

Chapter 1

Network-Oriented Modeling and Its Conceptual Foundations

An Introduction

Abstract To address complexity of modeling the world's processes, over the years in different scientific disciplines isolation and separation assumptions have been made, and in some disciplines they have turned out quite useful. They traditionally serve as a means to address the complexity of processes by some strong form of decomposition. It can be questioned whether such assumptions are adequate to address complexity of integrated human mental and social processes and their interactions. Are there better alternative strategies to address human complexity? This is discussed in this chapter, and it is pointed out that a Network-Oriented Modeling perspective can be considered an alternative way to address complexity, which is better suited for modeling human and social processes.

1.1 Introduction

To address complexity of modeling the world's processes, over the years different strategies have been used. From these strategies isolation and separation assumptions are quite common in all scientific disciplines and have often turned out very useful. They traditionally serve as means to address the complexity of processes by some strong form of decomposition. This also holds for classical disciplines such as Physics, where, for example, for mechanical modeling for building construction only forces from objects on earth are taken into account and not forces from all other objects in the universe, that still do have some effects as well. It is recognized that these distant effects from sun, moon, planets and other objects do exist, but it assumed that they can be neglected. For such cases within Physics such an isolation assumption may be a reasonable choice, but in how far is it equally reasonable to address complexity of human mental and social processes? Over the years within the Behavioural and Social Sciences also a number of assumptions have been made in the sense that some processes can be studied by considering them as separate or isolated phenomena. However, within these human-directed sciences serious debates or disputes have occurred time and time again on such a kind of assumptions.

They essentially have the form of arguments pro or con an assumption that some processes can be studied by considering them as separate or isolated phenomena. Examples of such separation assumptions to address human complexity concern:

- mind versus body
- cognition versus emotion
- individual processes versus collective processes
- non-adaptive processes versus adaptive processes
- earlier versus later: temporal separation

It can be questioned whether, for example, mind can be studied while ignoring body, or cognition while ignoring emotion, or sensory processing in isolation from action preparation. Or, put more general, in how far are these traditional means to address complexity by separation still applicable if the complexity of human mental and social processes has to be addressed? Do we need to break with such traditions to be able to make more substantial scientific progress in this area addressing human processes? And, not unimportant, are there adequate alternative strategies to address human complexity?

In this chapter, first in Sect. 1.2 the five separation assumptions mentioned above are discussed in some more detail. Next, in Sect. 1.3 it is discussed how as an alternative, interaction in networks can be used to address complexity. In Sect. 1.4 the development of a Network-Oriented Modeling perspective is discussed. Section 1.5 focuses on the need for a temporal dimension to address the dynamics, in particular to handle cyclic causal connections and realistic timing in human processes. In Sect. 1.6 the Network-Oriented Modeling approach based on temporal-causal networks is briefly pointed out, which is the modeling approach used in this book, and is discussed more extensively in Chap. 2. Section 1.7 discusses the scope of applicability of the approach. Finally, Sect. 1.8 provides an overview of the chapters in the book.

1.2 Addressing Human Complexity by Separation Assumptions

The position taken in this book is that indeed a number of the traditional separation and isolation habits followed in order to address human complexity have to be broken to achieve more progress in scientific development. Partly due to the strong development of Cognitive, Affective and Social Neuroscience, in recent years for many of the issues mentioned above, a perspective in which dynamics, interaction and integration are key elements has become more dominant: a perspective with interaction as a point of departure instead of separation. Given this background, for each of the separation issues listed above this will be discussed below in more detail. It will be pointed out how in many cases separation assumptions as mentioned lead to some types of discrepancies or paradoxes.

Mind versus Body

A first isolation assumption that has a long tradition is the assumption that the mind can be studied in separation from the body. There has been debate about this since long ago. Aristotle (350 BC) referred to considered properties of ‘mind and desire’ as the source of motion of a living being: he discusses how the occurrence of certain internal (mental) state properties (desires) within a living being entails or causes the occurrence of an action in the external world; see also Nussbaum (1978). Such internal state properties are sometimes called by him ‘things in the soul’, ‘states of character’, or ‘moral states’. In that time such ‘things’ were not considered part of the physical world but of a ghost-like world indicated in this case by ‘soul’. So, in this context the explanation that such a creature’s position gets changed is that there is a state of the soul driving it. This assumes a separation between the soul on the one hand, and the body within the physical world on the other hand. How such nonphysical states can affect physical states remains unanswered. Over time, within Philosophy of Mind this has been felt as a more and more pressing problem. The idea that mental states can cause actions in the physical world is called *mental causation* (e.g., Kim 1996, 1998). The problem with this is how exactly non-physical mental states can cause effects in the physical world, without any mechanism known for such an effect. Within Philosophy of Mind a solution for this has been proposed in the form of a tight relation between mental states and brain states. Then it is in fact not the mental state causing the action, but the corresponding (physical) brain state. Due to this the separation is not between the soul or mind, and the body, but between the brain and the body (Bickle 1998; Kim 1996, 1998).

However, this separation between brain and body also has been debated. More literature on this from a wider perspective can be found, for example, in Clark (1998), Lakoff and Johnson (1999), Wilson (2002). It is claimed that mind essentially is embodied: it cannot be isolated from the body. One specific case illustrating how brain and body intensely work together and form what is called an embodied mind is the causal path concerning feelings and emotional responses. A classical view is that, based on some sensory input, due to internal processing emotions are felt, and based on this they are expressed in some emotional response in the form of a body state, such as a face expression:

stimulus → sensory representation → felt emotion
→ preparation for a body state → expressed emotion in body state

However, James (1884) claimed a different order in the causal chain (see also Damasio 2010, pp. 114–116):

stimulus → sensory representation → preparation for a body state
 → expressed emotion in body state → sensed body state
 → representation of body state → felt emotion

The perspective of James assumes that a *body loop* via the expressed emotion is used to generate a felt emotion by sensing the own body state. So, the body plays a crucial role in the emergence of states of the brain and mind concerning emotions and feelings. Damasio made a further step by introducing the possibility of an *as-if body loop* bypassing actually expressed bodily changes (e.g., Damasio 1994, pp. 155–158; see also Damasio 1999, pp. 79–80; Damasio 2010):

stimulus → sensory representation → preparation for body state
 → representation of body state → felt emotion

An as-if body loop describes a predictive *internal simulation* of the bodily processes, without actually affecting the body, comparable to simulation in order to perform, for example, prediction of action effects, mindreading or imagination; e.g., Becker and Fuchs (1985), Goldman (2006), Hesslow (1994, 2002, 2012). Damasio (1999, 2010) distinguishes an emotion (or emotional response) from a feeling (or felt emotion). A brief survey of Damasio's ideas about emotion and feeling can be found in (Damasio 2010, pp. 108–129). According to this perspective emotions relate to actions, whereas feelings relate to perceptions of own body states triggered by these actions:

... feelings are not a passive perception or a flash in time, especially not in the case of feelings of joy and sorrow. For a while after an occasion of such feelings begins – for seconds or for minutes – there is a dynamic engagement of the body, almost certainly in a repeated fashion, and a subsequent dynamic variation of the perception. We perceive a series of transitions. We sense an interplay, a give and take (Damasio 2003, pp. 91–92).

