technique is the *pyramid*, in which each entity is represented by a layer, and the higher an entity is in the hierarchy, the higher it is in the diagram. Often (for example, in the case of social pyramids), but not always (e.g., Maslow's hierarchy), the width of the layer reflects the size of the represented layer. The drawback of this technique is that it can reflect only a linear order (a sequence) of the layers and, in some cases, their approximate sizes. In other words, this technique reveals only an order hierarchy of the layers, without giving any description about the inner structure of the given system.

In contrast, graphs are applicable for describing not only order hierarchy, but other hierarchy types as well, most importantly flow hierarchy, meanwhile allowing for a much more detailed visualization of the inner structure of the system as well. For these reasons, visualization of flow hierarchy is the most commonly used technique for representing hierarchical systems.

Because of the lack of loops and cycles, the representation of a "pure" hierarchical system would be a tree. However, in real-life cases, such systems occur only very rarely. Accordingly, trees often correspond to the ideal and/or theoretical case, while graphs that are more complex (have cycles, undirected edges, etc.) are better suited to representing real-life cases.

This representation is closely connected to the concept of control (or flow) hierarchy, in which the entities (which are represented by nodes in the corresponding graph) are organized into a system of subordinate-superordinate relations, which correspond to the edges of the graph. Accordingly, orders and information flow along the edges (hence the name) from the superior unit(s) towards the inferior element(s), while requests and information flow in the opposite direction. Typical examples are the ranks in armies, various state and church organizations, corporations, etc.

2.2.2   Techniques Reflecting the Overall Hierarchy Level

Let us consider a graph representing a (real life or artificial) system. The graph can be large, having many communities and sub-communities, and therefore be difficult to draw in a way that is reasonably accessible for overview. However, we would like to know *how hierarchical* the original system is, preferably in a visual form.

The most widely accepted method for visualizing the hierarchical nature of *small networks* is the one proposed by Sugiyama et al. (1981). For such graphs, this technique provides an informative and clear hierarchical layout by layering the vertices into horizontal rows in such a way that the edges are directed downwards. This method is often referred to as the "*layered graph drawing*" or "*hierarchical graph drawing*" method.

The main steps are as follows (Fig. 2.10):

(i)   *Cycle removal* (a pre-processing step). If the directed input graph is not acyclic, a minimal set of "reversal edges" has to be identified and reversed in order to obtain an acyclic digraph. (Identifying such a minimal edge-set is an NP-complete problem.)
      (These reversed edges, as well as other changes within the graph, will be restored to their original state in a later step.)

(ii) *Layer assignment*. Partitioning the vertex set of the graph into layers in such a way that each edge is directed from a higher level towards a lower one, with the following properties:

   a. the number of layers is kept small
   b. as few edges as possible span a large number of layers
   c. the assignment of nodes into layers is balanced.

(iii) *Insertion of "dummy vertices."* "Long" edges (edges spanning multiple layers) are chopped up into a series of shorter ones by inserting so-called "dummy vertices" into the graph. After this step, each edge will connect nodes on adjacent layers.

(iv) *Edge concentration* (optional step). The aim of this step is to reduce the number of edge crossings and the edge density between adjacent levels. It might reduce the number of dummy vertices as well, but, as important drawbacks, it may increase the number of layers and also modify the graph.

(v)   *Vertex ordering* (or "crossing minimization"/"crossing reduction" step). The nodes within the layers are permuted in such a way that the numbers of edge-crossings are minimized between the adjacent layers.

(vi) *x-Coordinate assignment*. The aim of this step is to position the nodes (that is, assigning them an *x* coordinate) within each layer in such a way that the edges become as straight as possible, and the nodes are centred with respect to their neighbours. This positioning should be consistent with the permutation applied in the previous step.

(a) Input digraph, *G*.

(b) Cycles removed.

(c) After leveling.

(d) Edge crossings minimized.

(e) Edges straightened.
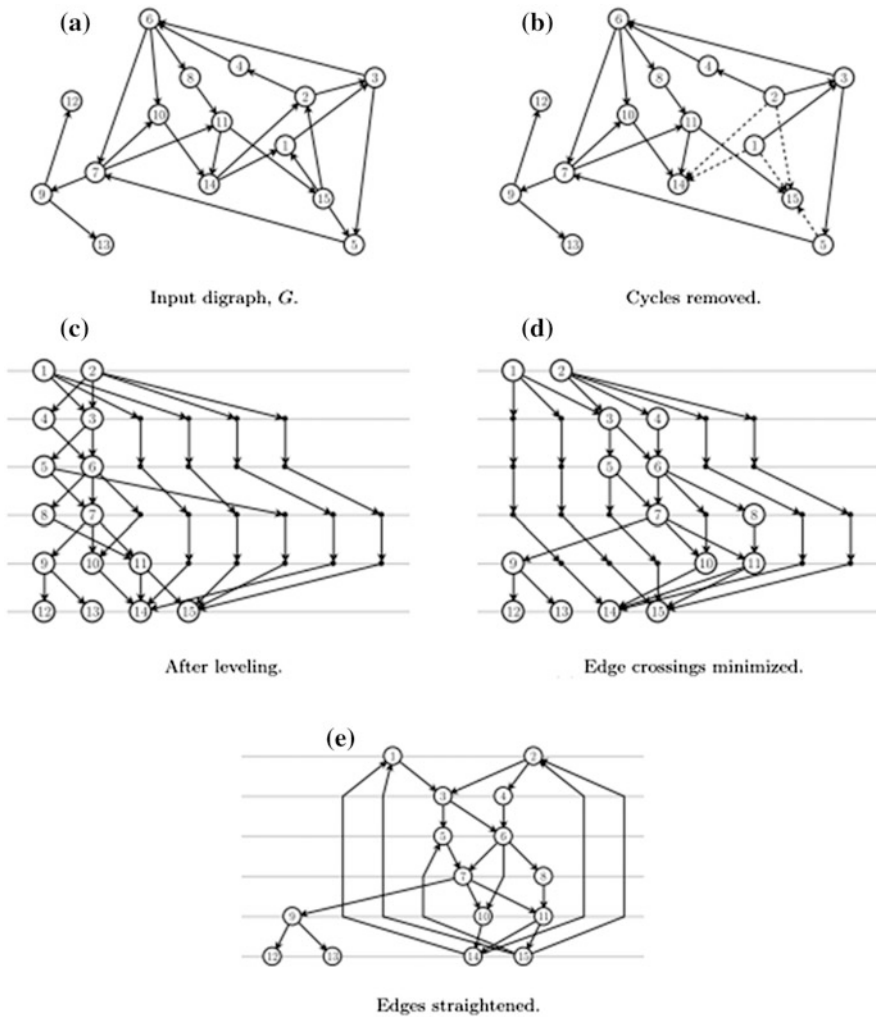
Fig. 2.10 The main steps of the Sugiyama algorithm. It is hard to see the hierarchical structure of the input graph a, whereas it is clearly visible on the output graph e. This method is appropriate for relatively small graphs (up to a few hundred nodes). Reproduced from Healy and Nikolov (2013)

(vii) *Final step*. Changes that have been introduced into the graph in previous steps are reversed so that the edges return to their original state:

    a. edges reversed in the "cycle removal" (first) step are reverted to their original direction

    b. dummy vertices that have been inserted in step (iii) are removed from the graph, and the corresponding "long" edges are drawn back in a way that avoids intersections and crossings. This might be done by drawing the edges as polygonal chains or spline curves.
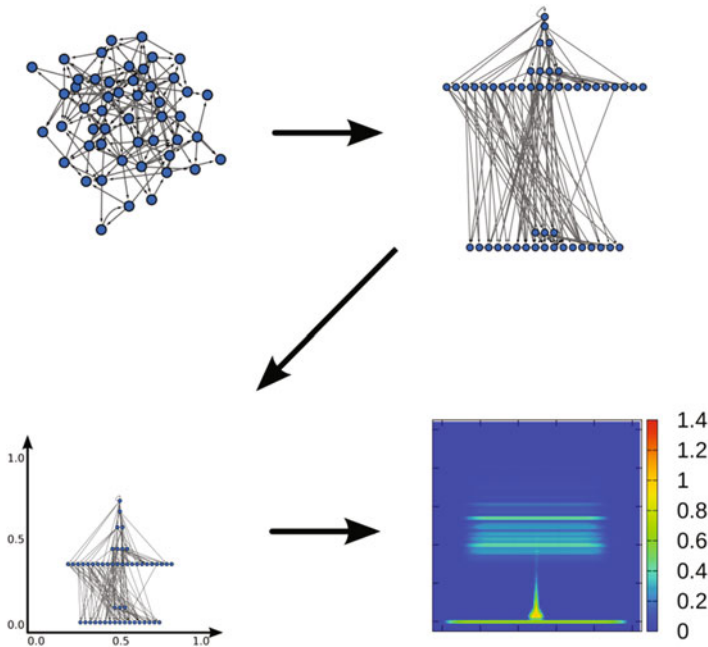
Fig. 2.11 The main steps of the visualization process. Firstly, the layout is computed, based on the local reaching centrality, $C_R(i)$, values (top right). Next, the levels are separated with a logarithmic ratio, and then each layout is scaled into the unit square (bottom left). Finally, the rescaled layouts are plotted in the unit square with the obtained node-density (bottom right, see the colour bar as well). In the heat maps, the colour scale shows $\log(\log(\rho(x, y) + 1) + 1)$, where (x, y) is the average density of the ensemble. Reproduced from Mones et al. (2012)

For a detailed analysis and description of this method, see also (Healy and Nikolov 2013). Although this method is very popular for small networks, it has some serious drawbacks as well, which become especially important for large graphs:

- for bigger networks (graphs with more than a few hundred nodes), the generated layout becomes difficult to overview/interpret;
- the steps are NP-complete or NP-hard, which makes the usage of several different heuristics necessary, and the results therefore less well-defined.
- independently of the hierarchical nature of the given network, the method provides a hierarchical layout that is often misleading;
- the meaning of the levels is not defined;

Next, we discuss a method proposed by Mones et al. (2012) that solves the above problems and is easily applicable, even for *large complex networks* (see Fig. 2.11).

The algorithm of the proposed method is as follows:

1. Rank the nodes according to their *local reaching centrality* value, $C_R(i)$, where $C_R(i)$ is the ratio of nodes that can be reached from the focal node i, reflecting the "impact" of i on other nodes (see also Sect. 2.1.3). (Importantly, from the viewpoint of the algorithm, instead of $C_R(i)$, other local quantities can be used as well.)

2. Start to add nodes to the first, bottom-most level of the layout in an increasing order regarding their $C_R(i)$ values, until $\sigma_L < \varepsilon \, \sigma_G$. Here, σ_L is the standard deviation of the $C_R(i)$ values within the actual level, whereas σ_G is that within the entire graph. ε is an adjustable parameter, defining the "resolution" of the levels.

3. Once $\sigma_L \geq \varepsilon \, \sigma_G$, start a new level.

4. Repeat the 2nd and 3rd steps until every node has been put into levels. (Step 2 ensures that nodes with similar $C_R(i)$ values will be on the same level.)

5. In order to get a nice horizontal arrangement, align the centre of mass of each level above that of the next, that is, to the same vertical line.

6. The levels are arranged vertically in such a way that the distances between adjacent levels are proportional to the logarithm of the differences of the averages inside the certain levels: $(Y_{\ell+1}-Y_\ell) \propto \ln \left[\langle C_R \rangle_{\ell+1}-\langle C_R \rangle_\ell\right]$. ($Y_\ell$ is the vertical position of level ℓ, whereas $\langle C_R \rangle_\ell$ is the average of the $C_R(i)$ values within level ℓ.)

Fig. 2.12 Visualization of the three network types studied in Sect. 2.1.3, based on their local reaching centrality values. **a** An Erdős–Rényi (ER) graph. **b** A scale-free (SF) network. **c** A directed tree with random branching number between 1 and 5. For all three graphs, $N = 1000$ with the parameter ε set to 2/N. In the cases of the ER and SF graphs, <k> = 3. Reproduced from Mones et al. (2012)

Next, set the vertical distances of the levels in such a way that they become proportional to the differences between their average x_i values. Set the smallest distance to the same value as the horizontal distance between two adjacent nodes. Finally, set the distances to be proportional to the logarithm of the original differences in such a way that the height of the graph remains unchanged.

For large graphs, ε tunes the vertical extension of the layout.

Figure 2.12 shows the result of this method for (a) Erdős-Rényi, (b) scale-free, and (c) directed tree types of graph.

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Chapter 3
Observations and Measurements

3.1 Animal Groups

3.1.1 Dominance

This chapter gives an overview of the (quantitative) observations and measurements related to hierarchy, concerning both animals and humans. Although, according to our approach, humans are deeply embedded into the animal world, in order to give room for a detailed investigation regarding the similarities and differences, we discuss animal and human hierarchy in separate sub-chapters. Special emphasis is given to the phenomenon of dominance hierarchy (which, in case of humans, is complemented by the so called cultural hierarchy), leadership, and collective decision making.

From the viewpoint of an individual, both solitary and social lifestyles have their advantages and disadvantages, mainly defined by the access to resources, such as food or mates. A solitary animal does not have to share anything with others, but such an individual is constantly exposed to a much higher level of danger regarding predators, and also faces difficulties in finding mates for reproduction. Living in groups is safer with respect to predator avoidance, ensures the possibility of reproduction and creates an environment in which decision-making is more optimal because of information transmission among the members. At the same time, it raises competition among the members for resources and increases the probability of disease and parasite transmission.

If, on the whole, for a given species, the ratio of advantages/disadvantages is higher in the case of living in groups than in the case of a solitary lifestyle (that is, it ensures a higher chance of survival for the individuals), the animals will knit into groups. In such a case, effective regulating mechanisms are needed in order to reduce the level of aggression triggered by competition among the members.

The original version of this chapter was revised: Author name and affiliation have been changed. The erratum to this chapter is available at https://doi.org/10.1007/978-3-319-70483-8_7.

The evolutionary solution to this problem is the emergence of *dominance* hierarchy, a mechanism whose main purpose is to regulate access to resources. The mechanism is simple: higher-ranked individuals have primacy compared to their lower level mates. As one advances up the evolutionary tree, the structure of the dominance hierarchy becomes more and more pronounced and complex, accompanied by increasingly sophisticated strategies by which individuals try to attain higher and higher ranks. When it comes to chimpanzees, *Pan troglodytes*, our closest living relatives, we find that they use such elaborated methods in their everyday fights for position, which, even just a few decades ago, was believed to be solely a human practice. Such tools, among others, include coalition formation, manipulation, the exchange of social favours and the adaptation of rational strategies (de Waal 2007).

No surprise that—being embedded within such an evolutionary process—humans are very sensitive to hierarchical positions as well. The unappeasable longing to rise higher and higher in the hierarchy is a basic human characteristic (Weisfeld and Beresford 1982). From a physiological point of view, the mechanisms determining the rank of an individual are very similar between primates and humans (Sapolsky 2005)—and in mammals in general: for example, the level of *testosterone,* the principal male sex hormone, in the blood is found to be related to rank: in the case of various monkey species, a higher testosterone level was measured in higher-ranked individuals than in lower level animals (Eibl-Eibesfeldt 1990). Similar correspondence has also been found in humans: in an experiment, the testosterone level of young male tennis players was found to rise in instances of victory, and to fall in instances of defeat, whereas no change was detectable during training. In another experiment, the testosterone level of medical students was measured, before and after an exam. For those who passed the exam successfully, the level of the hormone arose, while for those who failed, it fell (Mazur and Lamb 1980). The level of the testosterone hormone and the inclination towards behaving dominantly form a positive feedback loop, as one intensifies the other.

The other hormone that constantly pops up in relation to dominance rank—primarily in connection with primates—is the g*lucocorticoid* steroid hormone, also known as the *stress hormone*. During the last few decades, many attempts have been made to study their relation, but the picture is still not clear (at least in stratified mammal societies), since various studies report contradictory findings. According to the original view, subordinate individuals must be exposed to a much higher level of stress than their higher-ranked mates, and thus their stress hormone level is higher as well. However, measurements revealed that it is exactly the higher-ranking individuals who have higher cortisol levels in their blood (Muller and Wrangham 2004). Other studies have found support for the original assumption, namely that glucocorticoid secretion is stronger in lower-ranking individuals in general, from which the only exception is the alpha male at the very top of the hierarchy, whose cortisol level is the highest in the whole group (Gesquiere et al. 2011). Furthermore, the correlation between the level of stress hormone and high rank was found to be the strongest during periods of social instability, which is no surprise, since during transitions in the hierarchical structure, it is the highest-ranking individuals who are exposed to the highest level of aggression
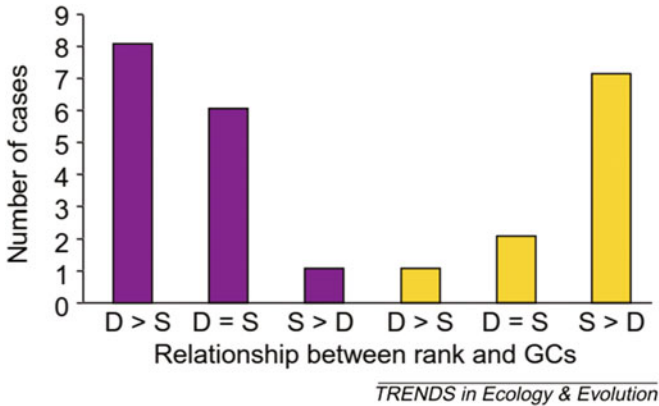
Fig. 3.1 Relation between the level of stress hormone and rank. Among species with cooperative breeding (purple bars on the left), the level of basal glucocorticoid (GC) is significantly higher in dominant individuals than in subordinates ($D > S$), in contrast with other species (yellow bars on the right), for whom the relation is vice versa. Reproduced from Creel (2001)

(Sapolsky 1983). The observed differences might be due to the variations in the social organizations of different species and populations (Sapolsky 2005). As such, Creel (2001) identifies the decisive factor determining the relation in the way group members help each other in breeding the offspring: in those species, among which cooperative breeding is common, rank and hormone level are in direct proportion, while in other species, they are in inverse proportion (see Fig. 3.1). (Cooperative breeding means that offspring are not only taken care of by their parents, but by other group members as well.)

Notably, being exposed to high levels of stress hormone over an extended period of time has a serious (negative) effect on the individual's health as well, especially on the cardiovascular, adrenocortical, reproductive and immune systems (complaints that are often referred to as "stress-related diseases"). For a review of the relation between rank and health in primate societies, see (Sapolsky 2005).

In humans, the phenomenon of a strong correlation between *socioeconomic status* and the appearance of various stress-related diseases has been known for a long time and has been well documented (Adler et al. 1994). Although socioeconomic status (among humans) does not cover the exact same concept of rank in the dominance hierarchy, it is still a good approximation to it (Sapolsky 2004), and, more importantly, it is easier to measure—which explains why human studies use this concept so frequently.

These findings refer to the relationship between the physiological state of an individual and its rank in the *dominance* hierarchy. As we shall see in the upcoming chapters, in human societies, besides the dominance hierarchy, another type of hierarchical structure emerges as well, what we will call "*cultural hierarchy*."

3.1.1.1   Measuring Dominance

The best known type of hierarchy is probably dominance hierarchy, according to which individuals belonging to the same group regulate their access to natural resources such as food, mating partners, nesting locations or a safe lair. While establishing the ranking system, members of the group interact, often aggressively, in the form of repeated fights and threats. The result of each encounter is remembered by both parties and, in the case of many species, by other group members as well. But after the order is set, subordinates will give way to their superiors without further fights or threats. The fundamental advantage of this arrangement is that it minimizes the aggression within the group, since individuals do not engage in fights continually, but only when creating or altering the dominance structure. In order to maintain such a structure, the individuals have to recognise each other, and they also have to remember their mates, along with the outcomes of the fights. In other words, they have to be able to create and maintain a mental model of the social structure within their group. This is the most likely reason as to why it only appears at a certain point in evolution, which is, according to our present knowledge, the point at which fish appear. (Unfortunately, the scope of the present book cannot cover the amazing organizational mechanisms driving the societies of social insects (Hölldobler and Wilson 2008); hence, in the following, we shall focus mainly on the dominance structures that determine the social lives of the most varied vertebrate species.)

The most simple dominance structure is called *despotism*. In such an order, one individual rules over all the others, who, contrastingly, have no rank distinctions among them. For example, bumblebees maintain such a structure, as was recognised and described by Swiss entomologist Pierre Huber in 1802 in a study that is now considered to be the first modern research in the field of dominance hierarchy (Huber 1802). Huber's work notwithstanding, real interest in the field did not emerge until a century later, when Thorleif Schjelderup-Ebbe described the dominance structure (which he called the "pecking order") of hens (*Gallus domesticus*) in his Ph.D. dissertation of 1922. Later, this expression, "pecking order," was extended to the dominance relations of other kinds of birds as well, while it is now often used in a general sense as a synonym for dominance hierarchy.