See further in Chap. 3, Sect. 3.2. This essentially shows a cyclic process involving both mind and body that (for a constant environment) can lead to equilibrium states for both emotional response (preparation) and feeling.

Cognition versus Emotion

Another assumption made traditionally is that cognitive processes can be described independently, leaving affective states aside. The latter types of states are considered as being part of a separate line of (affective) processes that produce their own output, for example, in the sense of emotions and expressions of them. However, this assumed separation between cognitive and affective processes has been questioned more and more. Specific examples of questions about interactions between affective and cognitive states are: how does desiring relate to feeling, and in how far do sensing and believing relate to feeling? To assume that desiring can be described without involving emotion already seems a kind of paradox, or at least a discrepancy with what humans experience as desiring. Recent neurological findings suggest that this separation of cognitive and affective processes indeed may not be a valid and fruitful way to go. For example, Phelps (2006) states:

The mechanisms of emotion and cognition appear to be intertwined at all stages of stimulus processing and their distinction can be difficult. (...) Adding the complexity of emotion to the study of cognition can be daunting, but investigations of the neural mechanisms underlying these behaviors can help clarify the structure and mechanisms (Phelps 2006, pp. 46–47).

Here it is recognized that an assumption on isolating cognition from emotion is not realistic, as far as the brain is concerned. Therefore models based on such an assumption cannot be biologically plausible and may simply be not valid. Moreover, it is also acknowledged that taking into account the intense interaction between emotion and cognition ‘can be daunting’; to avoid this problem was a main reason for the isolation assumption as a way to address complexity. However, Phelps (2006) also points at a way out of this: use knowledge about the underlying neural mechanisms. In the past when there was limited knowledge about the neural mechanisms this escape route was not available, and therefore the isolation assumption may have made sense, although the validity of the models based on that can be questioned. But, now Neuroscience has shown a strong development, this provides new ways to get rid of this isolation assumption. Similar claims about the intense interaction between emotion and cognition have been made by Pessoa (2008). In experimental contexts different types of effects of affective states on cognitive states have indeed been found; see, for example, Eich et al. (2000), Forgas et al. (2009), Winkielman et al. (2009), Frijda et al. (2000). Moreover, more specifically in the rapidly developing area of Cognitive Neuroscience (e.g., Purves et al. 2008; Gazzaniga 2009) knowledge has been contributed on mechanisms for the interaction and intertwining of affective and cognitive states and processes (for example, involving emotion, mood, beliefs or memory); see, for example, Dolan (2002), LaBar and Cabeza (2006), Pessoa (2008), Phelps (2006), Storbeck and Clore (2007).

Not only for desiring and believing the isolation assumption for cognition versus emotion is questioned, but also for rational decision making. Traditionally, rationality and emotions often have been considered each other’s enemies: decision making has often been considered as a rational cognitive process in which emotions can only play a disturbing role. In more recent times this has been questioned as well. For example, in Loewenstein and Lerner (2003, p. 619) it is pointed at the positive functions served by emotions:

Throughout recorded human intellectual history there has been active debate about the nature of the role of emotions or ‘passions’ in human behavior, with the dominant view being that passions are a negative force in human behavior (...). By contrast, some of the latest research has been characterized by a new appreciation of the positive functions served by emotions (Loewenstein and Lerner 2003, p. 619)

In particular, in decision making it may be questioned whether you can make an adequate decision without feeling good about it. Decisions with bad feelings associated to them may lack robustness. Many occasions may occur over time that trigger a temptation to change it into a decision with a better associated feeling. So, human experience in rational decisions and feelings about them is that they go or

should go in hand in hand and are not isolated. This indicates another paradox or discrepancy between the isolation assumption and how real life is experienced: emotions can be considered a vehicle for rationality (for more details, see Chap. 6). A brief sketch of the alternative perspective is as follows. Decision making usually considers a number of options for a choice to be made. Such a choice is often based on some form of valuing of the options. In this valuing process emotions come in: the predicted effect of some of the options relate to a more positive feeling than for other options. It has been found that such valuations relate to amygdala activations (see, e.g., Morrison and Salzman 2010; Murray 2007; Salzman and Fusi 2010). As valuing can be seen as a grounding for a decision, it turns out that an emotional type of grounding is involved. Bad decisions are those that are not solidly grounded by having a positive feeling about them. They may not last long, as any opportunity to get rid of them will be a temptation to reconsider the decisions. Recent neurological literature addressing this idea of emotional valuing and grounding of decisions relates the notion of value to the amygdala; e.g., Bechara et al. (2003), Bechara et al. (1999), Montague and Berns (2002), Janak and Tye (2015), Jenison et al. (2011), Morrison and Salzman (2010), Ousdal et al. (2014), Pessoa (2011), Rangel et al. (2008).

In Chap. 3 it is discussed how knowledge from Neuroscience can be used to find out how the integration of emotions and cognitive processes can be modeled, illustrated for a number of examples. In Chaps. 4 and 5, more specifically the role of emotions in generating dreams and learning during dreaming is discussed. In Chap. 6 the specific case of emotions as a basis for rational decision making is addressed in more detail.

Individual versus Collective

Yet another isolation assumption concerns the distinction between mental processes within an individual and social processes. The former are usually referred to the territory of Psychology, whereas the latter are referred to the territory of Social Science. The idea then is to study social processes as patterns emerging from interactions between individuals thereby abstracting from the processes within each of the individuals. This easily leads to some kind of paradoxes. For example, as persons in a group are autonomous individuals with their own neurological structures and patterns, carrying, for example, their own emotions, beliefs, desires and intentions, it would be reasonable to expect that it is very difficult or even impossible to achieve forms of sharedness and collectiveness. However, it can be observed that often groups develop coherent views and decisions, and, even more surprisingly, the group members seem to share a positive feeling about it. In recent years by developments in Neuroscience new light has been shed on this seeming paradox of individuality versus sharedness and collectiveness. This has led to the new discipline called Social Neuroscience; e.g., Cacioppo and Berntson (2005), Cacioppo et al. (2006), Decety and Cacioppo (2010), Decety and Ickes (2009), Harmon-Jones and Winkielman (2007). Two interrelated core concepts in this discipline are mirror neurons and internal simulation of another person's mental processes. Mirror neurons are neurons that not only have the function to prepare for

a certain action or body change, but are also activated upon observing somebody else who is performing this action or body change; e.g., Iacoboni (2008), Pineda (2009), Rizzolatti and Sinigaglia (2008). Internal simulation is internal mental processing that copies processes that may take place externally, for example, in mental processes in another individual; e.g., Damasio (1994, 1999), Gallese and Goldman (1998), Goldman (2006), Hesslow (1994, 2002, 2012). Mechanisms involving these core concepts have been described that provide an explanation of the emergence of sharedness and collectiveness from a biological perspective. This new perspective breaks the originally assumed separation between processes within individuals and processes of social interaction. This perspective is discussed in more detail in Chap. 7.

Adaptive versus Nonadaptive Processes

Another assumption that sometimes is debated is that mental and social processes are modeled as if they are not adaptive. In reality processes usually have adaptive elements incorporated, but often these elements are neglected and sometimes studied as separate phenomena. One example in a social context is the following. Often a contagion principle based on social interaction is studied, describing how connected states affect each other by these interactions, whereas the interactions themselves are assumed not to change over time (for example, qua strength, frequency or intensity). But in reality the interactions also change, for example based on what is called the *homophily principle*: the more you are alike, the more you like (each other); for example, see Byrne (1986), McPherson et al. (2001), Mislove et al. (2010). Another way of formulating this principle is: birds of a feather flock together. It can often be observed that persons that have close relationships or friendships are alike in some respects. For example, they go to the same clubs, watch the same movies or TV programs, take the same drinks, have the same opinions, vote for the same or similar parties. Such observations might be considered support for the contagion principle: they were together and due to that they affected each other's states by social contagion, and therefore they became alike. However, also a different explanation is possible based on the homophily principle: in the past they already were alike before meeting each other, and due to this they were attracted to each other. So, the cyclic relation between *the states of the members* and *the strength of their connection* leads to two possible causal explanations of being alike and being connected:

being connected \rightarrow being alike	(contagion principle)
being alike \rightarrow being connected	(homophily principle)

Such circular causal relations make it difficult to determine what came first. It may be a state just emerging from a cyclic process without a single cause. For more discussion on this issue, for example, see Aral et al. (2009), Shalizi and Thomas (2011), Steglich et al. (2010), Mundt et al. (2012). This phenomenon will be addressed in more detail in Chap. 11.

As another example illustrating how adaptivity occurs fully integrated with the other processes, the function of dreaming is discussed. From a naïve perspective, dreaming might be considered as just playing some movie, thereby triggering some emotions, and that's all. But in recent research, the idea has become common that dreaming is a form of internal simulation of real-life-like processes serving as training in order to learn or adapt certain capabilities. Dreaming makes use of memory elements for sensory representations (mental images) and their associated emotions (learnt in the past) to generate 'virtual simulations'; e.g., Levin and Nielsen (2007, pp. 499–500). Taking into account fear emotions that often play an important role in dreams, strengthening of regulation of such emotions is considered an important purpose of dreaming; see, for example, Levin and Nielsen (2007), Walker and van der Helm (2009), van der Helm et al. (2011), Gujar et al. (2011), Deliens et al. (2014), Pace-Schott et al. (2015), Sotres-Bayon et al. (2004). To this end in dreams adequate exercising material is needed: sensory representations of emotion-loaden situations are activated, built on memory elements suitable for high levels of arousal. The basis of what is called 'fear extinction learning' is that emotion regulation mechanisms are available which are adaptive: they are strengthened over time when they are intensively used. Fear extinction learning as an expression may sound a bit paradoxal; it is *not* a form of unlearning or extinction of acquired fear associations, but it is additional *learning of fear inhibition* connections in order to counterbalance the fear associations which themselves remain intact (e.g., Levin and Nielsen 2007, p. 507). Such a strengthening of connections can be described by a Hebbian learning principle (Hebb 1949); see also Chap. 2, Sect. 2.10. The processes of dreaming and the adaptive elements involved in it are addressed in Chap. 5.

Earlier versus Later: Temporal Separation

Another traditionally made separation assumption is that processes in the brain are separated in time. For example, sensing, sensory processing, preparation for action and action execution are assumed to occur in linearly ordered sequential processes:

sensing – sensory processing – preparing for action – executing action

For the case of emotions it was already discussed that such linear temporal patterns are not applicable. But also more in general it can be argued that such linear patterns are too much of a simplification, as in reality such processes occur simultaneously, in parallel; often a form of internal simulation takes place, as put forward, among others, by Hesslow (1994, 2002, 2012), Damasio (1994, 1999), Goldman (2006), Barsalou (2009), Marques and Holland (2009), Pezzulo et al. (2013). The general idea of internal simulation that was also mentioned above in the specific context of emotions and bodily processes, is that sensory representation states are activated (e.g., mental images), which in response trigger associated preparation states for actions, which, by prediction links, in turn activate other sensory representation states for the predicted effects of the prepared actions:

sensory representation states → preparation states → sensory representation states

The latter states represent the effects of the prepared actions or bodily changes, without actually having executed them. Being inherently cyclic, the simulation process can go on indefinitely, as the latter sensory representations can again trigger preparations for actions, and so on, and everything simultaneously, in parallel, as in the world no process is freezing to wait for another process to finish first. Internal simulation has been used, for example, to describe (imagined) processes in the external world, e.g., prediction of effects of own actions (Becker and Fuchs 1985), or processes in another person's mind, e.g., emotion recognition or mindreading (Goldman 2006) or (as discussed above) processes in a person's own body by as-if body loops (Damasio 1994). This breaks with the tradition that there is a temporal separation of processes such as sensing—sensory processing—preparing for action—executing action. In many of the chapters this is illustrated.

1.3 Addressing Complexity by Interaction in Networks Instead of by Separation

The separation assumptions to address complexity as discussed in Sect. 1.2 are strongly debated, as they all come with shortcomings. In this section it is discussed that in fact the problem is not so much in the specific separation assumptions, but in the general idea of separation itself. In social contexts it is clear that the intense interaction between persons based on their mutual and often interrelated cyclic relationships, makes them not very well suitable for any separation assumptions: all these interactions take place all the time, simultaneously, in parallel. And this does not only apply to social processes but also to individual mental processes, as will be discussed in some more detail here.