Since then, this topic has yielded a lot of attention from biologists, and it now has a vast literature. However, in the past few decades, scholars from other fields have also become interested in the *formation* of dominance hierarchies, most prominently economists, computer scientists, theoretical biologists and physicists, whose aim has been twofold: (i) to give an account of the *self-organizational process* that is behind the *formation* of dominance hierarchies (in both animal and human groups), and (ii) to develop techniques allowing the hierarchical relations among group members to be measured.

When trying to come up with such techniques, one immediately runs into the following problem: how should dominance be *quantified*, "measured"? A traditional way to overcome this problem is to sit for a long time at a (preferably hidden) observation point and watch the social life of the observed group, meanwhile

making as precise a record of their inter-individual interactions as possible. With this approach, many fascinating results have been reached, among which the best known are probably the ones related to the observations of primate societies, most notably chimpanzee groups (de Waal 2007). The biggest benefit of this approach is probably that *any* kind of interaction can be recorded (who eats first, who sleeps where, who "beats up" whom, how the conflicts are being resolved, etc.). However, this technique also requires an enormous amount of time, special conditions (ensuring *continuous* observation of the group in its *natural environment*, or in an environment in which the human impact is as limited as possible), and the ability to *recognize all* of the individuals with high confidence within the observed group. These are requirements that are not easy to fulfil.

The most recent techniques aim to automate the observations somehow: to take video records and analyse the results later with various computer programs (Ballerini et al. 2008; Pérez-Escudero et al. 2014), to put small GPS devices on the individuals so as to record their motion (Ákos et al. 2014; Nagy et al. 2010, 2013,
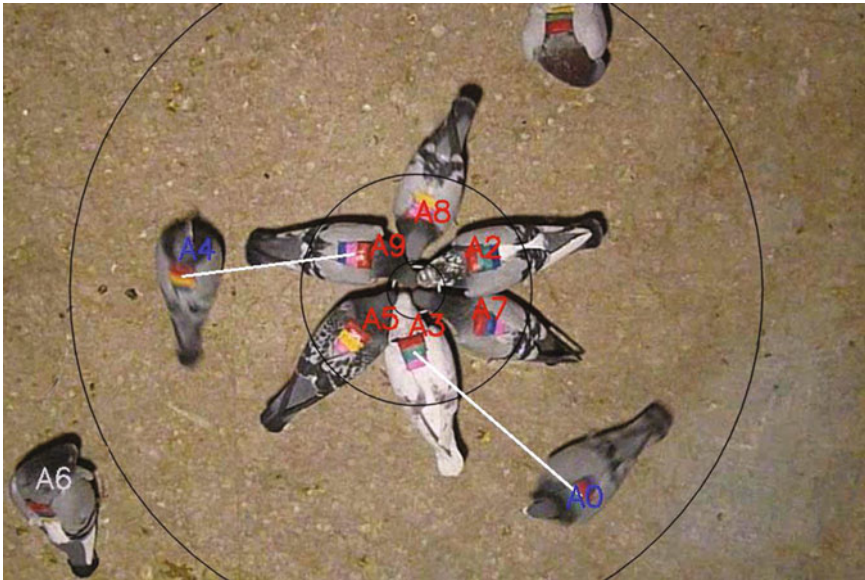
Fig. 3.2 The "colour-bar technique". A snapshot of the processed video sequence. The original video records the feeding-queuing activity of a group of homing pigeons. Each bird is marked with a unique combination of three colours (a "colour-bar") serving as an individual code for a computer program designed to identify the individuals automatically and process their behaviour. Circles divide the different activity regions: birds marked with red colour in the central circle are identified as the ones feeding, individuals marked with blue are identified as the ones queuing, and pigeons out of the external circle are identified as "not interested." Reproduced from Nagy et al. (2013)

see Fig. 3.2), or, in an even more recent technological development, to combine the data recorded with various sensors (Gerencsér et al. 2013).

The biggest disadvantage of the video records is that the individuals within the group have to be identified later (at least, if the inter-individual interactions are to be analysed). This problem turns out to be extremely difficult, primarily in regard to videos recording animals in their natural environment. For example, Ballerini et al. (2008) recorded the free flight of starling flocks (counting 2600 individuals) and restored the 3D positions of the birds using stereometric and computer vision techniques within the framework of the "Starflag" project, lasting from 2005 to 2007.

A way to overcome the problem of individual recognition on video records is to put some kind of identification marks on the individuals. However, this method can be used only in groups of a few dozen individuals at most. For example, Nagy et al. (2013) marked pigeons with a colour-bar (a unique combination of three, well-distinguishable colours on the back of each bird) and recorded their activity from above (see Fig. 3.2). In such a way, "only" the colour-bar recognition had to be solved in an automated way. (A task that also turned out to be highly non-trivial, since colours faded on the back of the animals, the birds covered each other from time to time, the efficiency of the recognition depended strongly on the actual lighting conditions, etc. However, even with such difficulties, the problem of individual recognition is still easier to solve through use of the "colour-bar technique" than without any crutch at all.)

Pérez-Escudero et al. (2014) introduced a method based on individual recognition as well, but instead of putting an artificial mark on the individuals, an algorithm (called idTracker) was designed to extract a characteristic fingerprint from each animal, which was then used to identify the individuals throughout the video. This technology prevents propagation of errors, and the correct identities can be maintained basically indefinitely. The algorithm has been tested on fish, flies, ants and mice, and was able to distinguish animals even when humans could not.

3.1.2 Leadership in Motion

As mentioned in Chap. 2, hierarchy is context-dependent, that is, the same group often organizes itself into different structures depending on the actual task. In the context of animal *leadership*, the hierarchical structure emerges during collective motion. It differs from dominance hierarchy in at least two fundamental ways: (i) followers follow the leader in an unprompted manner, and (ii) in case there is a target, the emerging hierarchy can be related to the way in which the information flows within a group.

Due to recent technological developments, data on a larger scale and with increasing precision have been gathered within this field of research, giving the topic a special importance.

The relation describing "who leads whom" in a group defines a stand-alone, quite easily measurable hierarchical structure (assuming that the one who is leading

is the "dominant" one and the one being led is the subordinate individual). This is called the *leadership network*, which is *not* directly related to dominance hierarchy (Nagy et al. 2010). Rather, it is probably an interaction among dominance, kinship, the inner state of the individuals (like hunger or fear) and some outer conditions. In this section, we shall give an overview of some quantitative results on *leadership*.

From the viewpoint of leadership (and hierarchy in general), a group whose members are able to identify each other on an individual level differs fundamentally from groups in which the members are basically identical, that is, they are unable to recognize each other. In the latter case, the group might reach a collective decision regarding, for example, the direction of motion either with or without a leader. In a case in which there is no leader, the decision can be made based on some very simple mechanism, such as direction alignment or mean value calculation, whereas in a case in which there *is* a leader (but still no individual recognition), leadership is still not a well-defined stable structure, but rather a temporal, continually changing network: it is based on temporal differences such as actual level of hunger, fear, spawning inducement, etc., or some pertinent information regarding predators or food location.

The first case (no individual recognition and no leader) can be described accurately with a model proposed by Vicsek et al. (1995). In this approach, self-propelled particles move with a fixed velocity along a 2D surface while aligning their direction of motion to that of others within a given distance.

When leadership emerges from differences in the inner states of the members (and there is still no individual recognition), the situation can be described with a model suggested by Couzin et al. (2005). In that paper, they have shown how a few informed individuals can lead an entire group in which the individuals do not know which of them (if any) has information. According to the model, even if the portion of the informed individuals is small, the group as a whole can achieve high accuracy regarding the proper direction towards the food location. In fact, the larger the group is, the smaller the portion of informed individuals is needed.

Entirely different is the case in which group members are able to identify each other on an individual level. Most mammals (and some birds, like pigeons) are like this, enabling the emergence of more stable hierarchical leadership structures. According to the biological observations, leadership still depends strongly on the actual inner state of the animals (Fischhoff et al. 2007), but, at the same time, from the point of view of the motion of the group, dominance hierarchy may play a fundamental role as well.

To study this question, Sárová et al. (2010) used GPS devices to record the motion of 15 cows belonging to the same herd for a period of three weeks. According to their findings, foraging motions and short-distance travel are not led by a particular individual, but are rather influenced in a graded manner: the higher the position occupied by an individual in the herd's hierarchy, the bigger the influence it exerted on the collective motion. Other observations revealed that Rhesus macaques prefer to join either related or high-ranking individuals, whereas Tonkean macaques exhibited no specific order at departure (Sueur and Petit 2008). In their review paper on this topic, Petit and Bon (2010) proposed that the process
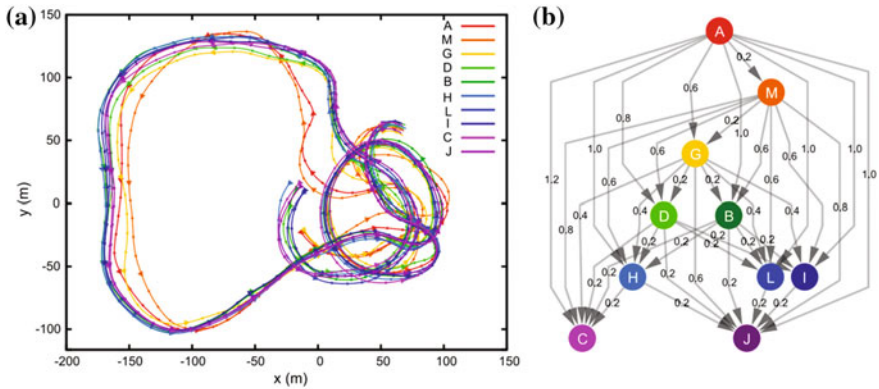
Fig. 3.3 The analysis of the flight of a flock of homing pigeon, recorded with ultra-light GPS devices. **a** A 2-min segment from a free flight restored from the GPS data log. Dots and triangles mark every 1 and 5 s, respectively. Triangles point in the direction of motion. Different letters and colours refer to different pigeons. **b** The leadership network reflecting a single flock flight shown in **a**. The arrows point from the leader towards the follower. The values on edges mark the time delay (in seconds) in the two birds' motion. Reproduced from Nagy et al. (2010)

of collective decision-making (regarding the collective motion of a group) can be interpreted as a combination of two kinds of rule: (i) an "individual-based," covering the differences in the inner states of the animals, such as hunger, physiology, energetic state, knowledge, spatial position within the group, position in the group's affiliation network, hierarchical rank, etc., and (ii) "self-organization," referring to the inter-individual interactions among group members.

In order to yield a detailed insight into the leader-follower relationships in a network of a flock of homing pigeons, Nagy et al. (2010) placed ultra-light GPS devices on members of a flock of 10 birds. In such a way, they obtained high precision data of the trajectories, which then were analysed using a variety of correlation functions inspired by approaches commonly used in the field of statistical physics. In particular, they analysed the pairwise interactions on the basis of the characteristic delay times between the birds' direction changes ("turns"). Using this method, they have revealed a dynamically changing, but well-defined hierarchy (leadership network) within the flock (Fig. 3.3). According to this study, the average spatial position of a bird within the flock correlates with its hierarchical rank.

The relationship between the spatial position of an individual within a moving group and its effect on the movement of others is also highlighted by Schaerf et al. (2016). By studying moving pairs of fish, they found that those in the front have greater mean changes in their speed and are less likely to move towards their partner than vice versa. Furthermore, the pair moves faster when the front position is occupied by the one who usually leads the pair.

Furthermore, many animal species live in "multilevel modular societies" in which smaller groups of closely related individuals form more coherent

Fig. 3.4 The motion of a herd of Przewalski horses ($n \approx 150$): hierarchy within hierarchy. Different harems, identified by the cohesive motion of their members, are marked by different colours. The white arrows indicate the leadership relations among harems: they point from the leader towards the follower sub-group. Reproduced from Ozogany and Vicsek (2015)

communities that are also more loosely connected, creating aggregations on a given level. Among others, primates, elephants, whales and horses live in such "embedded" societies (for the embedded hierarchical structure present in human societies, see Sect. 3.2.3). Ozogány and Vicsek (2015) studied the collective motion of a herd of Przewalski horses consisting of many harems (see Fig. 3.4) and found that this group structure has an effect on the collective motion of the herd as well, since the leadership network itself is modular and hierarchical: there is a leadership hierarchy *within* the dense sub-groups (or harems, in the case of horses), and there is a hierarchy *among* the harems.

However, these studies do not shed light on the following fundamental question: are the so-called "individual-based" traits, such as navigational ability or spatial position within the group, a *cause* or a *consequence* of leading? In other words: do they *govern* the self-organizing processes or are they the *consequence* of leadership, arising through another mechanism?

In order to address this question, Pettit et al. (2015) conducted measurements aimed at understanding how individual differences structure a flock and affect the information transfer among the birds, and, importantly, *how the leader/follower role affects the learning of navigational skills*. In the experiment, the homing flights of groups of up to 40 homing pigeons were tracked using GPS devices with a log
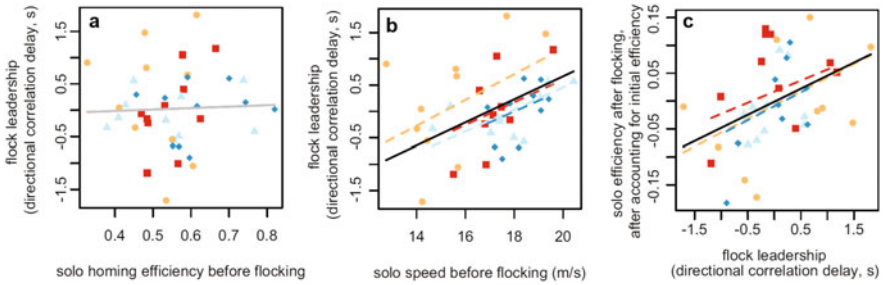
Fig. 3.5 Solo homing efficiency and speed compared to leadership. Each dot represents the mean value belonging to a bird, with different symbols for the different groups. Fit lines correspond to linear mixed models with group as a random factor. The estimated regression for the fixed effect, if it is significant, is black, or grey if it is not significant, as judged from a likelihood-ratio test against a model without that fixed effect. Dashed coloured lines show the random effects of the groups on slope and intercept. Reproduced from Pettit et al. (2015)

rate of 10 Hz. The "level of leadership" for each bird was defined based on the directional correlation delay time, the method introduced by Nagy et al. (2010).

According to the study, leadership hierarchies can arise from differences in the birds' typical speeds. They also found that leaders learn faster and become better navigators, even if leadership initially did not originate from navigational ability. *In other words, individual differences that originally concerned purely physical abilities (speed) with time turned into individual differences regarding cognitive capacities (navigational skills).* Figure 3.5 depicts this phenomenon: Speed did not correlate with homing efficiency before the group flight, but faster individuals did tend gradually to become leaders during the collective flight. After the flight, these faster pigeons also became more efficient (their navigational skills improved). This was the first time such a mechanism was reported.

The study also suggests that leadership might be an inevitable consequence of heterogeneous characteristics among individuals within a self-organized group. Furthermore, the role that an individual assumes during collective motion might have a far-reaching effect on the development of its abilities regarding how it learns about the environment and uses social information.

In an ingenious study, Boos et al. (2014) conducted an experiment to test (i) whether in the case of humans, collective motion and coordination can emerge from merely applying simple local rules, as is believed to be the case in animal groups, (ii) whether an informed minority can lead an uninformed majority to the minority's target, and if so, (iii) how the minority exerts its influence.

In order to hinder all sorts of communication (conscious and unconscious), except for the reading of the movement of others, subjects played via their avatars in a multi-client computer game. In order to activate two basic local rules, "cohesion" and "alignment," without direct instructions, a minority of the players were given greater rewards for reaching a pre-defined target, while the players belonging to the uninformed majority were given smaller rewards, but in equal measure.

("Cohesion" was one of the local rules expressing that the individuals are attracted towards their neighbours' positions within a local range, and "alignment" was the other, expressing that the individuals align their speed and direction within this range to that of their neighbours.) They found that (i) directed group motion can emerge from simple local rules in the case of humans, just as in the case of animal groups, (ii) within this context, an informed minority is able to lead the group to its target, and (iii) a minority can lead the group effectively if their members are among the first to make a move, with similar initial directions.

3.1.3 Leadership Versus Dominance

The assumption that *dominant* individuals are the ones who simultaneously *lead* the group is very persuasive and intuitive. However, as mentioned in the previous section (Sect. 3.1.2), leadership hierarchy and dominance hierarchy are *not* related to each other in such a straightforward manner. Rather, these hierarchies seem to coexist within the same group without creating any kind of conflict: when it comes to collective travel, those who have better navigation skills (Nagy et al. 2010) or better information (Couzin et al. 2005) will lead the group, and when it comes to feeding, mating, etc., relations defined by the dominance hierarchy will prevail (Nagy et al. 2013).

The dominance hierarchy and the leadership hierarchy were compared in a more systematic way in a flock of homing pigeons, consisting of ten individuals, by Nagy
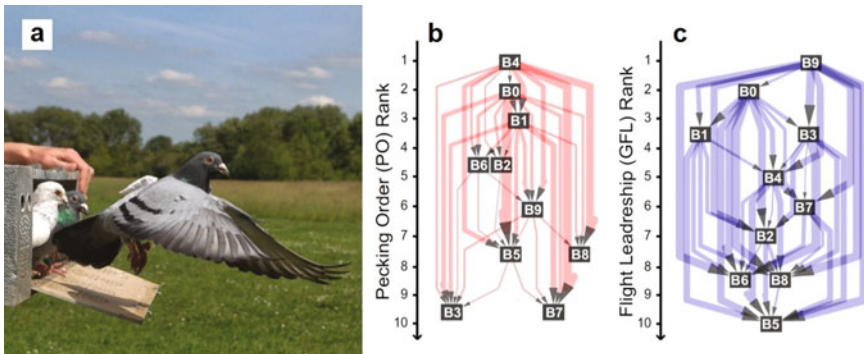
Fig. 3.6 The comparison of the (**b**) dominance and the (**c**) leadership networks in a flock of homing pigeons. **a** Releasing the pre-trained homing pigeons from their loft. The small white bag on the back of the bird holds the ultra-light, high-precision GPS device (Courtesy of Zs. Ákos). **b** The pecking order (dominance hierarchy). **c** The leadership network. In both, directed edges point from the leader towards the follower. The width of the arrow corresponds to the strength of the interaction. Nodes are ordered vertically according to the rank in the hierarchy, with the dominant ones on the top. The two hierarchies are different fundamentally. Reproduced from Nagy et al. (2013)
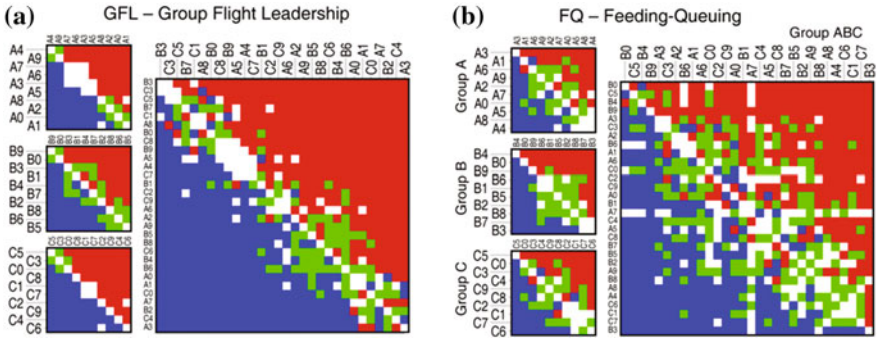
Fig. 3.7 Adjacency matrices of the mixed graph representation containing both undirected and directed edges for each interaction type (FQ in A, AA in B, PO in C, and GFL in D). The 10 × 10 matrices on the left side of each panel show the data for the groups A, B, and C (from Top to Bottom, respectively), and the 30 × 30 matrix contains data for the group of 30. Colour indicates the type of edge: red: directed edge pointing from dominant/leader (in the row) to the subordinate/follower (in the column); blue: directed edge, reverse direction of a red edge; green: undirected edge for mutual interaction; white: no edge. In each matrix, the individuals were ordered according to the NormDS scores of that interaction. Reproduced from Nagy et al. (2013)
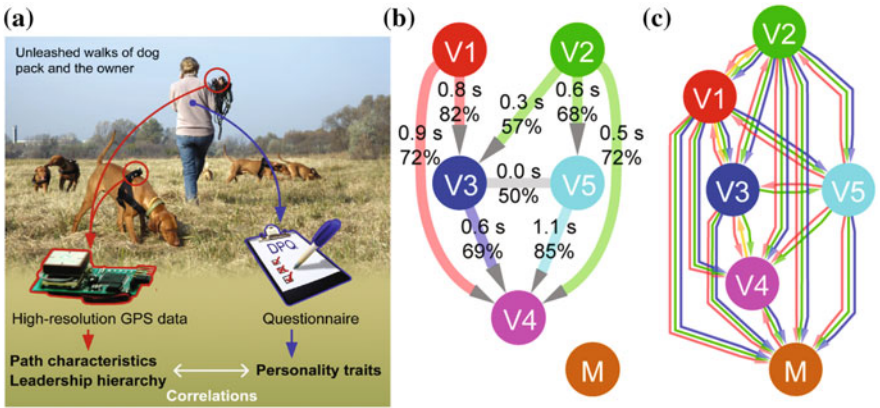
Fig. 3.8 The collective motion of dogs (belonging to the same household) is influenced by the underlying social structure and by differences in their personalities. **a** The unleashed walks of six dogs belonging to the same household, accompanied by their owner. During these walks, high-resolution spatio-temporal GPS trajectory data were collected and then analysed pairwise. **b** The basis of the analysis was the directional delay time, indicated by the arrows. The directed links point from the direction of the leader towards the follower. On the lines, the upper values belong to the time delays in seconds, whereas the lower values indicate the portion during which the leader of that pair was actually leading. All the dogs were 'Vizsla,' except for the one marked with "*M*," which was a mixed-breed. This dog did not participate in the "vizsla-network." **c** Dominance network of the dogs, derived from a questionnaire. The arrows point from the direction of the dominant individual towards the subordinate one. The colours represent the context of the dominance: red: barking; orange: licking the mouth; green: eating; and blue: fighting. Reproduced from Ákos et al. (2014)

et al. (2013). The two hierarchies were found to be different from each other (see Figs. 3.6b, c and 3.7). Dominance (pecking order, depicted in Fig. 3.6b) is known to be correlated to aggression and access to food, based on certain individual features, such as physical strength, in order to strangulate the violence to a low level within the flock. At the same time, the appearance of the stable leadership network during flights is likely to be due to a different set of individual competences.