In the domain of Neuroscience the structures and mechanisms found suggest that many parts in the brain are connected by connections that often are part of cyclic paths, and such cycles are assumed to play an important role in many mental processes (e.g., Bell 1999; Crick and Koch 1998; Potter 2007). As an example also put forward above, there is a growing awareness, fed by findings in Neuroscience that emotions play an important mediating role in most human processes, and this role often provides a constructive contribution, and not a disturbing contribution as was sometimes assumed. Usually mental states trigger emotions and these emotions in turn affect these and other mental states. It turns out that to address this type of circular effects, different views on causality and modeling are required, compared to the traditional views in modeling of mental processes. For example, Scherer (2009) states:

What is the role of causality in the mechanisms suggested here? Because of the constant recursivity of the process, the widespread notion of linear causality (a single cause for a single effect) cannot be applied to these mechanisms. Appraisal is a process with constantly changing results over very short periods of time and, in turn, constantly changing driving effects on subsystem synchronization (and, consequently, on the type of emotion). (...) Thus, as is generally the case in self-organizing systems, there is no simple, unidirectional sense of causality (see also Lewis 1996). (Scherer 2009, p. 3470)

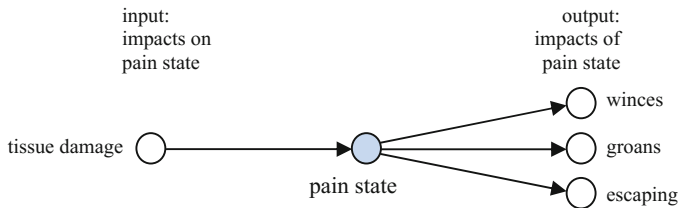


Fig. 1.1 Pain state with some of its causal relations

Also in the domain of Philosophy of Mind this issue of cyclic causal connections is recognized, for example, by Kim (1996). The idea is that a mental state is characterized by the way it mediates between the input it receives from other states and the output it provides to other states; this is also called the *functional* or *causal role* of the mental state. The idea is that each mental state is characterized by its causal role. For example, as a simplified example on the input side a mental state of being in pain is typically caused by tissue damage and in turn on the output side it typically causes wincing, groans and escape behavior (Kim 1996, p. 104); see Fig. 1.1. So, in this perspective the question what exactly is pain can be answered as the state that forms a causal bridge (or causally mediates) from tissue damage to wincing, groans, and escape behavior. Kim describes the overall picture as follows:

Mental events are conceived as nodes in a complex causal network that engages in causal transactions with the outside world by receiving sensory inputs and emitting behavioral outputs (Kim 1996, p. 104).

As input not only sensory input can play a role but also input from other mental states such as in the pain example ‘being alert’. Similarly, as output not only behavioral output can play a role but also other mental states can be affected, such as in the pain example feeling distress and a desire to be relieved of it. Within Philosophy of Mind this is often considered challenging:

But this seems to involve us in a regress or circularity: to explain what a given mental state is, we need to refer to other mental states, and explaining these can only be expected to require reference to further mental states, on so on – a process that can go on in an unending regress, or loop back in a circle (Kim 1996, pp. 104–105).

In Fig. 1.2 an example of such a cyclic causal path is depicted. Here mental state S_1 has a causal impact on mental state S_2 , but one of the states on which S_2 has an effect, in turn affects one of the input states for S_1 .

This view from Philosophy of Mind is another indication that a modeling approach will have to address causal relations with cycles well. To obtain an adequate understanding of such cycles and their dynamics and timing it is inevitable to take into account the temporal dimension of the dynamics of the processes effectuated by the causal relations. In principle, this situation makes that an endless cyclic process over time emerges, which in principle works simultaneously, in parallel, and in interaction with other processes. In such a graph at each point in

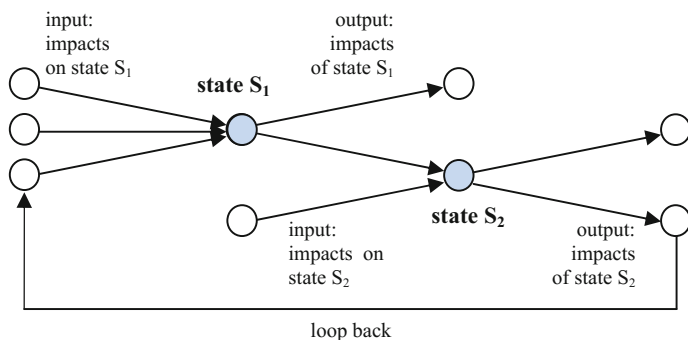


Fig. 1.2 Mental states with their causal relations conceived as nodes in a complex, often cyclic causal network (see also Kim 1996, p. 104)

time activity takes place in every state simultaneously (it is not that one state waits for the other). The notion of state at some point in time used here refers to a specific part or aspect of the overall state of a model at this point in time. Such an overall state can include, for example, at the same time a ‘being in pain’ state, a ‘desire to get relieved’ state, and an ‘intention to escape’ state. The overall state at some point in time is the collection of all states at that point in time. All the time the processes in the brain occur in parallel, in principle involving all specific states within the overall state, mostly in an unconscious manner. In this sense the brain is not different from any other part of the universe where everywhere processes take place simultaneously, in parallel. During all this parallel processing, any change in state S_1 in principle will lead to a change in state S_2 , which in turn will lead to another change in state S_1 , which leads to another change in state S_2 , and so on and on. The state changes in such a process may become smaller and smaller over time, and the cyclic process eventually may converge to an equilibrium state in which no further changes occur anymore; but also other patterns are possible, such as limit cycles in which the changes eventually end up in a regular, periodic pattern of changes (see also Chap. 12).

In the sense described above, mental processes can show patterns similar to patterns occurring in social interactions, where cycles of connections are natural and quite common. An example from the context of modeling social systems or societies can be found in (Naudé et al. 2008):

The paper outlines the challenges of modeling and assessing spatially complex human-ecosystem interactions, and the need to simultaneously consider rural-urban and rich-poor interactions. The context for exploring these challenges is South Africa, which has such stark poor-rich and associated rural-urban and other spatial disparities, that it is often described as a microcosm of the global division between developed and developing countries. Instead of rigid rural-urban dichotomies and other absolute, “container” views of space, there is a need to recognise spatial overlaps and complexities such as the pervasiveness of so-called translocal livelihood systems. Accordingly, much more *relational, network-oriented modeling approaches* are needed (Naudé et al. 2008, p. 1).

Also here it is claimed that separation in the form of what they call ‘container’ views of space falls short in addressing the complexities involved, and as an alternative a Network-Oriented Modeling approach is suggested to address human social complexity. Similar claims are made from the area of organization modeling by Elzas (1985):

The study of the process-type of organization, which still - at this moment because its relative novelty - requires modeling to evaluate, can benefit from certain network-oriented modeling formalisms because of the very nature of the organizational concept. (...) in addressing (...) the specific coordinating problems of the adaptively interrelated distributed-action organizational units as they are found in process-based organizational models (Elzas 1985, p. 162).

So, both from the area of the analysis of mental processes and from the area of analysis of social processes, the notion of network is suggested as a basis. In next section the notion of Network-Oriented Modeling is discussed in some more detail.

1.4 Network-Oriented Modeling

This chapter started in Sect. 1.2 by some reflection on traditional means to address complexity by assuming separation and isolation of processes, and the shortcomings, discrepancies and paradoxes entailed by these assumptions. In Sect. 1.3 the circular or cyclic, interactive and distributed character of many processes (involving interacting sub-processes running simultaneously, in parallel) was identified as an important challenge to be addressed, and it was recognized that a perspective based on interactions in networks is more suitable for this. In this section a Network-Oriented Modeling perspective is proposed as an alternative way to address complexity. This perspective takes the concept of network and the interactions within a network as a basis for conceptualization and structuring of any complex processes. Network-Oriented Modeling is *not* considered here as modeling *of* (given) networks, but modeling any (complex) processes *by* networks. It is useful to keep in mind that the concept network is a just a mental concept and this is used as a conceptual structuring tool to conceptualize any processes that exist in reality.

The concept of network is easy to visualize on paper, on a screen or mentally and as such provides a good support for intuition behind a model. Moreover, as the Network-Oriented Modeling approach presented here (see Sect. 1.6) also incorporates a temporal dimension enabling interpretation of connections as temporal-causal connections, the mental concept of network also provides support for the intuition behind the dynamics of the modeled processes.

The scientific area of networks has already a longer tradition within different disciplines of more than 60 years. But it has developed further and within many other disciplines, such as Biology, Neuroscience, Mathematics, Physics, Economics, Informatics or Computer Science, Artificial Intelligence, and Web Science; see, for example Boccaletta et al. (2006), Valente (2010), Giles (2012).

These developments already show how processes in quite different domains can be conceptualized as networks. Historically the use of the concept network in different domains can be traced back roughly to the years 1930–1950, or even earlier, for studying processes such as:

- brain processes in Neuroscience by neural networks; e.g. McCulloch and Pitts (1943), Rosenblatt (1958)
- metabolic processes in Cell Biology by metabolic networks; e.g., Ouellet and Benson (1951), Westerhoff et al. (1984)
- social interactions within Social Science by social networks; e.g., Bott (1957), Aldous and Straus (1966)
- processes in Human Physiology; e.g., Huber (1941), Wiener and Rosenblueth (1946)
- processes in engineering in Physics; e.g., Hubbard (1931), Bode (1945)
- processes in engineering in Chemistry; e.g., Treloar (1943), Flory (1944)

Within such literature often graphical representations of networks are used as an important means of presentation. After getting accustomed to such conceptualizations as networks of processes that exist in the real world, a belief may occur that these networks actually exist in reality (as neural networks, or as computer networks, or as social networks, for example), and *modeling by networks* happens sometimes to be phrased alternatively as *modeling networks*. However, it still has to be kept in mind that the concept ‘network’ is a mental concept used as a tool to conceptualize any type of processes. To make this distinction more clear linguistically, the phrase Network-Oriented Modeling is used as indication for modeling by networks. Within this book the preferred use of the word ‘network’ is to indicate a model or conceptualization of some process, not to indicate the process in the real world itself. For example, social media such as Facebook, Twitter, WhatsApp, Instagram,... do not form or create social networks in reality, but they create social interactions in reality that can be described (conceptualized, modeled) by (social) networks or by network models.

Network-Oriented Modeling offers a conceptual tool to model complex processes in a structured, intuitive and easily visualizable manner, but the approach described here also incorporates the dynamics of the processes in these models. Using this approach, different parts of a process can be distinguished, but in contrast to the separation and isolation strategy to address complexity, a network-oriented approach does not separate or isolate these parts, but emphasizes and explicitly models the way how they are connected and interact. Moreover, by adding a temporal dimension to incorporate a dynamic perspective, it is explicitly modeled how they can have intense and circular causal interaction, and how the timing of the processes is. As intense interaction in network models as a way of modeling requires a dynamic, temporal perspective, this will be discussed next.

1.5 The Dynamic Computational Modeling Perspective

The challenge to cope with a dynamical and cyclic picture of both mental processes and social interaction processes, imposes certain requirements on a modeling approach. The modeling approach has to be able to handle time and dynamics well. For example, in (van Gelder and Port 1995) the symbolic computational perspective is criticized as being not able to address the time-context of cognitive processes in an adequate manner. In contrast they propose a perspective in which cognition is considered as dynamics:

The alternative, then, is the *dynamical* approach. Its core is the application of the mathematical tools of dynamics to the study of cognition. (...) But the dynamical approach is more than just powerful tools; like the computational approach it is a worldview. The cognitive system is not a computer, it is a dynamical system. (...) The cognitive system is not a discrete sequential manipulation of static representational structures; rather, it is a structure of mutually and simultaneously influencing *change* (van Gelder and Port 1995, p. 3).

They compare the dynamical perspective to the symbolic computational perspective as described by Newell and Simon's (1976) *Physical Symbol System Hypothesis*:

According to this hypothesis, natural cognitive systems are intelligent by virtue of being physical symbol systems of the right kind. At this same level of generality, dynamicists can be seen as embracing the *Dynamical Hypothesis*: Natural cognitive systems are dynamical systems, and are best understood from the perspective of dynamics. Like its computational counterpart, the Dynamical Hypothesis forms a general framework within which detailed theories of particular aspects of cognition can be constructed (van Gelder and Port 1995, p. 5).

It has taken a number of years before the dynamical perspective was adopted more substantially in practical cognitive and neuroscientific modeling work; see for example:

Although the idea of applying dynamical systems theory to the study of neural and cognitive mechanisms has been around for at least two decades (Beer 2000; Kelso 1995; Thelen and Smith 1994; van Gelder 1998), the dynamical systems approach has only recently begun to figure prominently in neuroscience (...) (Schurger and Uithol 2015).

The notion of *state-determined system*, adopted from Ashby (1960) is taken by van Gelder and Port (1995) as a definition of what a dynamical system is:

A system is state-determined only when its current state always determines a unique future behaviour. Three features of such systems are worth noting.

First, in such systems, the future behaviour cannot depend in any way on whatever states the system might have been in *before* the current state. In other words, past history is irrelevant (or at least, past history only makes a difference insofar as it has left an effect on the current state).

Second, the fact that the current state determines future behaviour implies the existence of some *rule of evolution* describing the behaviour of the system as a function of its current state. For systems we wish to understand we always hope that this rule can be specified in

some reasonable succinct and useful fashion. One source of constant inspiration, of course, has been Newton's formulation of the laws governing the solar system.

Third, the fact that future behaviours are uniquely determined means that state space sequences can never fork (van Gelder and Port 1995), p. 6.

Ashby (1960) emphasizes the importance of the identification of state-determined systems in a wide variety of scientific domains; for more details on this notion, see Chap. 2, Sect. 2.9. This perspective on mental systems as state-determined dynamical systems put forward by Ashby (1960) and van Gelder and Port (1995) can be viewed as a further extension of the world view for the universe as developed much earlier, for example, by Descartes. As also discussed in Treur (2007, Sects. 2.1 and 2.2, pp. 58–59), Descartes (1634) introduced a perspective on the world that sometimes is called the *clockwork universe*. This perspective claims that with sufficiently precise understanding of the world's dynamics at some starting time, the future can be predicted just by applying a set of 'laws of nature'. He first describes how at some starting time matter came into existence in a diversity of form, size, and motion. From that time on, dynamics continues according to these laws of nature.