Using similar techniques, namely the pairwise directional correlation analysis of high-resolution spatio-temporal GPS trajectory data, Ákos et al. (2014) studied the collective motion of six dogs belonging to the same household during more than a dozen 30- to 40-min unleashed walks, accompanied by their owner (see Fig. 3.8). During the walks, the dogs adjusted their trajectory to that of the owner, but from time to time, they would run away and then turn back to her in a loop. On a shorter time scale, the leader-follower roles in a given pair changed significantly, whereas on a longer timescale, a consistent leadership structure was manifested.

The network constructed from these leader-follower relations is hierarchical, in which the position of a given dog correlates with rank (dominance), age, trainability, controllability, and aggression. (These values were derived from personality questionnaires.) According to these measures, there are some personality traits that tend to characterize the leader (dominant) dogs: they were found to be more controllable, trainable, aggressive, and also tended to be the older ones.

3.1.4 Collective Decision-Making

Animals living in groups continually face problems that require collective decision-making, such as when and where to rest or to forage, how to defend themselves from predators, how to navigate towards a distant target, etc. The personal notion of the group members depends on many factors, including information, experience or inner states such as hunger or exhaustion. Many theoretical studies focus on the cost/benefit ratio from the viewpoint of the group members, since if the individuals differ in their preferred outcome (and they usually do differ) some individuals will have to pay a higher "consensus cost" than others. ["Consensus cost" is the cost paid by the animal who foregoes its preferred behaviour in order to defer to the common decision (King et al. 2008)].

The first studies addressing the problem of collective decision-making mainly focused on two basic types, from both a theoretical and an experimental point of view. In a *despotic* situation, one or a few individuals make the decisions, while in an *egalitarian* (or *democratic*) situation, the members contribute to the final outcome to about the same degree. In nature, both types have been observed. On one hand, both theoretical and experimental studies show that the egalitarian decision-making process has a smaller average consensus cost than the despotic one

(Conradt and Roper 2003), while on the other hand, the despotic decision-making approach can increase the efficiency of a group (Couzin et al. 2011).

More recently, along with the technical developments applied by researchers in order to study the collective decision-making techniques, there have been some interesting observations in which egalitarian and despotic methods were alternated according to the circumstances. Using high-precision GPS data on pairs of pigeons, Bíró et al. (2006) studied the behaviour of the birds in cases of conflict over the preferred flight direction. If the difference was small (smaller than a certain critical threshold), then the birds averaged their directions (egalitarian decision-making), but if the difference rose above the threshold, either one of them could become the leader or the pair might split (despotic case).

Strandburg-Peshkin et al. (2015) identified similar decision-making methods among wild baboons. They also recorded the movement of the group members with high precision GPS devices over the course of the troop's daily activity. Baboons, too, do not follow dominant individuals, but rather the majority of the initiators (those starting off in a certain direction). When two groups of initiators (of similar size) head in different directions, the subsequent following depends on the angle between the motions: in a case in which the angle is small (less than roughly 90°), the animals compromise (choose a direction in between), but in a case in which the angle is large, they choose one direction over the other, randomly.

Importantly, these animal species live in highly hierarchical social structures, yet —according to the above studies—their collective decisions emerge via a shared "democratic" process, using simple rules.

In an interesting experiment, Couzin et al. (2011) studied the role of uninformed individuals (individuals without any preferences regarding the direction) when two groups of initiators with different preferred directions were influencing the group motion. Their main question was under what conditions—if any—a strongly opinionated and self-interested minority can exert its influence on the entire group. In the experiments, they used a fish species, golden shiner, whose individuals' motion can be predicted with high accuracy by a model using some simple rules: (a) avoidance of collision, (b) attraction and (c) alignment (Couzin et al. 2005). The first rule, avoidance, has the higher priority. In case others are not detected within a certain region, the individual will tend to become attracted towards and aligned with its nearest neighbours within a local range of interaction. Using the experimental set-up depicted in Fig. 3.9, the trajectories of the individual fish can be recorded precisely.

Some of the fish were trained to be attracted towards the blue target, some to be attracted towards the yellow target (to which the shiners exhibited a pre-existing bias), and some individuals did not have a direction preference at all. Among the trained fish, the *strength* of the preferences was also manipulated. When all of the individuals were trained to be attracted towards either the blue or the yellow target, the results were in accordance with the expectations: if the strength of the majority preference was at least as big as the minority preference, then the group reached the majority-preferred target with a higher probability. By increasing the strength of the
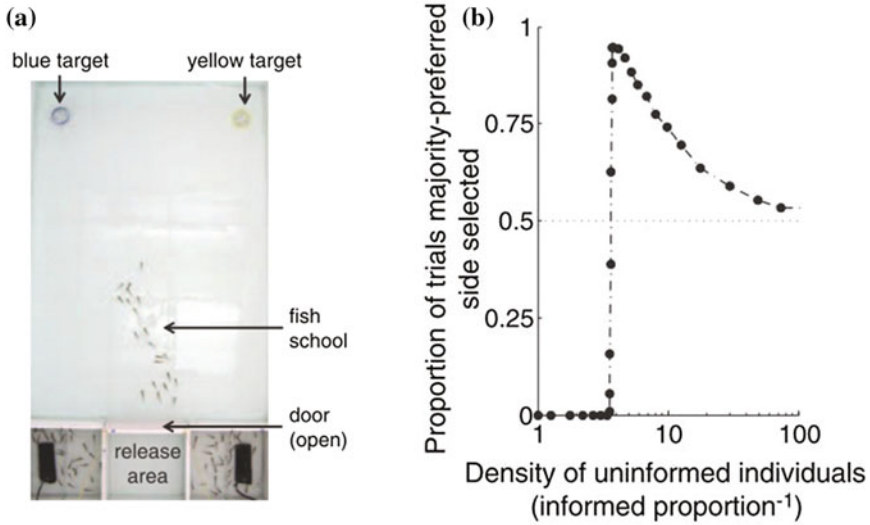
Fig. 3.9 The experiment conducted by Couzin et al. (2011). **a** An image from an experimental video with 6 and 5 trained, and 10 untrained individuals. **b** The model describing the trajectories of the group members predicts a sharp transition from a minority- to a majority-controlled outcome, as the density of uninformed individuals is increased. These simulations are in qualitative agreement with the observed behaviour. Reproduced from Couzin et al. (2011)

preference in the minority group above the preference-strength of the majority group, the minority was gaining control over the group behaviour.

The most interesting results were obtained by introducing uninformed individuals into the above set-up, namely, when the group was under the influence of a strongly opinionated minority, *adding the uninformed individuals to the group returned the control to the numerical majority.* As their number increased, this effect reached a maximum, and then slowly began to diminish. This study provided interesting new data for the often observed and widely believed argument that groups with members who are poorly informed or do not have any preferences about the decision to be made are particularly vulnerable to manipulation by determined and self-interested minorities (the latter being on the top of the knowledge-based hierarchy).

Most of the studies analyse the process of collective decision-making from an *informational* point of view, in which individuals make decisions based solely on their (personal or social) data. As Miller et al. (2013) points out, during this process, the effort to maintain group cohesion plays a fundamental role as well. Another basic factor in collective decision-making—apart from the knowledge, influence and group cohesion—is the structure of the *communication network* defining the way information is spread among the members. A communication network is considered to be effective if it ensures that information can spread among the entire group via a minimum number of connections.

By comparing data gathered from 24 species, Pasquaretta et al. (2014) found correlation between the neocortex ratio and the efficiency of the communication network. Both modularity (showing how strongly the group is clustered) and centralization (the ratio of central individuals) were found to be inversely related to the efficiency of the network, from which they concluded that those species which are more "tolerant" have more efficient networks.

As it turns out, leadership, and the way members of various social animal species achieve collective decisions, is based on many factors, such as information, actual physiological state, dominance, navigational competence, etc. The resulting leadership network is a complex, multiple-level hierarchical structure.

Motivated by the above findings, a computational model was created to identify the *optimal competence* and *pliancy* distributions within groups facing problems that had to be solved collectively (Zafeiris and Vicsek 2013). In the following, we shall discuss this model, along with the results. In our interpretation, "competence" is the ability needed to solve the given task (for example, navigational skill in the case of collective flight) and "pliancy" expresses the extent to which an individual relies on personal versus social information (learning through the observation of others).

3.1.4.1 Order hierarchy for Making Optimal Decisions

When a group faces a problem, some members have more clues, some others have fewer ideas regarding the solution. Some individuals tend to follow others, while some prefer to rely on their own information. But what are the proper ratios in an optimally performing group, and how do these characteristics relate to each other? In the present subsection, optimal performance is associated with finding an accurate solution incurring the smallest amount of "cost," in which the most important cost is competence, since acquiring it requires knowledge, experience, learning, etc. Other aspects can also appear as cost, most importantly the time factor.

In order to address the above question, four estimation problems were considered:

  i. The simplest: an external parameter that can be either -1 or 1 (yes or no, black or white, to follow or not to follow certain initiators, etc.). This can be called the "voting model," or "voting GPMM," where GPMM stands for "group performance maximization model."
 ii. A general and abstract, which is simultaneously simple, and thus widely applicable: Sequence-guessing (SG) GPMM, in which a sequence of values had to be estimated.
iii. A case study: The direction-finding GPMM, in which a pre-defined direction had to be found.
 iv. The "Flocking GPMM," in which a group of agents has to reach a pre-defined target by moving along a two dimensional surface. This one is a special case

compared to the others, because here the communication structure (network) of the agents is not fixed, but rather changing continuously according to the individuals' actual position.

In order to elicit the possible effects of the communication structure, the first three games (models/GPMMs) are played on different types of fixed communication network:

a. Small-world network (SW)
b. Erdős–Rényi (ER) network
c. And a real-life social network describing the friendship relations in a school (referred to as the "Friendship" or "Frnd" network).

Rather counter-intuitively, it was found that the optimal ability and pliancy distributions were quite independent of the type of network used.

The relevance of the fourth ("Flocking") GPMM originates from the fact that, in regard to animals, the most often studied collective decision-making scenario is the one during which the group has to navigate collectively towards a(n often pre-defined) target. (See also Sect. 3.1.2.) Accordingly, simulations were designed in which a group had to reach a target by the shortest possible way. In contrast with the other games, the communication network was not fixed, but varied continually as a function of the agents' location: each individual "saw," and thus interacted with others within a given range of interaction, "ROI."

In all cases, the collective decision was achieved via iterative rounds of inter-action. In each round, each agent made a guess (decision) in which he/she incorporated his/her own estimate (individual knowledge) with that of his/her neighbours (public information) to a varying extent. We call this disposition to follow others "pliancy," denoted by λ in (3.1).

Precisely, the behaviour of agent i is defined by the following equation:

$$Be_i^{(t+1)} = (1 - \lambda_i)f(Co_i) + \lambda_i\left\langle Be_j^t \right\rangle_{j\in R}, \tag{3.1}$$

where t is the time (number of iterations), Be_i is the (observable) behaviour of agent i, for example, its direction, and Co_i is the competence level (between 0 and 1, with higher values denoting better abilities). The estimation of agent i regarding the correct solution is a function of his/her competence: $f(Co_i)$. The (observable) average behaviour of the neighbours of member i at time step t is $\left\langle Be_j^t \right\rangle_{j\in R}$, where $j(\in R)$ denotes the neighbours. λ_i, the weight parameter, takes on values from the [0, 1] interval.

The optimization was done with a genetic algorithm, with the competence and pliancy values evolving. The fitness function depended on the group performance Pe and on the average competition level $\langle Co \rangle$, according to (3.2):

$$F = Pe - K\langle Co \rangle, \tag{3.2}$$

where K is a parameter reflecting the "cost of learning."

The best group characteristics were then approached by varying the distribution of the competence and pliancy values of the members. The process of problem-solving was stopped after some simple criteria were satisfied, e.g., a given number of steps were reached, the guesses converged or they achieved a pre-defined accuracy. The optimal distribution was associated with the average distribution of the pliancy and competence values belonging to the 500 best performing groups (most optimal, having the largest F).

Because of the simplicity of the model, many real-life cases can be mapped on it. The performance of the group, Pe, is quantifiable and characterized by a parameter taking values on the [0, 1] interval. Higher Pe values mean better performance. The contribution of member i to the collective problem-solving depends on its competence level Co_i, which also takes values on the [0, 1] interval. Here too, larger values correspond to better abilities. Some noise, explicitly or implicitly, was also incorporated into the models.

In the present subsection, we focus on the first three models in which the interactions were defined according to pre-defined networks.

In the Voting GPMM, having some analogy with the widely used Ising model, the group had to find the correct answer by choosing from two options (yes/no, −1/1, etc.). This minimal model consists of two steps only:

1. First, all actors make a guess that is correct according to the probability proportional to their competences.
2. Then, the agents count the guesses of their neighbours, based upon which the group casts a vote.
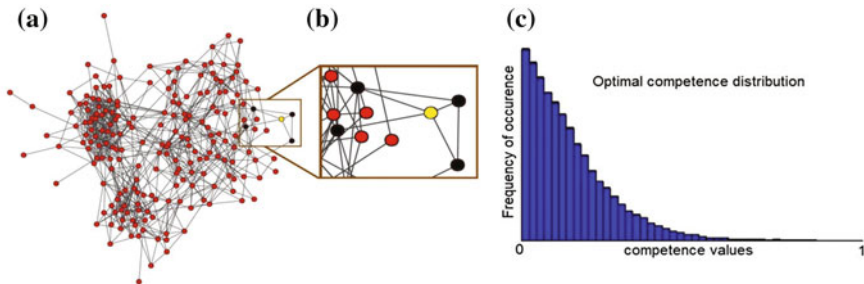
Fig. 3.10 The voting GPMM model. **a** "Friendship graph," the pre-defined communication network that was a real-life social network reflecting the amity relations in a high school among 204 students (after Harris 2009). **b** An enlarged part of the network showing the relations of a randomly selected node coloured yellow. **c** The optimal competence distribution: a highly skewed function with a fat tail. Reproduced from Zafeiris and Vicsek (2013)
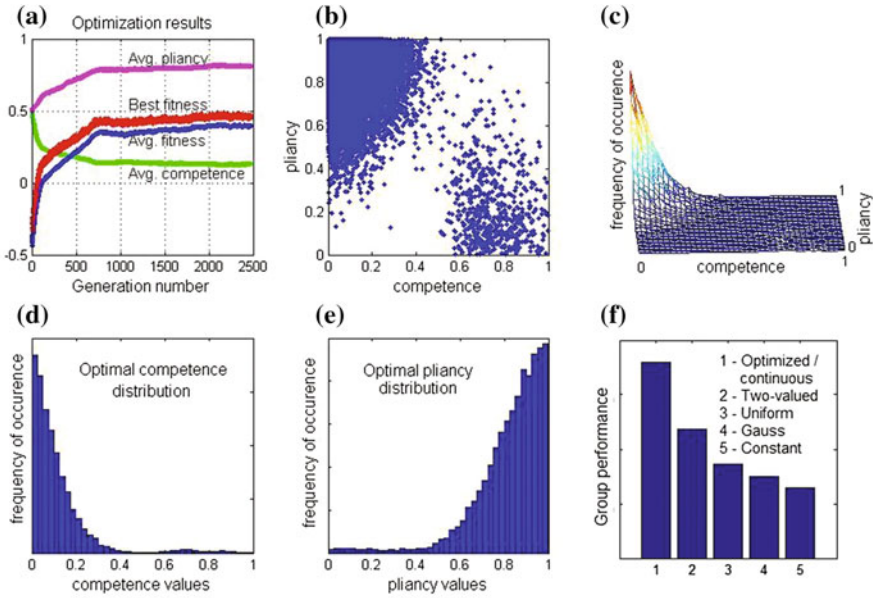
Fig. 3.11 Results for the Direction finding model on the Friendship graph. $K = 2$, the parameter describing the cost of knowledge. **a** The course of the optimization with the relevant values: pliancy, competence and fitness. **b** The competence and pliancy values depicted on a unit square. Each dot represents an individual. **c** The same as **b**, but here, axis z depicts the density of the points. A considerably greater number of agents have low competence values coupled to a high level of pliancy than vice versa. **d** Optimal competence distribution. **e** Optimal pliancy distribution. **f** Comparison of the group efficiencies Pe after 20 steps of iteration for the one identified as optimal and a selection of commonly assumed distributions. From left to right: Optimized/ continuous, two valued (allowed competence values were 0.1 and 0.9), uniform, Gaussian, and constant. In order to emphasize the effect of the distribution of the competence values, the pliancy values were set to be antagonistic for all five cases according to $\lambda_i = (1 - Co_i) + \xi$, where ξ is noise. The average competence level is identical in all cases. Reproduced from Zafeiris and Vicsek (2013)

The second step is done according to (3.1). Figure 3.10c shows the result for the optimal competence distribution when all $\lambda_i = 1$, that is, when the choices of the neighbours entirely determine the vote of an individual. This distribution ensures the highest rate of correct votes, and thus, the highest group performance as well.

The optimal competence distributions presented in Figs. 3.10c and 3.11d are typical in the sense that in all cases (that is, in all models with any parameter set and network type), the optimal values form a hierarchically ordered distribution, with progressively fewer members having high competence values than low. The only difference is that in the case of the Direction finding GPMM and Sequence guessing

GPMM, the fat tails are structured, having a smooth "hump" on them, while the tail belonging to the Voting GPMM is "smooth" (Fig. 3.10c). Furthermore—somewhat counter-intuitively—the particular structure of the underlying communication network does not have a relevant effect on the optimal distribution. For more details, see (Zafeiris and Vicsek 2013).

During the optimization process, the pliancy values (λ) and the competence values (Co) were evolved simultaneously and independently from each other. The first and foremost conspicuous result was that the pliancy values—in analogy with the competence values—formed a highly skewed distribution as well. However, in this case, agents with high pliancy values made up the majority (Fig. 3.11e).

Figure 3.11b, c grants a deep insight into the *relationship* between the competence and pliancy values in an optimized group, and sheds light on the origin of the "hump" as well. The location of each point in Fig. 3.11b is defined by the corresponding individuals' competences (x axis) and pliancy (y axis) values. Two kinds of agent appear: one kind clusters in the top left corner, corresponding to small competence and high pliancy values (these actors have "sheep mentality," and significantly outnumber the rest of the group), while the others have considerably higher competence values, mostly coupled with small pliancy. The hump—observable in most of the competence histograms—is due to the second kind of agent. It can be concluded that the simultaneous choice of both the competence and the pliancy values are essential, and the optimal choice results in a strong improvement of the efficiency of the group.

3.1.4.2   Continuous Versus Bimodal Competence Distributions

We believe that the reason behind the finding that continuous competence distribution eventuates higher group performance than the "bimodal" distribution (in which the competence values can be either 0 or 1) is due to a phenomenon that we call "information spreading or mixing," which can be summarized as follows:

Multi-level hierarchical interactions make the spreading (mixing) of information between the individuals much more efficient than in a "two-level" system.

This conceptual statement is based on the following assumptions: (i) the individuals do not know the competence level of the others, (ii) the pliancy values are approximately proportional to the inverse of the competence values (which is the general assumption in two-level systems), and finally, (iii) not all members interact with all of the others, but rather according to an underlying network—which is a natural assumption for groups beyond a certain size. Given these conditions, the two-level competence distribution can often result in temporarily or even permanently segregated groups maintaining different "opinions" or estimates, while the continuous distribution performs better.

The reason behind this possibility of segregation is that uninformed individuals have a strong tendency to follow the others (since they have high pliancy values). Sub-groups of the whole group can thus easily come to a conclusion corresponding

to a wrong estimate or solution, which they will maintain until a better estimate "diffuses" to their community from other groups having highly competent agents.