From the first instant that they are created, He makes some begin to move in one direction and others in another, some faster and others slower (or indeed, if you wish, not at all); thereafter, He makes them continue their motion according to the ordinary laws of nature. For God has so wondrously established these laws that, even if we suppose that He creates nothing more than what I have said, and even if He does not impose any order or proportion on it but makes of it the most confused and most disordered chaos that the poets could describe, the laws are sufficient to make the parts of that chaos untangle themselves and arrange themselves in such right order that they will have the form of a most perfect world, in which one will be able to see not only light, but also all the other things, both general and particular, that appear in this true world (Descartes 1634, Chap. 6: Description of a New World, and on the Qualities of the Matter of Which it is Composed).

Descartes emphasizes that after such a starting time nothing (even no God) except the laws of nature determines the world's dynamics:

Know, then, first that by "nature" I do not here mean some deity or other sort of imaginary power. Rather, I use that word to signify matter itself, insofar as I consider it taken together with all the qualities that I have attributed to it, and under the condition that God continues to preserve it in the same way that He created it. For from that alone (i.e., that He continues thus to preserve it) it follows of necessity that there may be many changes in its parts that cannot, it seems to me, be properly attributed to the action of God (because that action does not change) and hence are to be attributed to nature. The rules according to which these changes take place I call the "laws of nature" (Descartes 1634, Chap. 7: On the Laws of Nature of this New World).

This view on the world's dynamics is often compared to a clockwork. The view assumes that systematic relationships (laws of nature) are possible between world states over time, in the sense that (properties of) past world states entail (properties of) future world states. The clockwork universe view has been developed further by Newton, Leibniz, Laplace and others. The following quotation taken from Laplace (1825) sketches how an intellect could be able to determine (by means of 'a single

formula') future world states from a present world state, that by itself is the effect of past world states:

We may regard the present state of the universe as the effect of its past and the cause of its future. An intellect which at any given moment knew all of the forces that animate nature and the mutual positions of the beings that compose it, if this intellect were vast enough to submit the data to analysis, could condense into a single formula the movement of the greatest bodies of the universe and that of the lightest atom; for such an intellect nothing could be uncertain and the future just like the past would be present before its eyes (Laplace 1825).

The worldview of Descartes and others described above in principle focuses on the physical universe. As such it applies to all physical and also biological processes in the universe, for example, those in the brain. The dynamical perspective on cognition put forward by Ashby (1960) and van Gelder and Port (1995) can be viewed as an extension of the above worldview from the physical world to the mental world. As this dynamical worldview already is assumed to apply to the physical processes in the brain, it is an advantage that also assuming such a worldview for mental processes will make it easier to relate mental and neural processes, as discussed in Chap. 2, Sect. 2.3.

1.6 Network-Oriented Modeling Based on Temporal-Causal Networks

As discussed above, both internal mental processing and social processing due to social interactions often involve multiple cyclic processes and adaptive elements. This has implications for the type of modeling approach to be used. Within Network-Oriented Modeling, the network models considered have to integrate such cycles, and also allow adaptive processes by which individuals can change their connections. To model such dynamics, a dynamical modeling perspective is needed that can handle such combinations of cycles and the adaptation of connections over time. Therefore, within the Network-Oriented Modeling approach as discussed here, the dynamic perspective has to be incorporated as well: a temporal dimension is indispensable. This is what is achieved in the Network-Oriented Modeling approach based on temporal-causal networks described in Chap. 2; see also Treur (2016).

The Network-Oriented Modeling approach based on temporal-causal networks is a generic and declarative dynamic AI modeling approach based on networks of causal relations (e.g., Kuipers and Kassirer 1983, Kuipers 1984, Pearl 2000), that incorporates a continuous time dimension to model dynamics. As discussed above, this temporal dimension enables causal reasoning and simulation for cyclic causal graphs or networks that usually inherently contain cycles, such as networks modeling mental or brain processes, or social interaction processes, and also the timing of such processes. States in such a network are characterised by the connections they have to other states, comparable to the way in which in Philosophy of Mind mental states are characterised by their causal roles, as discussed in Sect. 1.3. Moreover, adaptive elements can be fully integrated. The modeling approach can

incorporate ingredients from different modeling approaches, for example, ingredients that are sometimes used in specific types of (continuous time, recurrent) neural network models, and ingredients that are sometimes used in probabilistic or possibilistic modeling. It is more generic than such methods in the sense that a much wider variety of modeling elements are provided, enabling the modeling of many types of dynamical systems, as described in (Chap. 2, Sect. 2.9).

As discussed in detail in Chap. 2 and (Treur 2016) temporal-causal network models can be represented at two levels: by a conceptual representation and by a numerical representation. These model representations can be used not only to display interesting graphical network pictures, but also for numerical simulation. Furthermore, they can be analyzed mathematically and validated by comparing their simulation results to empirical data. Moreover, they usually include a number of parameters for domain, person, or social context-specific characteristics. To estimate values for such parameters, a number of parameter tuning methods are available.

A conceptual representation of a temporal-causal network model in the first place involves representing in a declarative manner states and connections between them that represent (causal) impacts of states on each other, as assumed to hold for the application domain addressed. The states are assumed to have (activation) levels that vary over time. What else is needed to describe processes in which causal relations play their role? In reality not all causal relations are equally strong, so some notion of *strength of a connection* is needed. Furthermore, when more than one causal relation affects a state, in which manner do these causal effects combine? So, some way to *aggregate multiple causal impacts* on a state is needed. Moreover, not every state has the same extent of flexibility; some states may be able to change fast, and other states may be more rigid and may change more slowly. Therefore, a notion of *speed of change* of a state is used for timing of processes. These three notions are covered by elements in the Network-Oriented Modeling approach based on temporal-causal networks, and are part of a conceptual representation of a temporal-causal network model:

- **Strength of a connection** $\omega_{X,Y}$

Each connection from a state X to a state Y has a *connection weight value* $\omega_{X,Y}$ representing the strength of the connection, often between 0 and 1, but sometimes also below 0 (negative effect) or above 1.

- **Combining multiple impacts on a state** $c_Y(..)$

For each state (a reference to) a *combination function* $c_Y(..)$ is chosen to combine the causal impacts of other states on state Y .

- **Speed of change of a state** η_Y

For each state Y a *speed factor* η_Y is used to represent how fast a state is changing upon causal impact.

Combination functions in general are similar to the functions used in a static manner in the (deterministic) Structural Causal Model perspective described, for

example, in Wright (1921), Pearl (2000), Mooij et al. (2013), but in the Network-Oriented Modeling approach described here they are used in a dynamic manner, as will be pointed out below briefly, and in more detail in Chap. 2.