These results provide a framework for a wide selection of phenomena, including several recent observations, such as: how a few well-informed individuals are able to lead a group efficiently (Whallon et al. 2011; Conradt and List 2009; King and Cowlishaw 2009; Reebs 2000), the surprising observation made by company managers that a group of skilled workers do not outperform a group with diverse abilities (Surowiecki 2005; Hamilton et al. 2003), and the results of models optimizing the strategies of individuals performing a specific task as part of a collective. These findings emerge from the interaction dynamics within the collective.

3.2 Hierarchy in Humans

3.2.1 Our Biological and Social Heritage

In the previous sections of this chapter, we have presented results regarding dominance hierarchy, which seems to be ubiquitous in the animal world. Since humans belong to the animal kingdom inseparably, these mechanisms apply to us as well, but in forms partly overwritten by new mechanisms.

Anatomically modern humans—from whom our bodies are indistinguishable—appeared around 200,000 years ago. Like other social primate species, they lived in small face-to-face societies, organised according to mechanisms and principles similar to those that shaped other animal groups. However, somewhere between 120 and 50 thousand years ago, an (up to now not clarified) modification occurred in the mechanisms of social self-organisation. Anthropologists and historians (Harari 2013) often refer to this shift as "cognitive revolution." The two most fundamental elements of this new way of social self-organization are that after this transition, (i) humans have become capable of creating *formal roles* (such as chieftain, king, pharaoh, colonel, linemen, baker, etc.), and (ii) group members have become capable of creating *social rules* that they also willingly follow (and punishing those who do not). Formal *roles* are important for two fundamental reasons: (i) the social positions and ranks are defined independently of the actual individuals occupying them, and as such, the relations become stable, unaffected by the actual physiological state of the participants, and (ii) these social positions can be organised into any kind of hierarchical system (including egalitarianism). It will be the *rules* (accepted by all participants) that support and reinforce the emergent social structure by setting the duties and rights belonging to the various social roles—a.k.a. "appropriate behaviour" by the given society.

Such an arrangement makes it possible for the group members to cooperate to an unprecedented level and, furthermore, allows the group to grow in size to basically limitless degrees.

Table 3.1 Comparison of the two types of hierarchy present in human groups: dominance hierarchy and cultural hierarchy

Dominance hierarchy	Cultural hierarchy

• Genetically coded
  → Restricted variability: the basic features
     are the same within one species.
• Controlled mainly by hormones
  (testosterone, stress hormones, etc.)
  → Mostly instinctive
• Its main purpose is to minimise the
  inner-group aggression by determining
  access to common resources
	• Culturally coded
	  → Can take *any* form, from strict
	     dictatorship to complete
	     egalitarianism
	• Controlled mainly by the Neocortex
	  → Mostly conscious
	• Its main purpose is to harmonize the
	  behaviour of the group members via
	  political power

Importantly, only the *ability* enabling the creation of such roles and rules is coded genetically, whereas the specific nature of the hierarchy (social structure) is not. The latter is coded culturally, and thus, in order to distinguish it from dominance hierarchy, we shall refer to it as *cultural hierarchy*. Table 3.1 shows a comparison regarding the most important features of the two types of hierarchy. In human groups, both the dominance and cultural hierarchies are present, and although their origins and functioning are rather independent, they interact with each other in a unique way, and this interaction, from time to time, can create conflict within (or among) the group(s).

Distinguishing these two hierarchy types also resolves the question of how the hierarchical organization could possibly disappear in hunter-gatherer groups. According to this approach, it is very difficult to explain the predominantly egalitarian nature of hunter-gatherer groups, since we have inherited a strong tendency towards hierarchical group organization from the animal world (which would be the dominance hierarchy). To make the picture even more obscure, once humans settled down (around 10 to 15,000 years ago), hierarchies reappeared in an even more pronounced way. So, where did hierarchy disappear in between the two periods (Dubreuil 2010)? A probable answer is that it did not disappear anywhere; dominance hierarchy has been continually present throughout human history in all human societies, although often oppressed by culturally coded norms. According to our present knowledge, the (cultural) hierarchy of both the historical and the present-day hunter-gatherer societies have been mostly (but not always) close to an egalitarian structure.

In the following, when we refer to human hierarchies, we mean *cultural hierarchy*, if not stated otherwise.

3.2.2 Large-Scale Hierarchies in Societies

During the vast majority of the circa 200 thousand years of human history, people lived in small-scale, mostly egalitarian hunter-gatherer communities comprising

around 30-50 or, at most, a few hundred individuals. The beginning of the transition to larger scale and more complex societies happened only 10–12 thousand years ago, when humans first settled and engaged in agriculture and animal domestication. The first large, state-level societies appeared around 5 thousand years ago (in Egypt and Mesopotamia), and the scale of societies has been increasing ever since.

The deep reasons for these transitions—primarily the first one, marking the transition from the hunter-gatherer lifestyle to settled communities—are quite blurry. Although many theories have been proposed, none of them seems to be completely satisfactory or clinching. Furthermore, in accordance with the general nature of historical and anthropological interpretations, they are mostly descriptive, making it difficult to make predictions that allow for testing against measured data. However, in recent years, there has been a gratifying increase in formal (mostly, but not exclusively agent-based) models regarding historical and anthropological issues (Barceló and Castillo 2016; Grinin and Korotayev 2014; Pumain and Reuillon 2017). Agent-based models combined with game theoretical approach have also been proposed (Boix 2015; Greif 2006). The book by Turchin (2003) has a relevant analytical treatment of the problem.

In the present subsection, we will give an overview of two formal approaches describing large scale hierarchies in human societies. One approach, the work of Turchin et al. will be reviewed in more detail, while the work by Boix (2015) will be described only briefly. Although many important related works exist, we have selected here those two that offer a quantitative theory with predictions that make testing against real-life data possible.

In the search for the main driving forces behind historical patterns, Turchin and Gavrilets identify *warfare* and *multilevel selection* as the two main causes leading to complex, hierarchical societies (Turchin and Gavrilets 2009; Gavrilets et al. 2010). Their (here somewhat simplified) train of thought is as follows:

- Throughout most of human history, people lived in small-scale, mostly egalitarian societies.
- These tribes often engaged in warfare with each other, over various resources.
- Although selfish behaviour can be beneficial for the individuals within a group, when groups intensively compete with each other (for example, during warfare), those groups that have more cooperative and less selfish members have the advantage. Thus, human societies are subject to multilevel selection.
- On the one hand, warfare has the following effects on social evolution:
  - Groups become internally more cohesive
  - It drives technological progress, including military and organizational applications
  - It triggers the enlargement of group sizes, since "God always favours the big battalions"—as formulated by either Napoleon or Turenne.
- On the other hand, the capacity of the human brain has its limits, as it cannot handle social relations in detail among more than around 150 people [known as

the "Dunbar number" after Barton and Dunbar (1997)]. In other words, there is a limit to the size of egalitarian, face-to-face human groups.

Given the above, there exists a pressure on the group to grow in size while this enlargement has biologically rooted barriers. According to Turchin and Gavrilets, the evolutionary response to this dilemma was the appearance of:

1. the ability to demarcate group membership based on cultural traits (language, dialect, clothing, etc.)
2. hierarchical organization, allowing group sizes to grow basically ad infinitum, since each element within a given level of a strictly hierarchical system needs to have, at most, $n + 1$ connections: n is the "span of control", and the $+1$ accounts for its superior. Here element stands for a political entity (e.g., a village), thus, the constraint corresponding to the Dunbar number does not apply.

If this hypothesis holds, more intense warfare results in bigger polities (political entities) with more hierarchical levels. In order to test this hypothesis, they conducted numerical experiments by constructing the following agent-based model: The modelled area is divided into hexagonal cells (each representing a village), as shown in Fig. 3.12. Each of these autonomous local communities are characterised by:

• a base-line resource level, accounting for the heterogeneous environment, defining the productive/demographic potential of the region (a "tunable" parameter)
• actual resource level, the base-line resource level minus the costs of the various actions in which the given community participates
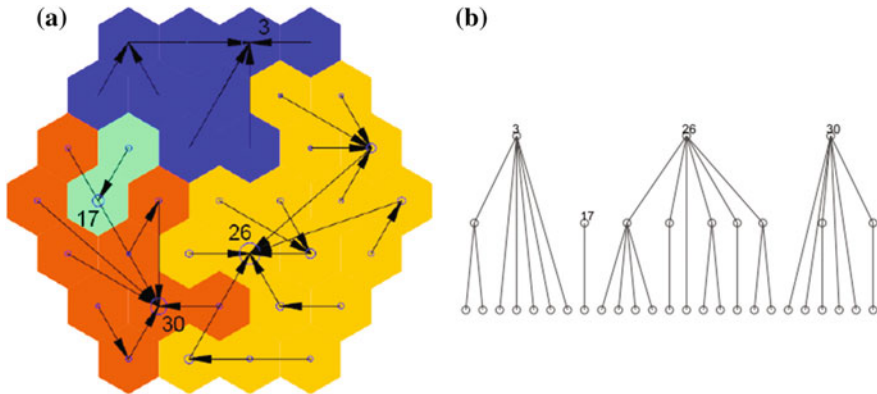

Fig. 3.12 An example of the model's realizations. This system consist of 37 communities organising themselves into four polities the numbers in the hexagons mark the chief communities. **a** Spatial view. **b** The hierarchical structure, being tree-like, as in most of the agent-based models of community formations. Reproduced from Gavrilets et al. (2010)

Each polity is organised in a hierarchical way (consisting of one or more villages/communities). Each subordinate community pays a fixed portion of its total resources to its chief village as tribute. Accordingly, the total resource level of a community is its base resource level minus the tribute it pays to its superior community plus the tribute it receives from its subordinates.

According to their estimated chances, polities may rebel or engage in warfare (as the result of conquest or being attacked), due to which their size permanently grows or decreases. A polity will attack its weakest neighbour if (i) it estimates that the attack will be successful, (ii) it is ready to pay the corresponding costs and (iii) it is not too devastated from previous wars. Quantitatively, the probability of an attack is:

$$A_{ij} = P_{ij} \cdot e^{-\beta c_{ij}} \cdot \frac{F_i}{F_{i,0}}, \tag{3.3}$$

where the terms are the following:

The first term, P_{ij}, which is the probability of an attack by community i on community j *being successful*, increases the probability of an attack. The probability of success is

$$P_{ij} = \frac{F_i^a}{F_i^a + F_j^a}, \tag{3.4}$$

where F_i is the power of polity i and 'a' is the 'success probability exponent.'

The second term, $e^{-\beta c_{ij}}$, accounting for the cost of warfare c_{ij}, decreases the probability of an attack. β is a parameter and $F_{i,0}$ is the maximum possible power of polity i.

Each time step is considered to be a year. Each year, the chief community of a polity decides whether or not to launch an attack on its weakest neighbour. If it decides to go to war, then it first attempts to conquer the bordering communities, followed by a series of "battles," until it either suffers a defeat or the chief community of the victim polity falls. Annexing the conquered communities may require restructuring the hierarchical organization of the winner polity, since the number of subordinates of any community has constraints (a parameter varying between 4 and 10).

When launching an attack, the direct subordinates of the aggressor chief community might decide to secede if they estimate that the attack will be unsuccessful. In this case, the chief polity attempts to suppress the rebellion, which, if successful, leads to spatial separation from the master state. All of the subordinate communities of the rebelling village will secede too.

This model provides a fission-fusion cycle reminiscent of the dynamics characterising early states of humans. More importantly, the effect of the intensity of warfare on the complexity and size of polities can be analysed. As can be seen in Fig. 3.13, a low level of warfare results in considerably smaller polities regarding the extent of their territories (Fig. 3.13a) with less hierarchical levels (Fig. 3.13b).
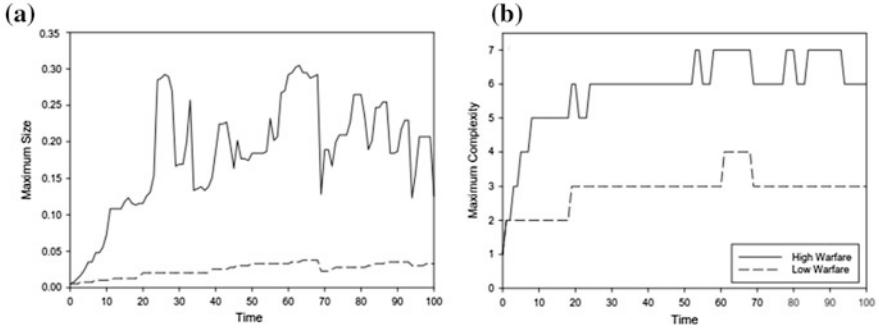
Fig. 3.13 The size (**a**) and the hierarchical complexity (**b**) of the polities under low and high pressure of war. According to the predictions of the model, intense warfare results in larger and more complex polities. Reproduced from Turchin and Gavrilets (2009)
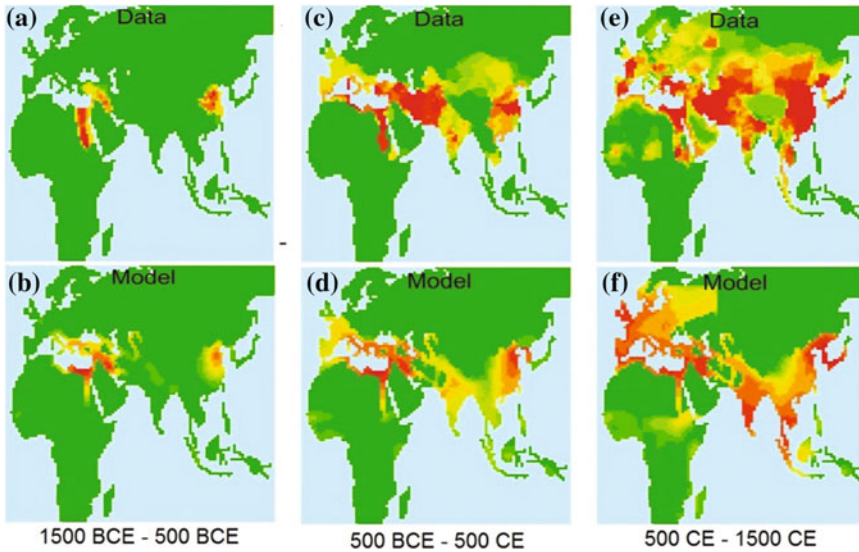
Fig. 3.14 Comparison of the predicted (**b**, **d**, **f**) and "measured" (**a**, **c**, **e**) data. The model predictions ("Data") are averages of 20 runs. The colour codes are as follows: green: the absence of large-scale polities within the given time period; yellow: moderate density of large polities; and red: regions where large polities arose frequently. Reproduced from Turchin et al. (2013)

In contrast, a high level of warfare results in larger and more complex polities, in accord with the case of historical societies (Turchin and Gavrilets 2009).

The final purpose of such models is to gain a deeper understanding of the dynamics of historical events by reproducing (at least some) properties of historical polities. Using an improved version of the above model, Turchin et al. (2013) tested its predictions for a realistic landscape of the Afro-Eurasian landscape against real

historical data. The main proposition to be tested was that costly institutions enabling large human groups to stay together within one political unit and function as one society evolved as a result of warfare. More specifically, they compared the model's predictions with a large dataset documenting the spatiotemporal distribution of historical (large-scale) societies appearing in the Afro-Eurasian lands between 1500 BCE and 1500 CE (see Fig. 3.14).

Until now, in this subsection, we have seen "political hierarchy" formed by superior and subordinate communities. But this is not the only type of hierarchy that is manifested in large-scale societies. *Inequality*, the wealth distribution among members, is another type, one that is triggering much more attention and, accordingly, has much more extensive literature. However, quantitative models are scarce in this field as well. Here, we shall briefly mention only one quantitative study.

By using a game theoretical approach, Boix (2015) argues that voluntary cooperation exists only in small-scale egalitarian communities, while economic growth inevitably brings about inequality (hierarchy), breaking down spontaneous cooperation. Economic growth usually results from technological development, such as plant domestication or the appearance of a new agricultural tool. According to his model, these changes *precede* the formation of a state—a statement that is in contrast with the mainstream view holding that the formation of a state came first, and inequality appeared as a result of it. (In his work, institutions play a much more limited role than is usually assumed.) According to his framework, group members benefiting from the technological change can be considered to be "producers," while those group members who are not will be the "looters." The state emerges as a result of this situation. The type of a given state depends on the primary military technology: if the technology favours looters (e.g., those who use horses), monarchies tend to rise, while military machineries favouring producers (e.g., a navy) call forth republican polities. The early states were mostly monarchies, but some of them were republican or mixed. Inequality tends to be higher in monarchical polities, but it depends on political institutions and other endowments as well.

3.2.3 Nested Hierarchy Structure of Human Societies

Up to this point, when discussing hierarchy, we have been considering *flow* hierarchy. However, the structure of human societies exhibits a *nested* nature as well, with a preferred scaling ratio between 3 and 4. (For the definition of nested hierarchy, see Sect. 3.2.) In other words, instead of a continuous spectrum of group sizes, it was argued that a geometrical series of 3–5, 12–20, 30–45, etc., individuals (Zhou et al. 2005) per group size can be observed.

Various anthropological studies report that both human (Kottak 1991) and non-human primate (Dunbar 1988) societies consist of a series of nested groups

classified as follows (Dunbar and Spoor 1995; Hill and Dunbar 2003; Zhou et al. 2005):

- **Support clique** is the smallest one, with the strongest emotional ties, "defined as the set of individuals from whom the respondent would seek personal advice or help in times of severe emotional and financial distress; its mean size is typically 3–5 individuals" (Zhou et al. 2005).
- **Sympathy group**, characteristically containing 12–20 individuals, represent those with special ("friendship") ties, contacting each other at least once every month.
- **Bands** (or **overnight camps**), reported in the ethnographic literature on hunter-gatherer societies (Dunbar 1993), refer to those more or less unstable groups of 30–50 individuals whose members belong to the same clan.
- **Clan** (or **regional group**) contains ca. 150 individuals. This formation is very typical in small-scale traditional societies, and this number, 150, has become known as the "*Dunbar number*," referring to the biological limits of human cognition. According to the *Social brain hypothesis* (Byrne and Whiten 1988; Barton and Dunbar 1997), the main evolutionary force acting on the formation of the primate brain has been the need to remember, coordinate and manage the complex social relations within a group. Since the stability of a group depends on the intimate knowledge of each other (meaning the ability to keep count of the social ties that allow the behaviour of the group mates to be predicted), the size of the brain (assumed to be proportional to its computational ability) imposes a limit on the group size. Above this limit, the group inevitably becomes unstable and splits up.
- **Mega-band** is the next (and penultimate) level identified in the literature, comprising about 500 individuals.
- **Tribe**, the final level, unites ca. 1000–2000 individuals, those belonging to the same linguistic unit.

Zhou et al. (2005) searched the sociological and other related literatures for quantitative data on such human groupings, based upon which they constructed a

Table 3.2 Human (and other primate) societies tend to have a well-defined inner structure consisting of nested communities with a scaling ratio between 3 and 4

	Group type	Mean group size
S_0	Ego (individual)	1
S_1	Support clique	4.6
S_2	Sympathy group	14.3
S_3	Band	42.6
S_4	Clan	132.5
S_5	Mega-band	566.6
S_6	Tribe	1728

The table shows the names of these communities (2nd column) and their mean sizes (3rd column). Reproduced from Zhou et al. (2005)

dataset consisting of 61 groups. The 3rd column of Table 3.2 indicates the mean values of the sizes for all six group types.

Next, they calculated the ratio of the sizes of the successive groups S_{i-1} and S_i, and found that

$$\frac{|S_i|}{|S_{i-1}|} = 4.58, 3.12, 2.98, 3.11, 4.28, 3.05 \tag{3.5}$$

for $i = 1,\ldots,6$. $|\ldots|$ denotes the average group size (3rd column in Table 3.2), and the mean value of these ratios is 3.52. Based on these values, they concluded that "humans form groups according to a discrete hierarchy with a preferred scaling ratio between 3 and 4" (Zhou et al. 2005).

Being interested in similar questions, Hamilton et al. (2007) reviewed the ethnographic literature on hunter-gatherer societies and analysed the data of 1189 social groups belonging to 339 such societies. They also found a self-similar structure with a scaling ratio close to 4. Importantly, their database contained groups from highly distinct cultures from five continents.

These findings all indicate that there exists a kind of biologically-rooted attribute defining fundamental features of human (and primate) social self-organization. Further support for this view came from the statistical analysis of a large-scale, high-precision, internet-based social network formed by the players of a massive multiplayer online game (MMOG) called *Pardus* (Fuchs et al. 2014). In this game (http://www.pardus.at), more than 400,000 players control avatars living in a virtual, futuristic world. Their interaction is based on an internal, private (one-to-one) messaging system through which they can communicate without restrictions. Among other actions, they can create friendships, express their sympathy or revulsion, they can trade, cooperate or defect. As a result, a superposition of dense social networks of various types (trade, friendship, communication) is spontaneously created.

The most important result is that even though the game is purely virtual—and, as such, it does not allow for face-to-face human interaction—a highly structured social system emerges, one that strongly resembles those found among hunter-gatherers and other "real-life" human societies.

On the low levels of the friendship and communication networks, the support cliques appear, containing 5.1 individuals on average. The next level contains the "clubs" (corresponding to the sympathy groups), with 11.5 members on average. On the middle scale, "alliances" appear: this type of group is a formal establishment within the game. The average size of this formation is 24.7, and the biggest alliance contains 136 members—a value pretty close to the Dunbar number. In fact, by analysing the same game, Pardus, Szell and Thurner (2010) found that the upper limit for friendship and other communication communities is exactly the Dunbar number, a value that does not seem to change with the use of digital media (Dunbar 2012).

The next organizational level, the "political factions," is pre-defined by the game designers, so at this level, we finish the discussion of spontaneously emerging

communities. However, it is important to note that, even under such conditions, the group sizes on these higher levels remain on the same order of magnitude as the ones observed in real-life human societies.

3.2.4   Phenomenological Theory of Collective Decision-Making

This subsection addresses a common situation in which hierarchy manifests itself in a specific way. The problem to be solved is complex (or "multidimensional") and, as such, requires several "specialists" to be solved efficiently. Thus, there is a simple two-level hierarchy involved: within a given field involving distinct/ particular knowledge, specialists are significantly better at solving problems than non-specialists. Furthermore, as will be shown, in an optimally working group, specialists will have at least some level of knowledge/insight related to other sub-problems (Zafeiris et al. 2017). Thus, the situation has some analogies with that of Sect. 3.1.4, in which—in order to find the best solution—the abilities of the group members were distributed according to an order hierarchy. But here, a similar condition should hold simultaneously for a number of sub-problems.

The process of collective decision-making has generated great scientific interest for a long time (Clearwater et al. 1991; Forsyth 2006; Surowiecki 2005; Planas et al. 2015), since it is a highly relevant aspect of social group behaviour. In particular, it has been measured, argued and shown analytically that the "wisdom of crowds" can go qualitatively beyond that of individuals (Surowiecki 2005). This statement is true for both animal and human communities (Conradt and List 2009; Nagy et al. 2010; Couzin et al. 2011). An essential, but rarely considered case is when the problem has many "dimensions," i.e., it has many facets and aspects. Under such conditions, the performance of the group (the quality of the collective solution) is highly influenced by the composition of the group. Apparently, if the group members are identical, the performance of the group cannot go beyond the performance of its members. However, if the problem to be solved is complex, i.e., has a number of different aspects or dimensions (Vicsek 2002), then a group with members specialized in their own respective fields of expertise is expected to be much more efficient in providing a high quality answer than a uniform community. The stress is on the independent nature of the sub-problems, making the problem multidimensional. In a way, solving multidimensional problems can be considered a quantitative approach to the problem of labour division (Smith 1970; Durkheim 1997) in the context of collective decision-making: the task is to bring about a decision, and the division is made among the specialists who work out the solutions for the various sub-problems.

In spite of the above almost trivial observation regarding the necessity of specialists in heterogeneous/diverse groups, a quantitative demonstration of its validity requires a carefully constructed framework. Prior works involving quantitative

analysis primarily focused on problems that could be regarded as "one-dimensional" (Surowiecki 2005; Page 2010; Hong and Page 2001; Zafeiris and Vicsek 2013) in the sense that the problem to be solved needed a single kind of ability (for example, navigational skill). In the case of one-dimensional problems, it has been demonstrated—by using approaches from theory (Page 2010; Hong and Page 2001), agent-based simulations (Guttal and Couzin 2010), genetic optimization (Zafeiris and Vicsek 2013) and observations (Hamilton et al. 2003; Ruderman et al. 1996)—that diverse groups can outperform homogeneous ones.

Some scenarios covered by the model presented below include (i) a board of directors for a large company, (ii) groups of animals searching for resources, (iii) a government, (iv) a scientific team for interdisciplinary research, etc. In the example of the board of directors, a potential candidate for a problem could be the question of where to build the next factory. The various aspects of this problem are quite diverse, each of them requiring specific knowledge, like the history of the given country, characteristics of the labour force, education, local taxation laws, geographical and logistic conditions, potential markets in the region, and so on. Importantly, the members of the group cannot get any information about the quality of their proposals from an "outsider" knowing the optimal solution ab ovo.

The formal description of the collective decision-making process is the following: We consider groups of N individuals solving a problem P having M sub-problems P_j ($j = 1,2,…,M$), so that each sub-problem needs a unique (specific) skill/ability in order to be addressed (it should be pointed out that P is not specified further). Thus, a set of $N \times M$ abilities, $A(i, j)$ ($i = 1,2,…,N$) or levels/ degree of skill is to be considered. $A(i, j)$ corresponds to the ability of an individual i to give the best answer for the jth sub-problem (in other words, ability corresponds to competence).

Next, it is assumed that $A(i, j)$ takes values from the unit interval [0, 1]. It is important to note that the cost of obtaining an ability A is typically not a linear function of A, since achieving the capacity of perfect knowledge ($A = 1$) is much more costly than achieving partial knowledge (e.g., $A = 0.5$). For the sake of simplicity, we assume that the cost C for obtaining ability A is $C = f(A) = Const\ A^x$ (where $1 < x$, and *Const* is a constant corresponding to the relative weight of the costs).

In this framework, the optimization is done with a genetic algorithm, where the evolving parameters are the $A(i, j)$ values. The initial distribution is random, and the fitness function (to be maximized) is

$$F = Q - C, \tag{3.6}$$

where Q is the quality of the final collective decision.

In other words, high fitness values correspond to distributions providing the best possible solution for the smallest possible (or for a given prefixed) cost. Then, the process of collective decision-making is divided into four basic stages.

1. Each member i suggests a solution for each sub-problem P_j in a way that the quality of the given proposition Q_{ij} depends only on i's competence, A_{ij}. This assumption, in the simplest case, means that $Q_{ij} = A_{ij}$, although, importantly, the addition of noise did not change our results.

2. This is, perhaps, the most essential step of the algorithm: group members, one after another, provide an evaluation of the proposals of the other members. If a member has zero ability to evaluate the proposal for a given sub-problem, then the contribution of this member to choose an otherwise excellent proposition becomes totally erratic. Conversely, even a relatively small ability to estimate the right quality of a proposal results in a decreased level of randomness in the evaluation and, in this way, provides a more accurate estimate of the quality of the proposition. Formally, this step is described as follows: The evaluation of member i' regarding the quality Q_{ij} is denoted by $E_{ij}^{i'}$ and it is proportional to Q_{ij} (the quality of that given proposal). The *accuracy* of the evaluation $E_{ij}^{i'}$ is distorted by a stochastic factor representing the fact that those members who have lesser ability to evaluate a proposal belonging to a given field of expertise j (that is, $A_{i'j}$ is small) tend to make mistakes during their evaluation with an amplitude involving randomness:

$$E_{ij}^{i'} = Q_{ij} \times A_{i'j} + \left(1 - A_{i'j}\right) \times Rand, \qquad (3.7)$$

where *Rand* is a random number from the (0, 1) interval.

3. "Roundtable discussion." This step refers to the stage in which somebody (most often, but not always an expert in the given field) tries to convince other members of the group of her/his opinion by sharing her/his ideas. Formally, $X\%$ ($X = 10, 20$ or 30) of the N members is chosen in proportion to their ability in the given field to present their evaluations, to which the evaluations of others converge.

4. Finally, the quality of the solution for a given P_j is obtained by accepting the proposal of member i^* receiving the highest average evaluation. The quality Q of the solution for the original problem P is then obtained by aggregating these proposals (having the highest evaluations) for all of the $j = 1...M$ fields, after the last round.

The most important result is summarized in Fig. 3.15c, where each column represents a sub-problem (specialty), and each row refers to an individual (group member). The colour of the square in the ith row and jth column corresponds to A_{ij}, according to the colour bar (Fig. 3.15d). As can be seen, there is exactly one red square in each column, meaning that exactly one expert is needed for each field. By and large, these results overlap with the general intuition (holding that a well-performing group needs a specialist for all fields, but no additional "extra knowledge" is required from other members). What is less intuitive is that the rest of the squares are not homogeneously dark blue (corresponding to close-to-zero
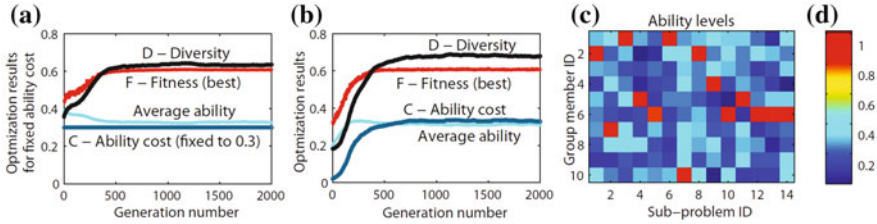
Fig. 3.15 The process (**a**, **b**) and the result (**c**) of calculating the optimal distribution of abilities, $A^{OPT}(i, j)$, using a genetic algorithm as the optimization method. The course of the optimization: the fitness (F), the diversity (D) and the average ability level as a function of the generation number (G). In sub-figure **a**, the ability *cost* (C) is fixed to 0.3 (hence, the fitness function F depends only on the performance of the group Q). In sub-figure **b**, the fitness F is calculated as $F = Q - C$, that is, C is not fixed. The averaging is made over a population size of 2000 groups. The corresponding diversity, D, is indicated by a black line. The groups consisted of $N = 10$ members and the problem P had $M = 14$ sub-problems. Sub-figure **c** displays the optimal ability matrix visualized by colours—the scale being indicated in **d**. These results describe a generic case, into which a few plausible assumptions are incorporated: the sub-problems have equal importance (weight) and $X = 30\%$ of the members play a role in the roundtable discussion. The most relevant message of **c** is that there is one specialist for each sub-problem and, perhaps rather intriguingly, the specialists are found to have a clearly non-negligible competence concerning several of the other sub-problems. If we add some cost for the case in which a single person is a specialist of more than one sub-problem, the solution ceases to have multiple specialities per person. Reproduced from Zafeiris et al. (2017)

knowledge), but rather span all shades of blue, meaning that in a group, an optimal decision can be made if the members have at least some idea about the other members' fields of expertise. This result is likely to be due to a better flow of relevant information among the group members.

Figure 3.15a, b depicts the course of optimization: the fitness function F, the quality of the solution Q, the cost C and the diversity D, as a function of the generation number G. In all cases, we find that the optimal distribution of the abilities is highly diverse. Diversity is calculated according to (3.8),

$$D = \frac{\sum_{i,j}\left[\left(\max_i A_{ij}\right) - A_{ij}\right]}{M \cdot (N - 1)}, \tag{3.8}$$

because this definition—motivated by Freeman (1978)—differentiates appropriately among the diversity of distributions in a way that is both in agreement with the intuition and sensitive enough within the range determined by the actual distributions of A_{ij}–s.

The plots in Fig. 3.15 display the behaviour of the model for $N = 10$ and $M = 14$, but these features of the optimal ability distribution do not differ qualitatively for other sets of N and M. Random initial conditions correspond to relatively low fitness values and high costs. The efficiency/fitness of a group quickly

increases at the first stage of optimization. It is to be noted that higher fitness values
(*F*) correspond to higher diversity values (*D*).

On the left (sub-picture **a**), the ability cost is fixed, referring to a more general
situation in which a fixed amount of resource can be distributed among the
members. Sub-picture **b** belongs to the case in which there is no pre-defined limit
regarding the growth of the ability values, except for the fitness function in which it
appears as a cost. (Note that the *average ability* is not the same as the *cost of ability*,
because *C* is not a linear function of *A*.)

Up to this point, a certain ratio of evaluators (commenters) were assumed during
the discussion phase. By fixing various values X_e ($e = 1,2,…$) for this ratio and
assuming a related cost function $C_t = \text{Const}_t\, f(X_e)$, the full cost function becomes
the sum of the formerly introduced C and C_t.

Figure 3.16 shows how the efficiency (fitness) of a group depends on the number
of contributors for various time-dependent cost coefficients. It is interesting to note
that for a range of parameters, the optimal number of contributors is scattered across
a range of around 30% of the size of the group. In this way, we can also support a
widely observed phenomenon regarding the relation between the efficiency of a
meeting and its duration.

The above results are also exemplified by a number of studies on collaboration,
especially on the creative groups formed by scientists working on solving
increasingly complex problems. At a recent meeting on interdisciplinary science
(Ball 2015), it was concluded that productive interdisciplinary researchers have a
deep knowledge of at least one field, but also a working awareness of others. In
other words, during broad collaborations, individuals' breadth is as important as
their depth of knowledge within their own field of expertise. In fact, Uzzi and
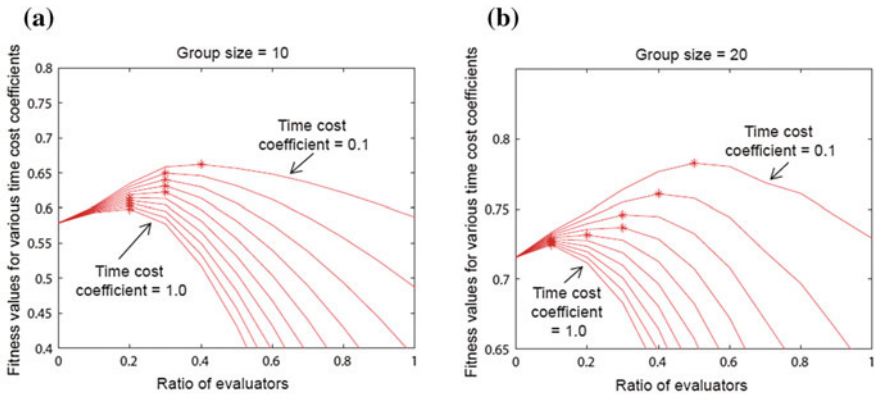

Fig. 3.16 Efficiency of a group as a function of the number of commenters during the negotiation
phase, for various time cost values, in a group consisting of **a** 10 and **b** 20 members. For a range of
the parameters, the maximum is scattered around 0.3% of *N*, where *N* is the size of the group

collaborators have shown, using huge bibliographic data sets (see, e.g., Wuchty et al. 2007; Uzzi et al. 2013), that papers of high impact tend to be produced by larger collaborations involving groups with a broader scope of knowledge. One interpretation of these observations is likely to be related to the growing relevance of interdisciplinary research, requiring various kinds of specific scientific input.

The formalism discussed in the present subsection covers applications to more specific cases corresponding to various real-life situations. It can be considered as the decision-making equivalent of the "division of labour" concept. It can also be easily generalised to cases with various relative weights/influences of the members of a group (depending, e.g., on their social status in an organization). Additional future research could address further interesting questions, such as, e.g., the effect of "overlapping" problems, the optimal size of a group for a given number of sub-problems, the most reasonable time interval spent on discussions, etc. Furthermore, the bilateral relations among the members (which may be interpreted as an underlying network) can also play an important role in finding the best solution.

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Chapter 4
Experiments on the Emergence and Function

By the nature of the subject, it is very difficult to obtain data about the emergence of hierarchy in actual living systems. In most cases, the process is too slow, and documentation of the relations among the organism is too difficult to capture in all of the required detail. For example, it is clear that evolution resulted in hierarchies both concerning single organisms and entire social communities of them. The available data is more like a timeline than a set allowing for a deeper insight into the process itself. In this chapter, we discuss two experiments that were used/designed to determine how a hierarchy of leader-follower relationships can emerge in a group of humans over a week, or even as little as about an hour.

4.1 The Liskaland Camp Experiment

4.1.1 The Liska Model of Economy

In his theory, Hungarian economist Tibor Liska, Sr. introduced a model (the "Liska model") of a "trans-capitalistic" socio-economic system. This model was presented in detail and for the general public by Tibor Liska, Jr. in several publications (Liska 2006, 2008 and 2011); Liska, Jr. would also go on to take part in other, more recent experiments related to the subject (see later). This system would be trans-capitalistic, as it would operate in a way that is self-regulating, through a "pure" market and competition free from limits to a higher degree than present day capitalism. In this model, property itself is fully open to competition, as gaining control over property in open competition is regarded as a fundamental human right. The model allows the state merely to play the role of a "referee." Accordingly, this system requires a drastic reduction in the role of the public sector and must be totally self-controlled. The self-controlled economy would also manage redistribution, education, environmental problems and all other socio-economic

subsystems much more efficiently than present-day economies. The theory envisions a society without taxation, in which all income is fully personal and all property (that is, means of production) is social, but in personal stewardship. The research produced substantial results.

In the model, the means of production should be owned by those who can generate the maximum profit from them, so properties would be openly and freely competed for. Everybody must have the right and the option to become a runner in this competition, starting from a base level and, depending on her/his performance, moving forward. To achieve this goal, a new form of ownership is proposed, called *personal social ownership*. It stands between private ownership and tenancy-type holding of property, while its status is significantly closer to private ownership. On the basis of personal social ownership, the bidder who guarantees the maximum long-term profit will be selected for the position as owner, under the condition that he/she can keep this position only as long as the maximum long-term profit is being produced.

The basic principle is that anyone has the right to make decisions, and that the individual's further possibilities should depend on the result. According to Liska, Sr., "…systems in which one decides and others bear the cost of the decision are not desirable." The model assumes that people want to arrange their own things and do not like it when others tell them what to do. While the other expectations of the model are relatively easily justifiable, this one is an exception. There are numerous people who do not like to make decisions, even concerning their own interests. They prefer to follow a leader who tells them what is right and what is wrong.

Among the elements of the model, the two most essential have been elaborated in precise detail.

– *Social inheritance* means that the income produced by one generation will be redistributed among the members of the next generation, which would also guarantee the most efficient way of spending money.
– *Personal social ownership* would meet the selection criteria of putting the right person in the right place, the right person being the one who is able to manage the property in the most profitable way.

4.1.2 The Experiment

Due to the above-mentioned tendency of people to try to follow those who they think are better at making good decisions, we expect that in a simple realization of the "Liska economy," a system of leader-follower relationships would gradually build up. Such a highly simplified version took place at a 2012 summer camp called "Liskaland" for participants with various backgrounds (the related results—see

below—have not been published). The camp was a mini-society following the rules of the Liska model. Participants had to make financial decisions and competed to gain more "öki," the currency of the camp, with those who turned out to be the most successful after a week winning prizes. In the Liska model, certain rules of the game are set, but otherwise the state and the public sector play an extremely minimal role, the emphasis being on unlimited market competition (Cropanzano and Mitchell 2005). The participants in the camp could bid for ownership of certain enterprises on the first day. These enterprises basically provided all services, such as accommodation, food, etc., for the duration. Nothing was free—participants had to buy these services. They also had to organize the functioning of these services (as owners of the services or as paid helpers of the owners). The camp lasted for 8 days. Each day of camp represented 1 year, so events happened fast, with enterprises often switching between owners. Financial decisions had to be made about situations in which there were several uncertain factors (what will be the income of the enterprise, etc.). Further details can be found in Liska (2011).

Dataset—96 people (mainly university students) participated in the camp, 82 of whom were competitors, with the rest taking part as either organizers or workers in the "state" companies, such as the bank. On the first day, the competitors were asked to fill out a questionnaire, with 73 complying. The average age of the respondents was 22 (Mones et al. 2013).

In the case of a range of *monetary transactions*, competitors had to check into a *computer system* with a username and password to manage their transactions. At this point, they were presented with questions on the computer monitor regarding their decision-making. They were offered pen-drives as incentives to answer the questions, and the camp leaders also repeatedly asked participants to help in the research. As additional incentive, those who cooperated were offered information on how others had marked them in their own replies to these questions. In this paper, we concentrate on answers to the following query: "Whose decisions did you follow (by making similar decisions) when making economic and other decisions?" Participants were given this information in conjunction with the statement: "Following someone's decision means that you have reached a decision because you found out about that person's decision and chose to act in a similar fashion." In reaction, they could choose one or more people from the participants of the camp. 72% of the competitors answered the questions at least once during camp.