Combination functions can have different forms. How exactly does one impact on a given state add to another impact on the same state? In other words, what types of combination functions can be considered? The more general issue of how to combine multiple impacts or multiple sources of knowledge occurs in various forms in different areas, such as the areas addressing imperfect reasoning or reasoning with uncertainty or vagueness. For example, in a probabilistic setting, for modeling multiple causal impacts on a state often independence of these impacts is assumed, and a product rule is used for the combined effect; e.g., Dubois and Prade (2002). In practical applications, this assumption is often questionable or difficult to validate. In the areas addressing modeling of uncertainty also other combination rules are used, for example, in possibilistic approaches minimum- or maximum-based combination rules are used; e.g., Dubois and Prade (2002). In another different area, addressing modeling based on neural networks yet another way of combining effects is used often. In that area, for combination of the impacts of multiple neurons on a given neuron usually a logistic sum function is used: adding the multiple impacts and then applying a logistic function; e.g., Grossberg (1969), Hirsch (1989), Hopfield (1982, 1984), Beer (1995).

So, there are many different approaches possible to address the issue of combining multiple impacts. The applicability of a specific combination rule for this may depend much on the type of application addressed, and even on the type of states within an application. Therefore the Network-Oriented Modeling approach based on temporal-causal networks incorporates for each state, as a kind of parameter, a way to specify how multiple causal impacts on this state are aggregated. For this aggregation a number of standard combination functions are made available as options and a number of desirable properties of such combination functions have been identified (see Chap. 2, Sects. 2.6 and 2.7), some of which are shown in Table 1.1.

These options cover elements from different existing approaches, varying from approaches considered for reasoning with uncertainty, probability, possibility or vagueness, to approaches based on recurrent neural networks; e.g., Dubois et al.

Table 1.1 Overview of some standard combination functions $c(V_1, \dots, V_k)$

Name	Description	Formula $c(V_1, \dots, V_k) =$
ssum_λ(..)	Scaled sum	$(V_1 \times \dots \times V_k)/\lambda$ with $\lambda > 0$
product(..) cproduct(..)	Product Complement product	$V_1 \times \dots \times V_k$ $1 - (1 - V_1) \times \dots \times (1 - V_k)$
min(..) max(..)	Minimal value Maximal value	$\min(V_1, \dots, V_k)$ $\max(V_1, \dots, V_k)$
slogistic_{σ,τ}(..)	Simple logistic sum	$1/(1 + e^{-\sigma(V_1 + \dots + V_k - \tau)})$ with $\sigma, \tau \geq 0$
alogistic_{σ,τ}(..)	Advanced logistic sum	$[(1/(1 + e^{-\sigma(V_1 + \dots + V_k - \tau)}) - (1/(1 + e^{\sigma\tau}))](1 + e^{-\sigma\tau})$ with $\sigma, \tau \geq 0$

(1991), Dubois and Prade (2002), Giangiacomo (2001), Zadeh (1978), Grossberg (1969), Hirsch (1989), Hopfield (1982, 1984), Beer (1995). In addition, there is still the option to specify any other (non-standard) combination function, preferably taking into account the desired properties.

The above three concepts (connection weight, speed factor, combination function) can be considered as parameters representing characteristics in a network model. In a non-adaptive network model these parameters are fixed over time. But to model processes by *adaptive networks*, not only the state levels, but also these parameters can change over time. For example, the connection weights can change over time to model evolving connections in network models.

A conceptual representation of a temporal-causal network model can be transformed in a systematic or even automated manner into a numerical representation of the model as follows (Treur 2016):

- at each time point t each state Y in the model has a real number value in the interval $[0, 1]$, denoted by $Y(t)$
- at each time point t each state X connected to state Y has an impact on Y defined as **impact** $_{X,Y}(t) = \omega_{X,Y} X(t)$ where $\omega_{X,Y}$ is the weight of the connection from X to Y
- The *aggregated impact* of multiple states X_i on Y at t is determined using a *combination function* $\mathbf{c}_Y(\cdot)$:

$$\begin{aligned} \mathbf{aggimpact}_Y(t) &= \mathbf{c}_Y(\mathbf{impact}_{X_1,Y}(t), \dots, \mathbf{impact}_{X_k,Y}(t)) \\ &= \mathbf{c}_Y(\omega_{X_1,Y}X_1(t), \dots, \omega_{X_k,Y}X_k(t)) \end{aligned}$$

where X_i are the states with connections to state Y

- The effect of **aggimpact** $_Y(t)$ on Y is exerted over time gradually, depending on speed factor η_Y :

$$\begin{aligned} Y(t + \Delta t) &= Y(t) + \eta_Y[\mathbf{aggimpact}_Y(t) - Y(t)]\Delta t \\ \text{or } dY(t)/dt &= \eta_Y[\mathbf{aggimpact}_Y(t) - Y(t)] \end{aligned}$$

- Thus, the following *difference* and *differential equation* for Y are obtained:

$$\begin{aligned} Y(t + \Delta t) &= Y(t) + \eta_Y[\mathbf{c}_Y(\omega_{X_1,Y}X_1(t), \dots, \omega_{X_k,Y}X_k(t)) - Y(t)]\Delta t \\ dY(t)/dt &= \eta_Y[\mathbf{c}_Y(\omega_{X_1,Y}X_1(t), \dots, \omega_{X_k,Y}X_k(t)) - Y(t)] \end{aligned}$$

For modeling processes as adaptive networks, some of parameters (such as connection weights) are handled in a similar manner, as if they are states. For more detailed explanation, see Chap. 2, Sect. 2.10.

Summarizing, as will be discussed in more detail in Chap. 2, the Network-Oriented Modeling approach based on temporal-causal networks described here provides a complex systems modeling approach that enables a modeler to design conceptual model representations in the form of networks described as cyclic graphs (or connection matrices), which can be systematically transformed into

executable numerical representations that can be used to perform simulation experiments. The modeling approach makes it easy to take into account on the one hand theories and findings from any domain from, for example, biological, psychological, neurological or social sciences, as such theories and findings are often formulated in terms of causal relations. This applies, among others, to mental processes based on complex brain processes, which, for example, often involve dynamics based on interrelating and adaptive cycles, but equally well it applies to social interaction processes and their adaptive dynamics. This enables to address complex adaptive phenomena such as the integration of emotions within all kinds of cognitive processes, of internal simulation and mirroring of mental processes of others, and dynamic social interaction patterns.

1.7 Scope of Applicability and Achievements

Concerning the scope of applicability, it has been shown (see Chap. 2, Sect. 2.9) that any smooth continuous state-determined system (any dynamical system described as a state-determined system or by a set of first order differential equations) can also be modeled by temporal-causal networks, by choosing suitable parameters such as connection weights, speed factors and combination functions. In this sense it is as general as modeling approaches put forward, for example, in Ashby (1960), Forrester (1973, 1987), Thelen and Smith (1994), Port and van Gelder (1995), van Gelder and Port (1995), Beer (1995), Kelso (1995), van Gelder (1998), and approaches such as described, for example in Grossberg (1969), Hopfield (1982, 1984), Hirsch (1989), Funahashi and Nakamura (1993).