Local reaching centrality—A directed network was then built based on the answers. In the network, each node represented a participant, and there was an edge pointing from A to B if participant B followed the decision of participant A (i.e., B marked A in the questionnaire, see Fig. 4.1). As a simple filtering procedure, those participants who were chosen by a single participant but did not choose anyone themselves were removed, thus reducing the effect of incidental answers. In order to describe the influence of each participant, the local reaching centralities, $C_R(i)$, were calculated (see Sect. 2.1.2).
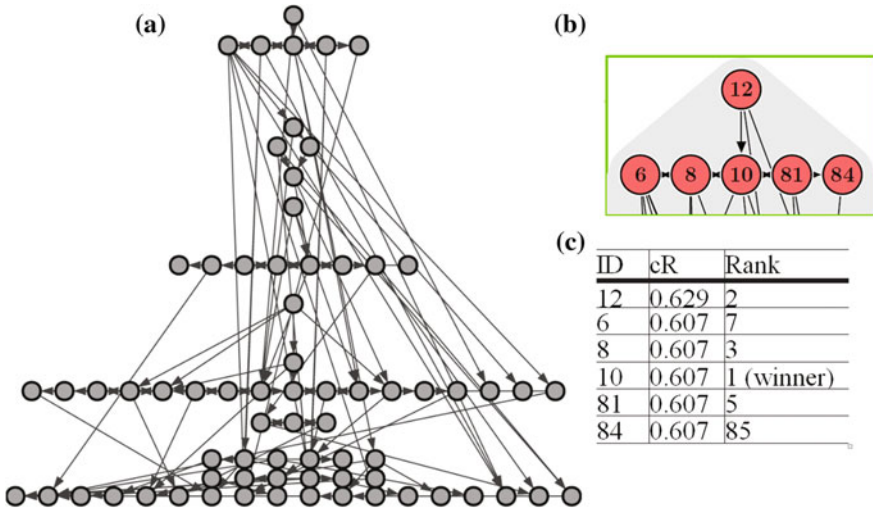
Fig. 4.1 Network of leader-follower relationships corresponding to the directed interactions between the participants of the "Liskaland" experiment. The graph in **a** was generated by the approach reviewed in the visualization part. Reproduced from Nepusz and Vicsek (2013). In **b**, the uppermost part of the whole network is shown, while **c** shows the corresponding ID-s, reaching centralities and final ranks of the participants. Visualization was made according to Sect. 2.2.2

4.1.3   Results

Hierarchical layout—Visualization of the hierarchical relations inside the network of decisions resulting from following others is based on the distribution of $C_R(i)$ (see Sect. 2.1.2).

In Fig. 4.2, we plot the histogram of the local reaching centrality of the Liskaland network in comparison with those of the random network. The random network (Erdős–Rényi graph) is generated by taking N number of nodes and adding M number of directed edges between randomly chosen nodes (with uniform distribution), where N and M are the respective numbers of nodes and edges in the Liskaland network. The corresponding distribution of the random network is determined from the average of 10^6 realizations. It is obvious that the distribution of $C_R(i)$ in the Liskaland network is more heterogeneous, having a high peak at very small values and decreasing slowly. This means that most participants do not have any influence on the others. However, there is a small fraction of participants who have significant local reaching centrality. Contrastingly, the distribution of $C_R(i)$s in the random graph is dominated by the peak at large values, meaning that most of the nodes can reach a very large portion of the graph. This suggests that the role of participants in the Liskaland network is more heterogeneous compared to the random graph, which is a sign of the hierarchical organization. The above observation is also confirmed by the global reaching centrality values: for the Liskaland
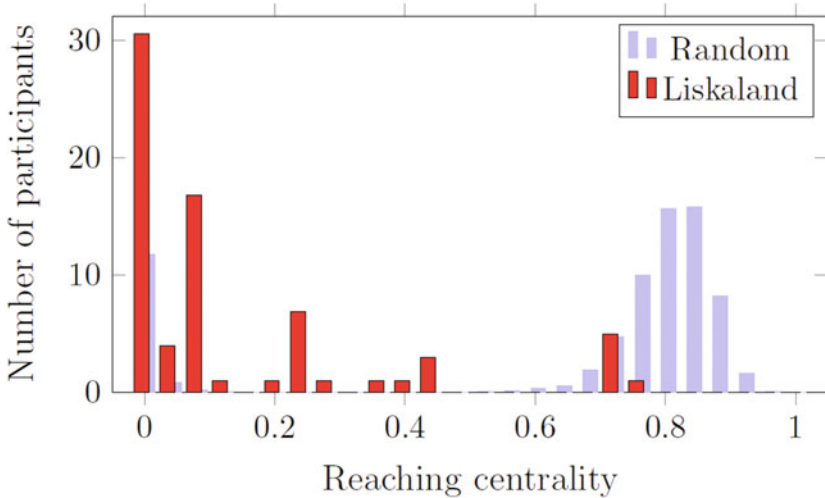
Fig. 4.2 Distribution of the reaching centrality values for the network of interacting participants and for a random network of the same size

network, $G_R^{(Liskaland)} = 0.628$, while for the random network, $G_R^{(Random)} = 0.194$ with a standard deviation of 0.057. The statistics on the random graph are obtained by a sample of the size 10^6. This means that the experimentally observed network is more hierarchical than a corresponding random graph with a significance level of more than 99.9%.

4.2   Picturask

4.2.1   The "Game"

Next, we discuss an experiment called Picturask (Mones et al. 2015), which was conducted over the Internet. The subjects participated in a game in which everyone had to take part in a common task (estimating the number of circles in an image), and the players were able to see others' guesses by clicking on the other players' tiles (displayed on the screen in order to inform the players about their performance). The player's actions through the game were recorded, and these records were later used to infer the behaviour of the players. After the game, in-depth interviews were conducted with some of the players to see if the quantitative evaluations were in agreement with the players' intentions.

From the social psychological aspect, the players in the game form a small group structure, which can be characterized by interdependence in which individuals act in a common interpersonal space, while they influence each other's actions in a

special way (Johnson and Johnson 2005). In Picturask, this space is somewhat artificial, because it is determined by the rules of the game; for example, direct communication was not allowed: players could only see the others' anonymized guesses. It was up to the player as to whether he/she considered and/or accepted the tip of a number of selected other players as advice.

This setting is similar to the one considered in social exchange theory (Cropanzano and Mitchell 2005), in which the subject of interaction is the information about each other's tips. Players gain this information from the colour of the tiles, and therefore tiles can be identified as heuristics. The theory of heuristics describes the stereotyping pattern of human beings in which a complex question may often be answered through a simplifying method—like players tending to judge a tip based on the colour of the tiles (darker is better).

Altogether, 170 users signed up for the game, 96 of whom participated in more than 90% of the turns. The majority (89%) of the players were of age 18–28, thus 65% of them had received at least a bachelor's degree or equivalent, and 33% were high school graduates. 56% of the players were female. Subjects were divided into three groups to play the game, each group playing on different weeks, for three consecutive days. Participation was encouraged by a 2000HUF reward (equivalent to 6.7 EUR, approximately 1% of the average salary in Hungary). The four players with the best results were assured special awards as motivation.

4.2.2 Methods

Players participated in the experiment online, from home or any other place they could gain access to the World Wide Web. The game was based on standard LAMP architecture, and players were able to participate through a standard Internet browser. The competition involved making 45 decisions/guesses and took less than an hour per session. Sessions were arranged for 3 times per week, each starting at 7 pm, over a time interval of 3 weeks.

During the game, the participants were asked to make a simple estimation: they had to guess the number of bubbles on randomly generated images (Fig. 4.3). As the game advanced, the correct answer changed with a relatively slow frequency in order to mimic the collective decision-making process modelled by Nepusz and Vicsek (2013). The actual number of circles changed once every five turns, although this was unknown to the players. Whilst answering, the player could see the previous answers of a maximum of 10 other players in each turn by clicking on its tile (Fig. 4.4). This act was considered "asking for advice," and the player being asked was called an advisor. One of the motivations for this process was to see if the results of the related agent-based simulations (Nepusz and Vicsek (2013), Sect. 5.1) could be reproduced in real life.

Depending on the ratio of advice that turned out to be correct, the tiles of the rivals became darker, indicating those advisors who gave the player the best advice. The estimated knowledge (the ratio of correct advice) was also displayed on the
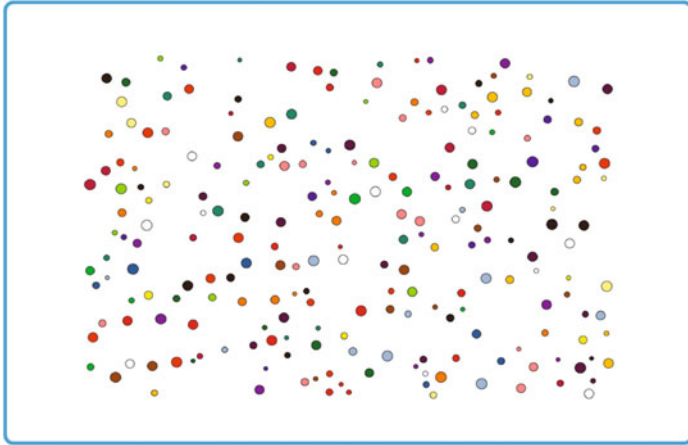
Fig. 4.3 This is a sample picture illustrating the type shown to the players, who have to guess the interval between two numbers (see Fig. 4.4) into which the number of coloured disks falls
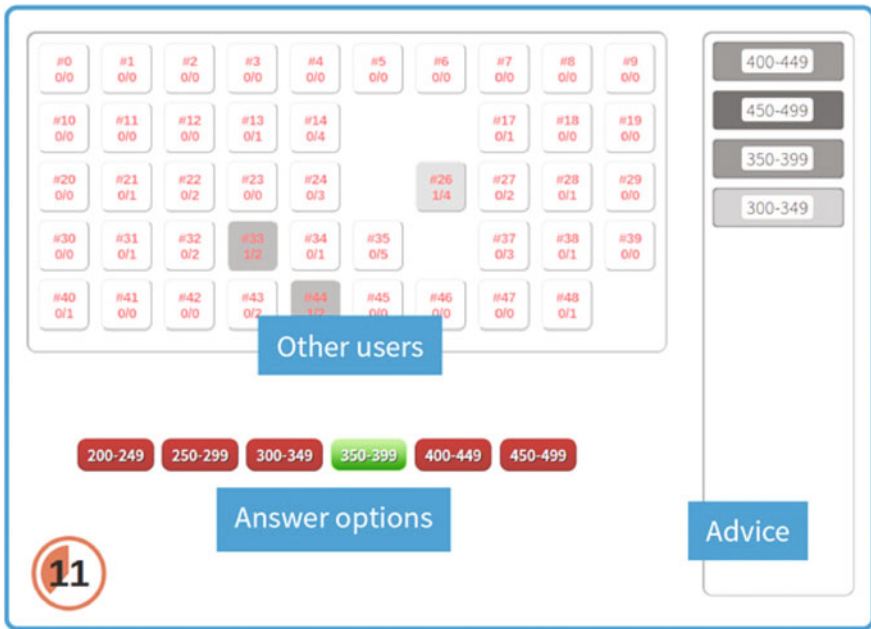
Fig. 4.4 Snapshots of the Picturask interface. The task was to estimate the number of circles shown for a limited time (5 s). On the answering interface (above), users were allowed to see the previous answer of other selected users (10 at most, chosen by them). These were provided by a panel of the others (Other users), which also displayed the success ratio of the previously chosen users encoded in the colour of each tile. Inquired advice was displayed in the Advice panel

rival tile, but no other information was available. In fact, the rivals were displayed in a random permutation for each player in order to avoid potential biases introduced by the order of the tiles (Fig. 4.4).

For the analysis of the game logs, various methods were used in order to represent the social structure at the end of the game with a graph. In this graph, *nodes* represented the players, and a directed edge indicated a leader-follower type relationship between the players: in the case in which the source node often asked advice from the target node, the direction of the edge pointed from the target to the source node (Fig. 4.5). *Global reaching centrality* (*GRC*) was used to quantitatively describe the level of hierarchy in the resulting networks. Importantly, *GRC* was significantly higher in real set-ups than in those with a randomized version of the corresponding networks or the randomized control experiments.
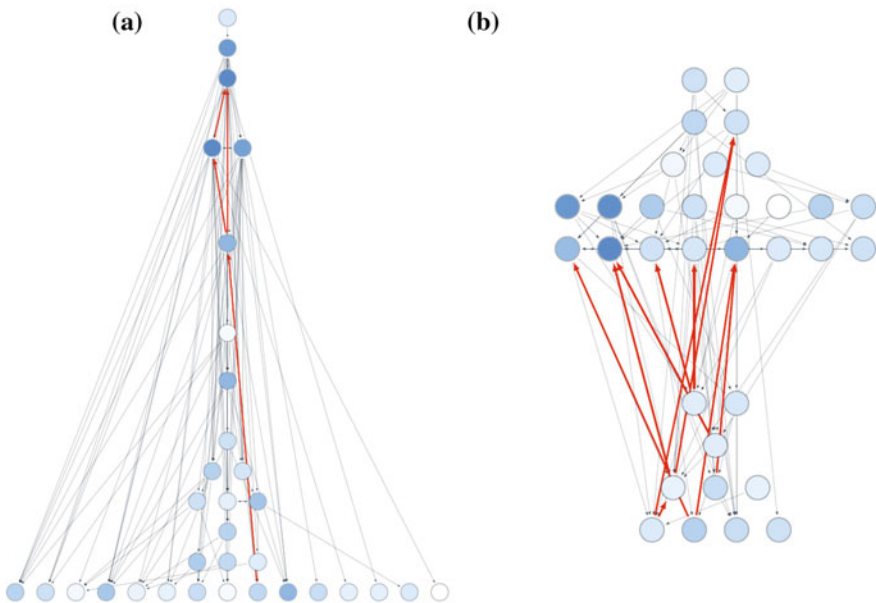
Fig. 4.5 Hierarchical structure of the leader-follower relationships. Two illustrative examples of the structures that emerged during the game as players queried advice from others: **a** Game 6 (regular experiment). **b** Game 9 (control experiment). Colour intensity indicates the performance of the users, and edges pointing upward in the network are drawn in red. As the structure of the consecutive levels indicates, the network of influences in the regular experiments features hierarchical characteristics in contrast to the one found in the control experiment. Visualization was made according to Sect. 2.2.2

4.2.3 Results

The primary conjecture about the experiments was that since the less well-performing players would prefer to ask the advice of better performing individuals, they would voluntarily arrange themselves into a hierarchical network. Therefore, out of the nine games, two were so-called control experiments, in which the advice provided was randomized, thus eliminating apparent differences in performance between players.

It is worth mentioning that although the resulting structures in the real and control experiments were rather different, the majority of the players did not notice any difference between the true and the scrambled games/guesses. This likely indicates the existence of a characteristic time that is necessary to discover differences in performance; otherwise, the social structure remains random.

Based on the interviews conducted after the 9 sessions were over, it became clear that there had been three main stages of decision-making in Picturask. First, the player makes an initial guess, then, he/she collects information from others, and lastly, at the end of the one minute given for an answer, the player makes a final decision using the information collected. It is important to separate the information gathering from the decision-making process.

The only information a player knew about the others was the colour of the tile corresponding to the ratio of correct advice given by the person represented by the tile. Even if the players did not understand what the exact meaning of the tile was, they used it as a heuristic: linking good performance with the colour of the tile. Thus, the colour had two functions: in most cases, it indicated the pool of possible advice givers and the order of in which they should be asked advice (the darker the better), but it could also give more weight to the advice of certain players.

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Chapter 5
Modelling Emergence and Control

In this chapter, we will consider some of the dynamical aspects of hierarchical systems as obtained from simulations of the related models. Although the emergence of hierarchy and the optimal ways of controlling the processes in a hierarchical structure represent two of the most relevant aspects of the subject of hierarchy, the related results are far from complete. Further research in these directions is of essential importance.

Relation to game theory: In the related works, emergence is typically considered a result of optimizing a quantity that is called by various names (e.g., performance, effectiveness) but is analogous to the notion of fitness. And, much like in game theory, fitness has a positive ingredient (benefits) and a negative part associated with disadvantages (costs). Although the models we discuss can be mapped onto games, our preference will be to use the language and the techniques of networks, agent-based modelling and statistical mechanics.

5.1 Emergence of Hierarchy in Model Systems

This section is about approaches involving simple models that are capable of reproducing the emergence of multi-level network structures based on the degree to which the units (individuals) are able to contribute to the efficiency (capacity to operate on a high level) of the system. We shall adopt terminologies that are, on one hand, used in statistical mechanics and network science, while, on the other hand, are also typically used in the context of organizations and the underlying networks of collaborations. However, we expect this framework to be applicable to a significantly larger class of systems. Thus, we consider the groups of humans as a paradigm, but our approach is so general that it is expected to be applicable to simpler systems, such as groups of collaborating animals (apes, wolfs, etc.), as well as complex machines constructed by people.

There are only relatively few works on how a hierarchical network structure emerges. We first briefly discuss two works that describe the emergence of networks having only undirected edges, but that can be considered to be hierarchical from the point of view of self-similarity. Mengistu et al. (2016) investigate the changing structure of networks using evolutionary arguments. They evolved graphs that can be regarded as computational abstractions of animal brains. Such structures are commonly called artificial neural networks (ANNs) and can solve hierarchical Boolean logic problems (Fig. 5.1). Evolving the ANNs with or without a cost to network connections leads to qualitatively different results. Specifically, the experimental treatment selects so as to maximize performance and minimize connection costs (*performance and connection cost*, P&CC), whereas the control treatment selects for performance only (*performance alone, PA*)

A comparison of the evolved networks (under varying conditions) resulted in the conclusion that the P&CC networks are significantly more hierarchical—and modular—than those of the P&A ones, and solve a significantly greater number of sub-problems.

Lee et al. (2011) used a game theoretical type model to investigate how social structures emerge. In their approach, a number of feedback couplings from the behaviour of the agents to their environment was assumed, and this is why it could be considered a multi-adaptive game. The expressions they used were relatively simple—and somewhat arbitrary—but the resulting behaviour of the network of agents was still very rich, since even the strategies of the agents were evolving as a function of their interaction network configurations. In one of the phases, the simulated networks had the scaling of the distribution $P(k)$ of the degrees k of the nodes, as well as the clustering coefficient $C(k)$ as a function of the degree of the nodes. (Here, $C(k)$ is the average of the ratio of the triangles around a given node to the total number of potential triangles.) Such a simultaneous scaling was shown by Ravasz et al. (2002) to correspond to a self-similar structure. Since the
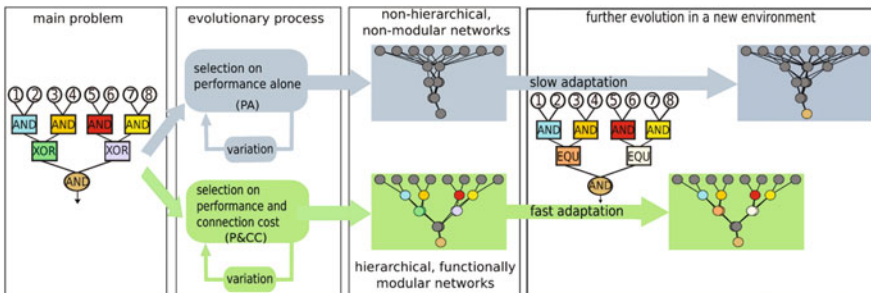
Fig. 5.1 The main hypothesis. Evolution with selection for performance alone results in non-hierarchical and non-modular networks, which take longer to adapt to new environments. Evolving networks with a connection cost, however, create hierarchical and functionally modular networks that can solve the overall problem by recursively solving its sub-problems. These networks also adapt to new environments faster. Reproduced from Mengistu et al. (2016)

edges were undirected, we consider this type of self-similarity to be a less pronounced manifestation of hierarchy than the one based on directed flows.

Now, we turn to discussing directed hierarchical networks. Corominas-Muntra et al. (2013) do not discuss realistic criteria leading to emergence, but their work is still interesting from the point of view of our subject. They consider a set of possible mechanisms leading to a very wide set of potentially realizable hierarchical structures with directed edges. Four major kinds of hierarchy were identified by analysing the large voids in the morphospace defined by the authors. Two of them matched those structures that were expected from random networks with similar connectivity, thus suggesting that non-adaptive factors were at work. Ecological and gene networks define the other two domains, indicating that their topological order is the result of functional constraints. We presented more features of these results within a different context in Sect. 2.1.3.

Next, we describe in more detail a model that was designed to investigate the way in which advantageous leader-follower relations result in the emergence of hierarchy in the presence of a changing environment (Nepusz and Vicsek 2013).

The assumptions of the model were the following:

(i)   A group of people is embedded in a changing environment. Better adaptation (by which we mean the ability to ascertain the new conditions as quickly as possible) represents one of the core advantages an individual can have.

(ii)   The individuals possess different abilities that allow them to persist on their own in such a constantly varying environment.

(iii) The actors constantly monitor the decisions of their group mates, with those observations altering their own decisions. The effect on their own decisions is proportional to the degree to which they trust the judgment of that particular other group member, as compared to their own level of competence. The degree of trust is dependent on the prior success of the observed group mates.

(iv)   Maintaining a connection with another group member has a cost (effort).

Once the above assumptions are integrated into a set of rules that correspond to a game theoretic-like, stochastic model, a collaboration structure emerges in which the leader-follower relationships manifest themselves in the form of a multi-level, hierarchical network. This network is, at the same time, both stable and sensitive to the changes in the environment, according to which it is capable of re-wiring itself in a dynamic fashion. Omitting any of the above four assumptions leads to the multi-level, hierarchical structure failing to emerge.

The main steps of the decision-making process are:

1. The state of the environment is simply given by a value of either 1, 2 …or l. After the state assumes one of these values, it sticks to it, and changes to a randomly selected alternate state only with a probability p, where p is in the range of 0.05–0.2.

2. The actors have different abilities to determine the state of the environment (that is, to "adapt" to the environment), described by a pre-defined parameter taking values from the [0, 1] interval according to some distribution. In each turn, the guess of each individual is based on the weighted average of (i) its own estimation, and (ii) its interactions with the other $k = 1, 2,…, m$ most trusted other actors. (k typically ranges between 2 and 7).

3. In each round, after each agent has finished with the decision-making, the actual state of the environment is revealed, allowing the actors to find out which one of them has made the correct decision and which one of them has estimated incorrectly.

4. Based on the above information, the so-called 'trust matrix' ($T(i,j)$) is updated, in which the values correspond to the degree to which actor i trusts actor j. This trust is proportional to the number of rounds during which agent i made use of the estimate of agent j in such a way that the guess of agent j contributed positively to the guess of agent i. Accordingly, the trust-level of an individual is based on her/his prior performance. Agents who are more trusted are "listened to" more frequently.

By iterating the above steps, the dynamics of the system typically converge into a trust matrix in which the values depend on the original abilities of the actors in a non-trivial way. A typical run starts with a uniform trust matrix (except for the values in the diagonal positions) converging into a state that corresponds to a set of interactions and a hierarchical structure that performs much better (see Fig. 5.2).
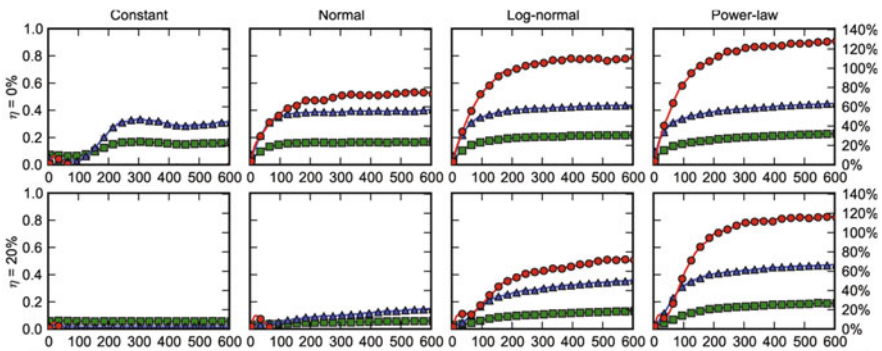
Fig. 5.2 The dynamics of the model as a function of time and noise for various ability distributions. Each column represents a different ability distribution with the same mean and a variance. The distributions are: (i) constant, (ii) normal, (iii) log-normal and (iv) power-law, respectively. The upper row corresponds to the noiseless case, whereas the middle one corresponds to 20% relative noise, where noise stands for randomly perturbing the decisions directly following from the rules of the model. The middle and bottommost curves correspond to two different hierarchy measures: (1) fraction of forward arcs and (2) global reaching centrality (GRC). In both cases, the hierarchy level is expressed through numbers between 0 and 1, where 0 corresponds to "no hierarchy" and 1 corresponds to "maximal hierarchy." The topmost lines (small red circles) show the improvement of the overall performance. Reproduced from Nepusz and Vicsek (2013)

Fig. 5.3 An early, less stable state of the emerging hierarchical network (**a**) and a more stable, persistent solution (**b**) corresponding to the local maximum of performance of the network showing the nodes copying decisions (indicated by arrows) of the other members of the group. The numbers (environment) to be guessed are denoted by colours. Network (**b**) is reminiscent of the experimental result displayed in Fig. 4.1a
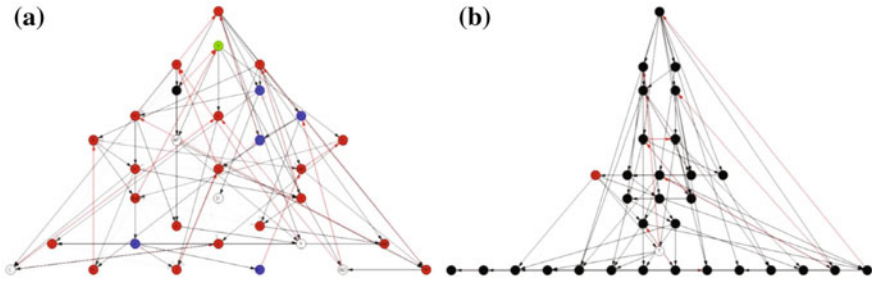
To create a graph from the trust matrix, the following procedure is enacted: each agent is a node in the graph and the weight of the edge (reflecting the degree to which actor i trusts actor j) is the element (i,j) in the matrix. Only the strongest ties are taken into account in the network. The resulting graphs have a hierarchical structure, with multiple levels in them (Fig. 5.3). These structures emerge over time, as depicted in Fig. 5.2, during which two complementary hierarchy measures are shown: the 'global reaching centrality,' GRC, proposed by (Mones et al. 2012), and the normalized fraction of forward arcs, defined by (Eades et al. 1993). Both measures are discussed in detail in Sect. 2.1.2.

Thus, the actors in the model show a strong tendency to structure themselves into a multilevel hierarchical organization that—apart from being commonly seen—is an "intuitively natural" form of self-organization that has recently been supportively demonstrated by a human experiment as well, called "Liskaland" (see Sect. 4.1)

5.2 The Complex Efficiency Landscape of Hierarchical Organizations

In this section, the emergence of optimal network structures is discussed using an approach that is reminiscent of the one introduced by statistical physicists to interpret complex systems using relatively simple rules of units and interactions. The original—so-called spin-glass—approach assumes spin states (up or down) in the nodes of a network. The interaction along the edges is randomly ferromagnetic or antiferromagnetic, and the configuration of the network is fixed, ranging from lattices (Edwards and Anderson 1975) through scale-free (Kim et al. 2005) to full graph (Sherrington and Kirckpatrick 1975).

The essential new feature of the treatment we describe below is that optimization occurs not by looking for a locally optimal state of the spins in the nodes of a pre-defined network, but rather through a search of optimal networks with the states of the nodes being fixed. Thus, the approach represents a search for extrema—as a function of the underlying network topology—in the complex efficiency landscape. In addition to the above (ferromagnetic or antiferromagnetic links), in contrast to spin-glass models, the edges in the underlying network of interactions have a direction.

The sign associated with an edge corresponds to collaboration (positive) or antagonistic (negative) relations. Searching for optimal states, then, is carried out by modifying the network topology so that both the collaborating partners (within an organization) and the flow of influences result in a maximal efficiency.

Within such an approach, it is possible to address the question of the spontaneous emergence of hierarchical networks displaying behaviours, some of which are analogous to those of glasses. By glassy behaviour, we mean that while we are searching for a stable state, our structures do not converge to a unique network with a well-defined extremal value of their efficiency (an analogue of the energy in the physics literature). Instead, glassy systems "freeze" into various disordered structures representing local extrema full of strains or frustrations.

5.2.1   Modelling Organizations

The relations in an organization can be represented by a network made of *directed edges* corresponding to the leader-follower relations in the system. In this approach, the ability of member i to contribute to the effectiveness of the organization is denoted by a_i. In an ideal case, the direction of an edge between members i and j would point from i to j if $a_i > a_j$ (it is advantageous and, indeed, typically the case that agents with higher abilities can enforce their decisions on agents with smaller abilities, i.e., occupy a higher position within the organizational hierarchy). However, with some finite probability, in a realistic case, a proportion p of all of the links between two members points from the less knowledgeable to the more knowledgeable person (Zamani and Vicsek 2017).

Next, it is assumed that on an absolute value scale, the contribution of the members is between 0 and 1. In addition, the joint contribution of two members $E_{eff,ij}$ is linearly proportional to their abilities, i.e., $E_{eff}(i,j) = a_i a_j$. However—and this is an essential point when one considers the relationships between sophisticated creatures—the interaction between two individuals can be both harmonic and antagonistic, with probabilities $(1-q)$ and q, *respectively*. In the "harmonic" case, the contribution of the two members is positive, while on the other hand, if they are in an antagonistic relationship, their interaction will result in a decrease of the total efficiency, thus their interaction enters the expression for the efficiency as a negative contribution.

Assuming that the total performance of the organization can be represented as the contribution of the pairwise interactions, it follows that

$$E_{eff}(p,q) = 1/N \sum_{ij}^{N} J_{ij}(p,q)a_i a_j \qquad (5.1)$$

with the summation running over nodes that have at least one incoming or outgoing edge. (Remark: in the original publication, $1/N$ was used to normalize the efficiency, however, $1/M$ is a more appropriate quantity for this purpose). According to the above arguments about the possible relations between two interacting members, we assume that J_{ij} can be equal to 1 or -1. For the a_i values, it is quite natural to use randomly generated numbers on the unit interval following a bounded *log-normal distribution* (which can be argued to be characteristic for the outputs of complex entities).

The sign of J_{ij} and the direction of the edge ij are decided by two factors: (1) whether the ij edge points from the larger to the lower ability of the participants i and j, and (2) whether these participants are compatible or antagonistic. Thus, (with the corresponding probabilities):

  (i) $J_{ij} = 1$ if the ij edge points from a node with larger ability to one with a smaller ability ($a_i > a_j$) and the two individuals cooperate (and $J_{ij} = -1$ otherwise)
 (ii) $J_{ij} = -1$ if the ij edge points from a node with smaller ability towards one with a larger ability and the two individuals are antagonistic (and $J_{ij} = 1$ otherwise)
(iii)   If there is no edge between i and j, then $J_{ij} = 0$.
 (iv)   A further essential restriction has to be taken into account to make the system more realistic (much as was described in Sect. 5.1). In addition to the above, it should also be required that the total number of edges of a node cannot exceed a pre-defined value.

5.2.2   Simulations and Results

The numerical experiments start out with a full graph, with N nodes each associated with a constant ability a_i and with edges pointing from larger ability sites to lower ability ones with a probability of $1-p$. In addition, 1 or -1 is associated with each edge, independent of their direction (however, because of the term $1-p$, the number of negative edges for small p will occur in a larger overall number for the $a_i > a_j$ cases than for $a_i < a_j$), so that the efficiency values and the structure of the graph become coupled.

The next step is to search for locally optimal networks. This will be a particular subgraph containing M edges within the full graph of N nodes, where N is the total number of possible members and M is the actual one. The initial configuration is a

randomly connected subgraph of $M = 3\,N$ edges. Throughout the calculations, the number of edges within the subgraphs satisfy the criteria that, *on average*, the ratio of their edges pointing from a site with larger to a smaller ability will be equal to $1-p$. Furthermore, as explained above the expression 5.1) the probabilities for $J_{ij} = 1$ are $(1-p)(1-q)$ and pq while for $J_{ij} = -1$ they are $(1-p)q$ or $p(1-q)$. p and q correspond to the probabilities of an inverse direction of the edge ij (from *i to j* for $a_i > a_j$ and for an antagonistic collaboration, respectively. It is very important to stress at this point that we enforce the above rules hold for the subgaphs of M edges as well! Of course, for simplicity, one can assume that $p = q$ and this would result in a single free parameter only.

The search is much like a Monte Carlo simulation, where efficiency plays the role of energy times -1. In each step, a randomly selected edge is eliminated and the next two random nodes are chosen, which are not yet connected by one of the $M-1$ edges. The sign and the direction of the new edge, J_{ij}, is chosen according to conditions (i)–(iv) outlined in Sect. 5.2.1. A new randomly generated edge is accepted if it results in an increasing efficiency and also if there is a small probability of it decreasing the efficiency.

Repetition of the procedure results in a distribution of the individually obtained locally optimal efficiencies. The corresponding histogram (probability density function—PDF) can be constructed for various N values to see the size effect. The properties of the networks corresponding to the locally optimal states were also investigated from the point of view of their hierarchical nature using the GRC measure (see Fig. 5.4).

In Fig. 5.4a, few characteristic dependences of the related networks are depicted. Figure 5.4a shows that larger systems are likely to be more efficient, while Fig. 5.4b shows that, for larger networks, the optimal configurations seem to fall into two classes, with one having a smaller structure and the other a distinctly more hierarchical structure. In order to illustrate the variety of the optimal structures, in Fig. 5.4, a number of typical examples are shown. These include smaller and larger networks ($N = 16$, $N = 128$), and networks for smaller or larger GRC for $p = q = 0.2$. For visualization, we use the method described in detail in Sect. 2.2.2.

According to the above results, the structures of the obtained networks (Fig. 5.5) are such that they possess perhaps the two most important features of complex systems: the simultaneous presence of adaptability and stability. Stability is associated with the presence of a local optimum. Only significant perturbations can "kick" a given arrangement of the participants out of this favourable state. However, if the perturbation is large enough (the external conditions significantly changed), the network can adapt itself and settle into an alternative, more optimal configuration that suits the new conditions better. The efficiency of the hierarchical structure is higher than a randomly chosen sum of the contributions of the pairwise interactions. These features are analogous with those of the glasses, including spin glasses.
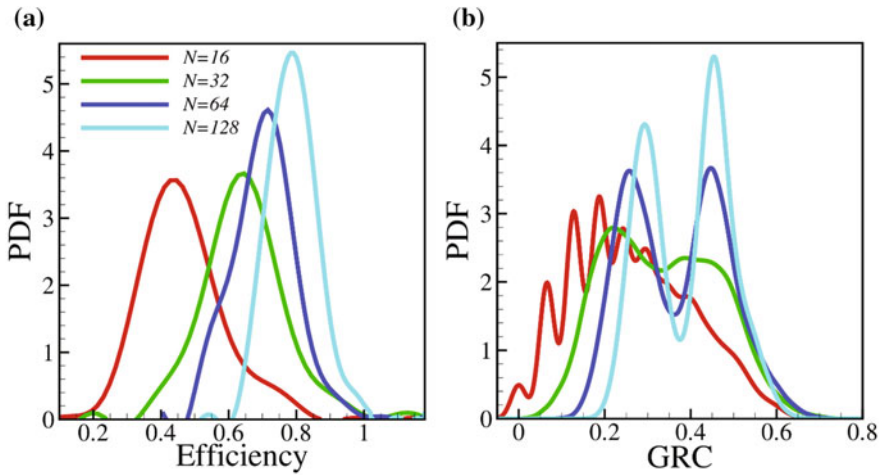
Fig. 5.4 Distribution of the local maxima of the efficiency values (**a**) and Global Reaching Centrality (GRC) values (**b**) for the locally optimal states. Averaging over the initial full graph (250 initial full graphs, and 250 local optimal states for each graph) of N nodes and the initial subgraphs of 3 N edges and for $p = q = 0.2$ was carried out. There is an overall tendency of the PDF-s to be a function of the system size. GRC and the average efficiency grows with increasing N. Reproduced from Zamani and Vicsek (2017)
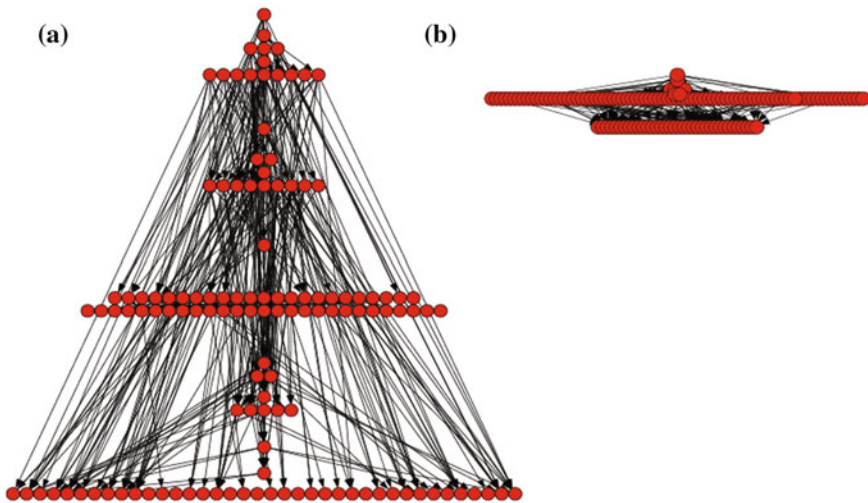
Fig. 5.5 Hierarchical graphs in selected local optimal states of networks. The number of nodes is $N = 128$, the other two parameters are $p = q = 0.2$, **a** $GRC = 0.62$, **b** $GRC = 0.25$. Reproduced from Zamani and Vicsek (2017)

5.3   Controlling Hierarchical Networks

In this section, we will overview two approaches from a field that—although very important—have for some reason been overlooked by researchers in recent decades: the *controllability properties* of complex networks. This field is about the study of the conditions under which a network can be driven from any initial state into any final state within a finite number of steps.

This definition implies that the nodes have a state, for example, the amount of traffic flowing through a node in, say, a traffic or communication network, or the transcription factor concentration in a gene regulatory graph. The question is as to how and where one has to intervene in order to drive the system into a desired (pre-defined) condition.

5.3.1   Structural Controllability—Controlling Nodes

The first approach, proposed by Liu et al. (2011), investigates the controllability properties of weighted directed networks. The main idea is to identify a set of the so-called *driver nodes* (a set of vertices through which the dynamics of the entire system can be controlled). The nodes of the network are assumed to behave according to non-linear processes, but their behaviour is approximated by the following linear dynamics:

$$\frac{d\vec{x}(t)}{dt} = A\vec{x}(t) + B\vec{u}(t), \tag{5.2}$$

where $\vec{x}(t) = (x_1(t), \ldots, x_N(t))^T$ is the state vector of the N nodes (in which $x_i(t)$ describes the state of node i at time t), A is the $N \times N$ adjacency matrix, capturing the interaction strength among the elements of the systems (which are the nodes of the graph), and B is an $N \times M$ matrix defining the *driver nodes*: these are the vertices, which are to be controlled from the outside in order to drive the system to the desired state. Finally, $\vec{u}(t) = (u_1(t), \ldots, u_M(t))^T$ is the time-dependent input signal, the vector controlling the system. The justification of this approximation is that, according to Slotine and Li (1991), the controllability of a nonlinear system is in many aspects *structurally similar* to that of a linear system.

A dynamic (A, B) is said to be "structurally controllable" if it is possible to choose the non-zero elements in A and B in such a way that the network can be driven from any one state to any other final state by appropriately choosing the elements of $\vec{u}$. This property, structural controllability, is important, because in real-life complex systems, the weights of A (the link weights of the network) are usually unknown, or just partly known. A structurally controllable system can be shown to be controllable for almost all weight combinations, thus this property helps to overcome the incomplete knowledge of the link weights in A. Then, the minimum number of driver nodes is determined by the *maximum matching* in the graph, which is a maximal set of links that do not share start or end vertices. A node

is *matched*, if an edge in the maximum matching points at it, otherwise it is *unmatched*. Then, from here, the task is basically solved, because according to Yu et al. (2010), full control can be gained over a directed network if and only if each unmatched node is directly controlled and there are directed paths from the input signals to all matched vertices.

The key results of this study are the following (see also Table 5.1 in the next section):

- The number of driver nodes within a complex network is mainly determined by the network's degree distribution.
- Sparse inhomogeneous networks (a type of graph very often seen in relation to real-life complex systems, often the ones that have evolved to control another underlying process, such as a transcriptional regulatory network) are the most difficult to control (they need many input signals).
- In contrast, dense and homogeneous graphs need only a few driver nodes in order to be controlled.
- And finally, the most counterintuitive result is that the driver nodes tend to avoid the high-degree nodes ("hubs"), both in models and real-life systems. In other words, control signals control the hubs only indirectly, which is, according to Nepusz and Vicsek (2012), due to the fact that, in this approach, the driver nodes are not able to control their subordinate vertices independently from each other.

Importantly, these results apply for linear nodal dynamics.

5.3.2 Switchboard Dynamics—Controlling Edges

Nepusz and Vicsek (2012) proposed dynamics that take place along the edges, instead of on the nodes, and lead to significantly different controllability properties for the same real-life networks. The motivation is visualized in Fig. 5.6, demonstrating that hierarchical networks—in cases in which the nodes are directly controlled by one of their neighbours or by driver nodes—need a disproportionally large number of driver nodes. In this model, the state variables correspond to the edges of a directed complex network, and the vertices of the network act as linear operators that map state variables of inbound edges to outbound edges. This is called *switchboard dynamics*, exactly because of this property: each node acts as a "switchboard-like device" mapping the signals coming from the inbound edges to the outbound edges, by applying a linear operator called a mixing or switching matrix. That is, each node has a separate switching matrix, M_i, enabling the nodes to control their subordinates separately.

This arrangement is reminiscent of the characteristics of many real-life networks in which each node constantly processes information coming from its inbound edges and forwards them in a differentiated way via its outbound edges. A plausible example can be an arbitrary social communication network in which the nodes are the persons who constantly receive and forward messages, but in ways dependent on the recipient.
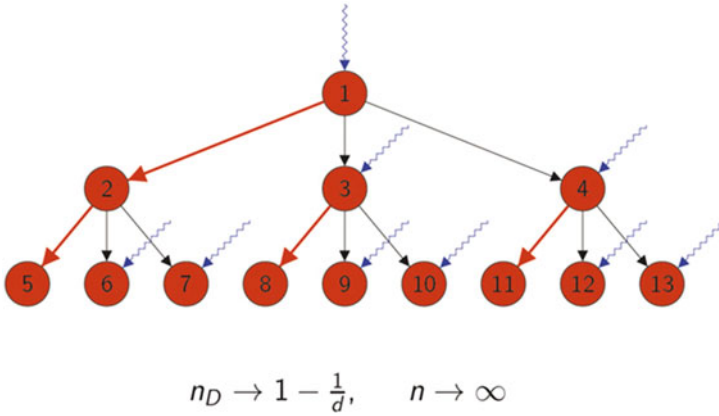
$$n_D \rightarrow 1 - \frac{1}{d}, \qquad n \rightarrow \infty$$

Fig. 5.6 When node controllability is considered, a given node can influence the state of only one of its neighbours. This requires a relatively large number of nodes to be controlled from "outside" (denoted by wavy lines). Thus, an alternative approach may be more efficient. Reproduced from Nepusz and Vicsek (2012)

In this switchboard dynamics framework (SBD), each *edge* has a *state*, which is denoted by the $\vec{x} = [x_j]$ state vector. For each i node, there belongs a $\vec{y}_i^+$ and $\vec{y}_i^-$ vector pair, consisting of those x_j edge-state values that correspond to the incoming and outgoing edges, respectively, of node i. For example, in Fig. 5.7a, the inbound edges of node i are c and d, whose states are defined by the values of x_c and x_d, whereas its outbound edges, $e, f,$ and g, are in the state described by the values x_e, x_f and x_g, respectively. The switching matrix of this node, $\boldsymbol{M}_i$, has three rows (out-degree, number of outgoing edges) and two columns (in-degree, number of incoming edges). The dynamics are controlled from the outside by adding an *offset vector* (or *control signal*) $\vec{u}_i$ to the state vectors of the outgoing edges of node i, marked with red undulate arrows in Fig. 5.7a.

The dynamics of the network are described by the following equation:

$$\frac{d\vec{y}_i^+}{dt} = M_i \vec{y}_i^-(t) - \tau_i \otimes y_i^+(t) + \sigma_i \vec{u}_i(t), \tag{5.3}$$

where σ_i is 1 if node i is a driver node (see Sect. 5.3.1), and 0 otherwise. The vector τ_i includes damping terms corresponding to the edges in $\vec{y}_i^+(t)$, and finally, $\otimes$ denotes the entry-wise product of two vectors of the same size.

In order to simplify the equation, the state variables and control signals are implicitly considered as time-dependent, even if the time variable is omitted. By re-writing (5.3) in terms of x_i, the dynamics of the system yield a more simplified form (5.4):

$$\frac{dx_j}{dt} = \sum_{k \in \Gamma_j^-} w_{kj} x_k - \tau_j x_j + \sigma_s u_j, \tag{5.4}$$
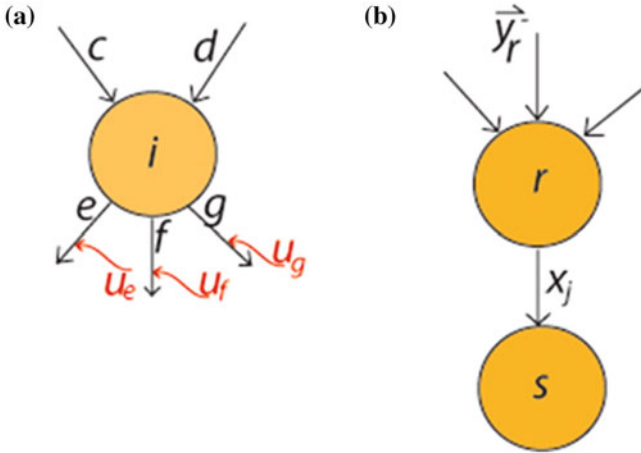
Fig. 5.7 **a** The dynamics of the system in the switchboard dynamics framework are controlled by adding an *offset vector* $\vec{u}_i$ to the state vectors of the outgoing *edges* of node i (marked with red undulate arrows). In case this vector is not a null-vector, node i is a *driver node*. **b** The state of an arbitrary edge j originating in node r and terminating in vertex s depends only on itself, x_j, and on the states belonging to the inbound edges of node r, that is, on the set $\vec{y}_r^-$

where w_{kj} is an element of the switching matrix $\boldsymbol{M}_r$ belonging to node r defining the information process between the inbound edge k and the outbound edge j. Note that the set Γ_j^- includes all of the state variables upon which the derivative of the state variable $\dot{x}_j$ depends, since it is effected only by itself, x_j, and upon the states of the edges ending at node r, that is, on $\vec{y}_r^-$: $\Gamma_j^- = \{\vec{y}_r^-, x_j\}$.

By defining all of the values in $\boldsymbol{M}_r$ that do not affect the state of x_j as zero (that is, those w_{kj} values that are not in the set Γ_j^-), we get (5.5):

$$\dot{x} = (W - T)\vec{x} + H\vec{u}, \tag{5.5}$$

where the $\boldsymbol{W}$, $\boldsymbol{T}$ and $\boldsymbol{H}$ matrices are:

- $\boldsymbol{W} = [w_{kj}]$, where w_{kj} can be non-zero if and only if the end-point of edge k is the starting node of edge j,
- The diagonal matrix $\boldsymbol{T} = [\tau_{jj}]$ contains the damping terms related to the edges, and
- $\boldsymbol{H}$ is also a diagonal matrix in which the jth diagonal element is $\sigma_{s,}$ if edge j originates in node s.

(5.5) basically describes a simple linear time-invariant dynamical system in which $\boldsymbol{W}$ is the adjacency matrix of the line graph $L(G)$ of the original graph G. This means that each node in $L(G)$ corresponds to an edge in G, as demonstrated with an example graph in Fig. 5.8a, b.

By applying the *maximum matching theorem*, in the same spirit as was done in the structural controllability framework by Liu et al. (2011), we get a set of *control*
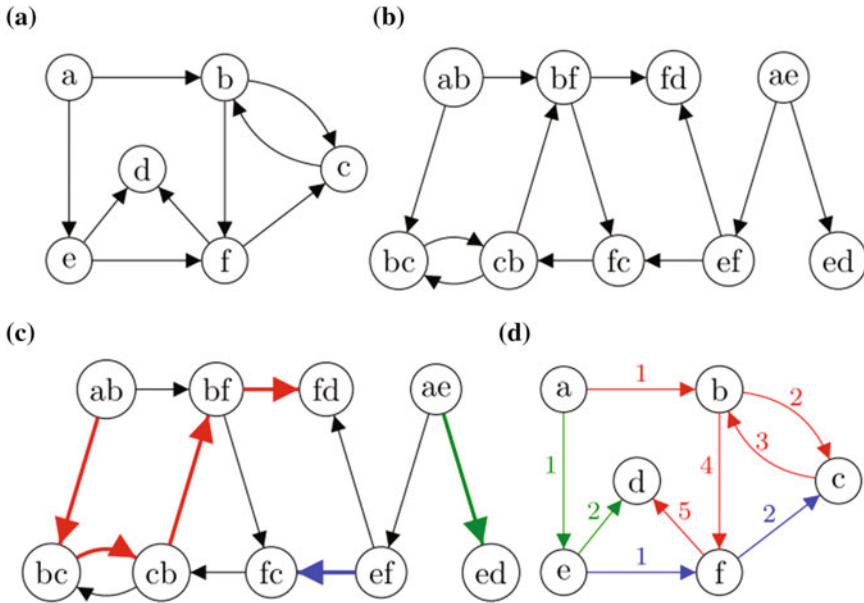
Fig. 5.8 Demonstration of the way in which the switchboard dynamics approach pinpoints the driver nodes. **a** A simple input network *G* with six nodes and nine edges. The control applies to the edges of the network, instead of the nodes. **b** The line graph *L(G)* corresponding to *G*. A linear time-invariant dynamic on the nodes of *L(G)* is equivalent to the switchboard dynamics in *G*. Node labels refer to the endpoints of the edges in *G*. **c** The maximum matching theorem applied to *L* *(G)* returning disjoint control paths. **d** The control paths in *G*, inferred from the results yielded from *L(G)*. Note how each path in the line graph *L(G)* became an edge-disjoint walk in *G*. The numbers on the lines represent the order in which the edges have to be traversed in the walks. The two driver nodes are **a** and **e**, since each walk starts from one of the two. Reproduced from Nepusz and Vicsek (2012)

paths and driven nodes in the line graph *L(G)*. Note that these are simultaneously *driven edges* in the original graph *G*, that is, a set of edges whose state should be modified in order to gain control over the network. Since edges can only be controlled from the nodes in which they originated, this set of edges defines the set of *driver nodes* as well: these are the vertices from which at least one driven edge originates. As was proven in Nepusz and Vicsek (2012), the *minimal* set of driver nodes in a graph *G* can then be determined by selecting those vertices in *G* for which $d_v^+ > d_v^-$, and one arbitrary vertex from each '*balanced component*.' (A balanced component is a connected component consisting only of nodes for which $d_v^+ = d_v^-$ and, above this, contains at least one edge).

The minimum number of driver nodes (nodes that are driven from the outside in order to gain control over the entire network) is found to be largely determined by the joint degree distribution of the network.

The following survey of 38 real-life networks, shown in Table 5.1, reveals that under this approach, transcriptional regulatory networks are well-controllable with a

Table 5.1 Controllability properties of real networks

Type	#	Name	Nodes	Edges	n_D^{SBD}	n_D^{Liu}	n_D^{ER}	n_D^{Dgr}
Regulatory	1	Ownership-USCorp	7253	6726	0.160	0.820	0.339	0.085
	2	TRN-EC-2	418	519	0.222	0.751	0.366	0.148
	3	TRN-yeast-1	4441	12,873	0.034	0.965	0.415	0.033
	4	TRN-yest-2	688	1079	0.177	0.821	0.381	0.137
Trust	5	Collage[a]	32	96	0.344	0.188	0.418	0.315
	6	Epinions[a]	75,888	508,837	0.336	0.549	0.445	0.448
	7	Prison[a]	67	182	0.403	0.134	0.411	0.451
	8	Slashdot[a]	82,168	948,464	0.323	0.045	0.458	0.392
	9	Wikivote[a]	7115	103,689	0.281	0.666	0.463	0.620
Food web	10	Grassland	88	137	0.318	0.523	0.381	0.297
	11	Little rock	183	2494	0.639	0.541	0.463	0.649
	12	Seagrass	49	226	0.449	0.265	0.436	0.433
	13	Ythan	135	601	0.304	0.511	0.432	0.337
Metabolic	14	C. Elegans	1173	2864	0.182	0.302	0.409	0.309
	15	E. coli	2275	5763	0.182	0.382	0.409	0.309
	16	S. cerevisiae	1511	3833	0.185	0.329	0.409	0.313
Electronic circuits	17	s208a	122	189	0.451	0.238	0.381	0.431
	18	S420a	252	399	0.456	0.234	0.385	0.440
	19	S838a	512	819	0.459	0.232	0.381	0.442
Neuronal and brain	20	C. Elegans	297	2359	0.549	0.165	0.449	0.499
	21	Macaque	45	463	0.333	0.022	0.446	0.457
Citation	22	arXiv-HepPh[a]	34,546	421,578	0.356	0.232	0.459	0.577
	23	arXiv-HepTh[a]	27,770	352,807	0.359	0.216	0.460	0.569

(continued)

Table 5.1 (continued)

Type	#	Name	Nodes	Edges	n_D^{SBD}	n_D^{Liu}	n_D^{ER}	n_D^{Dgr}
WWW	24	Google	15,763	171,206	0.670	0.337	0.457	0.612
	25	Polblogs	1490	19,090	0.509	0.471	0.460	0.501
	26	nd.edu	325,729	1,497,134	0.271	0.677	0.433	0.301
	27	Standford.edu	281,904	2,312,497	0.665	0.317	0.450	0.653
Internet	28	P2p-1	10876	39,994	0.334	0.552	0.425	0.344
	29	P2p-2	8846	31,839	0.344	0.578	0.423	0.344
	30	P2p-3	8717	31,525	0.343	0.577	0.424	0.344
Social communication	31	Twitter[a, b]	41.7×10^6	1.47×10^9	0.402	–	0.476	0.434
	32	UCIOnline	1899	20,296	0.216	0.323	0.456	0.375
	33	WikiTalk	2,394,385	5,021,410	0.022	0.968	0.399	0.026
Organizational	34	Consulting[a]	46	879	0.522	0.043	0.458	0.460
	35	Freemans-1[a]	34	645	0.412	0.088	0.441	0.476
	36	Freemans-2[a]	34	830	0.588	0.029	0.439	0.465
	37	Manufacturing[a]	77	2228	0.597	0.013	0.468	0.424
	38	University[a]	81	817	0.519	0.012	0.451	0.532

[a]Networks in which the edges have been reserved compared to the original publication

[b]Results calculated from the degree distribution. From Nepusz and Vicsek (2012)

First five columns: _1_ type of network, _2_ its number, _3_ name, _4_ number of nodes and _5_ number of edges, respectively. 6th column: n_D^{SBD}, fraction of driver nodes in the switchboard dynamics framework. 7th column: n_D^{Liu}, fraction of driver nodes in the structural controllability framework (overviewed in Sect. 5.3.1), and 8th column: n_D^{ER}, fraction of driver nodes in the switchboard dynamics framework in randomized networks using the Erdős–Rényi model and n_D^{Dgr}, the degree-preserving configuration model. References to the real systems data can be found in Table 5.1 and the reference list of the Supplementary Material to Nepusz and Vicsek (2012)

small number of driver nodes, and also that most real-world networks are easier to control than random Erdős–Rényi networks with the same number of nodes and edges (last 3 columns).

Note that this is in deep contrast with the findings of Liu et al. (2011), who have concluded that regulatory networks need a high fraction of driver nodes and that randomized Erdős-Rényi networks are easier to control than the real-world ones.

The differences are also very spectacular in highly hierarchical, tree-like networks, in which the presence of central out-hubs rapidly increases the required number of driver nodes within the framework of Liu et al., while the same out-hubs can efficiently control many subordinate nodes in the switchboard dynamics—and thus decrease the required number of driver nodes. This is a central result, since such hierarchies are ubiquitous in nature and society, from scales as small as gene regulatory networks through leader-follower relationships, up to large-scale organizations.

Thus, the central corollary of the above research is that the presence (or absence) of a hierarchical structure appears to be an important factor in the controllability properties of large dynamical systems.

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Chapter 6
Conclusions

In this chapter, we summarize the main lessons one can learn about hierarchy by considering the results presented in the previous chapters. The first point we would like to make is that we concentrated on works involving quantitative results. There is a huge amount of literature on the vast qualitative or "narrative" interpretation of hierarchies, but the number of studies based on calculus is rather limited. As was already mentioned in the introduction, in this book, we describe studies related to hierarchy in general, and the particular cases we considered have been related to that domain of nature that can be described as assemblies of organisms that can communicate by processing information as unique individuals.

Before going into detail, we would like to point out a very general aspect of hierarchy. According to the studies we presented, hierarchy and complexity (as it is understood when the expression of complex systems is used) are intimately related. Complex systems are usually associated with many units displaying a wide variety of behaviour, but, more importantly for us, they are also associated with a property, which is summarized by the following statement: a complex system exhibits a qualitatively different behaviour (as a whole) from that of its units. Now, this is true for hierarchical systems as well, with the addition that this emergence of new qualitative behaviour can be associated with the existence of "hierarchical levels" of an underlying network within the systems.

6.1 General Features of Hierarchical Structures

Hierarchy has several manifestations. We classified these as order, embedded and flow hierarchies. The most compelling and complex of these is flow hierarchy, which assumes directed or undirected interactions among its units. The quantitative characterisation of the structure of a system having an underlying flow hierarchy is far from trivial. This is also true for the visualization of the hierarchical nature of the flow of information in a complex system. Correspondingly, in Chap. 2, we give

many related details. As it turns out, even the level of hierarchy is a problem that cannot be defined in a unique way. This is also true for visualizing the hierarchical nature of a system. We overviewed a number of suggestions for quantifying and making hierarchy visible, even in the case of flow hierarchies.

In all cases, a hierarchical system has "levels." Sometimes these levels are well-defined, but not always. Each level has its own behavioural patterns and may contain groups/units made of closely related organisms and separated from the other groups.

We argue that the most complex representation of a hierarchical system can be achieved by considering an underlying network of directed and undirected edges. In fact, we also conclude that in a system of organisms interacting through the exchange and evaluation of information, an approach based on flow hierarchy is the most suitable, and this is what we mostly consider in the book.

6.2 Origins of Flow Hierarchy

Our main observation is that complex hierarchical systems usually imply the relevance of the flow of information. This is so, in part, because the units are not fully informed about their environment. The above flow can have several manifestations: for example, the less informed units copy information (either freely provided or simply obtained by "watching"), or a person on a higher level gives orders to subordinates.

Based on the observations and models presented in this book, our main conclusions are that the origins of hierarchies in systems of organisms are related to two main factors:

 (i) optimizing the functioning and
 (ii) limits concerning the resources or costs involved.

Before going into a bit more detail, we point out that, in practice, both (i) and (ii) become dominant factors due to the incomplete flow of incomplete information. If every participant was aware of the exact requisite information all of the time, hierarchy would not be needed in most real-life cases.

Next, we shortly discuss point (i). First of all, optimization (searching for the best performing state/structure of the system) typically involves finding a "synchronized" regime of behaviour of the agents/actors. We assume that complex systems of organisms are optimal from the point of view of their structure: this is due to a natural competition/selection principle in the Darwinian sense of the process. There are two possible main variants of this aspect. In the first case, the individual units are "selfish"; they are trying to optimize only their own advantage through the interaction with the others. In this "soft" hierarchy, there is no external, global condition that would force the hierarchy to emerge. We could also associate these systems with a bottom-up structure. All of this can be studied both experimentally and through modelling.

The other main version of hierarchy is due to the simultaneous action of both of the above points (i) and (ii). It usually involves an external pressure (in the context of which the optimization, i.e., (i), has to take place). In this "hard" hierarchy, optimizing in the presence of this pressure is in the interest of the entire group of organisms, and it becomes the main determinant of the hierarchy. Examples include armies or even universities. There is a global goal that has to be achieved (win the battle, educate in many areas as efficiently as possible). Such hierarchies usually involve the direction of the ties between the units determining the behaviour of a subordinate as a function of the decision of the "boss." They are clearly organized from top to bottom.

The above points can also be approached more practically. Points (i) and (ii) can best be demonstrated by recalling two specific examples that, on the other hand, bear the essential features of most of the other possible examples. (A) Let us consider a system in which the participants are trying to optimize their own performance by copying the decisions of those group mates who are better at making good decisions. Without limitations, this process would inevitably lead to a star-like network, with everyone following the decisions of the agent with the highest ability to make the right choices. However, if the number of connections an agent can manage (as in real life) is limited, the above structure cannot be maintained, and rather, a cascade of information flow appears along a hierarchically organized network (also leading to a better average performance than independent decisions). (For example, if 3 is the maximum number of edges an agent can maintain, a simple tree-like structure—with one incoming and two outgoing edges—can optimally result in the best information flowing from the top to the many agents at the bottom of the hierarchy in an optimal way). (B) The simplest everyday example one can mention is that of an army (already mentioned above). If the decisions concerning many people have to be made in a short time scale, a hierarchical organization has a great advantage. Here, the limiting cost is time. Imagine an "egalitarian" army fighting against a "dictatorial" one. In short: until the egalitarian army—following many rounds of discussion—makes the decision as to which tactics to choose, the dictatorial (hierarchical) army—using a simple strategy—can override them.

6.3   Emergence of Hierarchy

Obviously, this is one of the most interesting questions one can raise in the context of hierarchies. Most of the related studies describe historical processes without calculations. However, there exist by now a few quantitatively treatable models that give insight into the "abstract" process of emergence.

The emergence of hierarchies can be discussed in terms of evolutionary biology and/or game theory, with a number of relevant differences. If one aims to incorporate realistic assumptions and the corresponding real-life-like behaviours, then

exact treatment is not possible. However, computer simulations are feasible (see, e.g., Chap. 5). In addition, numerical experiments aimed at shedding light on particular aspects of emergence, hardly realizable in the context of evolution, can be carried out.

Thus, we present in the book a few models that involve such notions (borrowed from game theory and evolutionary theory) as fitness, benefits and costs. These models include specific definitions/assumptions for the above notions and give new insight into the mechanisms or the reasons why hierarchy emerges from an originally random set of connections among the units of a system.

Finally, our book, by the nature of the subject, is far from complete. There are already many more and, we expect, there will be many more works on the topic, since the pool of phenomena related to hierarchy is inexhaustible. We hope that our book will stimulate works concentrating on quantitative treatments of this exciting field.

Erratum to: Why We Live in Hierarchies?

Erratum to:
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SpringerBriefs in Complexity,
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The original version of the book was inadvertently published with the following errors, which have been now corrected:

Affiliation of "Anna Zafeiris", "Biological Physics Department, ELTE, Budapest, Hungary" has been changed as "Department of Biological Physics, Eötvös Loránd University, Budapest, Hungary" in Frontmatter, which is a belated correction.

In chapter 3, the author name "Anna Zafeiris-Lazar" has been changed as "Anna Zafeiris".