To facilitate applications, dedicated software is available supporting the design of models in a conceptual manner, automatically transforming them into an executable format and performing simulation experiments. A variety of example models that have been designed illustrates the applicability of the approach in more detail, for example, as shown in a number of chapters in this book (see also Chap. 18, Sect. 18.4).

The topics addressed have a number of possible applications. An example of such an application is to analyse the spread of a healthy or unhealthy lifestyle in society. Another example is to analyse crowd behaviour in emergency situations. A wider area of application addresses socio-technical systems that consist of humans and devices, such as smartphones, and use of social media. For such mixed groups, in addition to analysis of what patterns may emerge, also for the support side the design of these devices and media can be an important aim, in order to create a situation that the right types of patterns emerge. This may concern, for example, safe evacuation in an emergency situation or strengthening development of a healthy lifestyle. Other application areas may address, for example, support and mediation in collective decision making and avoiding or resolving conflicts that may develop.

1.8 Overview of the Book

The book is composed of six parts:

- I. Network-Oriented Modeling: an Introduction
- II. Emotions all the Way
- III. Yourself and the Others
- IV. Analysis Methods for Temporal-Causal Network Models
- V. Philosophical, Societal and Educational Perspectives

For each part the chapters are briefly discussed here.

Part I Network-Oriented Modeling: An Introduction

This part is the introduction to the book, both conceptually and in a more technical sense. It consists of the current introduction Chap. 1, and a next Chap. 2 in which the Network-Oriented Modeling approach based on temporal-causal networks is introduced in detail.

Part II Emotions All the Way

In Part II a number of processes and models are discussed that address individuals and the way in which emotions are integrated in an interactive manner in practically all mental processes.

In Chap. 3 it is discussed how within Cognitive, Affective and Social Neuroscience more and more mechanisms have been found that suggest how emotions interact in a bidirectional manner with many other mental processes and behaviour. Based on this, in this chapter an overview of neurologically inspired temporal-causal network models for the dynamics and interaction for emotions is discussed. Thus an integrative perspective is obtained that can be used to describe, for example, how emotions interact with beliefs, experiences, decision making, and emotions of others, and also how emotions can be regulated. It is pointed out how integrated temporal-causal network models of such mental processes incorporating emotions can be obtained.

In Chap. 4 it is discussed how emotions play a role in generating dream episodes from a perspective of internal simulation. Building blocks for this internal simulation are memory elements in the form of sensory representations and their associated emotions. In the presented temporal-causal network model, under influence of associated feeling levels and mutual competition, some sensory representation states pop up in different dream episodes. As a form of emotion regulation the activation levels of both the feelings and the sensory representation states are suppressed by control states. The presented model was evaluated by example simulation experiments.

In Chap. 5 it is discussed how dreaming is used to learn fear extinction. Here fear extinction has been found not to involve weakening of fear associations, as was assumed longer ago, but instead it involves the strengthening of fear suppressing connections that form a counter balance against the still persisting fear associations. So, to regulate fear associations neural mechanisms are used that take care of

strengthening these suppressing connections, as a form of learning of emotion regulation. The presented temporal-causal network model addresses dreaming as internal simulation incorporating memory elements in the form of sensory representations and their associated fear, as in Chap. 4. But this time it is modeled how the regulation of fear that takes place during dream episodes, is strengthened. This adaptation or learning process is modeled as an adaptive temporal-causal network model based on Hebbian learning. The model was evaluated by a number of simulation experiments for different scenarios.

Chapter 6 addresses the role of emotions in rational decision making. Traditionally it has been assumed that emotions can only play a disturbing and non-rational role in decision making. However, more recently it has been found that neurological mechanisms involving emotions play an important role in rational decision making. In this chapter an adaptive temporal-causal network model for decision making based on predictive loops through feeling states is presented, where the feeling states function in a process of valuing of decision options. Hebbian learning is considered for different types of connections in the adaptive model. Moreover, the adaptive temporal-causal network model is analysed from the perspective of rationality. To assess the extent of rationality, measures are introduced reflecting what would be rational for a given environment's characteristics and behaviour. Simulation results and the extents of rationality of different variants of the model over time are discussed. It is shown how during the adaptive process this model for decision making achieves higher levels of rationality.

Part III Yourself and the Others

Part III focuses on persons functioning in a social context. Given that each person has his or her own beliefs, desires, intentions, emotions and still more mental states, it might be expected that social coherence is not often achieved. However, the fact that still often social coherence is observed presents a kind of paradox. This paradox can only be understood by assuming that some neurological mechanisms are responsible for this, and by analyzing more in detail how through such mechanisms influences from the social context affect internal mental processes.

First, in Chap. 7 an overview is presented of a number of recent findings from Social Neuroscience, that form an explanation of how persons can behave in a social manner. For example, shared understanding and collective power are social phenomena that serve as a form of glue between individual persons. They easily emerge and often involve both cognitive and affective aspects. As the behaviour of each person is based on complex internal mental processes involving, for example, own goals, emotions and beliefs, it would be expected that such forms of sharedness and collectiveness are very hard to achieve. Apparently, specific neurological mechanisms are required to tune the individual mental processes to each other in order to enable the emergence of shared mental states and collective behaviour. Having knowledge about these mechanisms provides a basis to modeling corresponding mechanisms in a computational setting. From a neurological perspective, mirror neurons and internal simulation are core concepts to explain the mechanisms underlying such social phenomena. In this chapter it is discussed how based on

such neurological concepts computational mechanisms can be identified to obtain temporal-causal network models for social processes. It is discussed how these models indeed are an adequate basis to simulate the emergence of shared understanding and collective power in groups.

Within a social context the notion of ownership of actions is important. Chapter 8 addresses this notion. It is related to mechanisms underlying self-other distinction, where a self-ownership state is an indication for the self-relatedness of an action and an other-ownership state to an action attributed to someone else. The temporal-causal network model presented in this chapter generates prior and retrospective ownership states for an action based on principles from recent neurological theories. A prior self-ownership state is affected by prediction of the effects of a prepared action as a form of internal simulation, and exerts control by strengthening or suppressing actual execution of the action. A prior other-ownership state plays a role in mirroring and analysis of an observed action performed by another person, without imitating the action. A retrospective self-ownership state depends on whether the sensed consequences of an executed action co-occur with the predicted consequences, and is the basis for acknowledging authorship of actions in social context. It is shown how a number of known phenomena can be obtained as behaviour by the model. For example, scenarios are shown for vetoing a prepared action due to unsatisfactory predicted effects. Moreover, it is shown how poor action effect prediction capabilities can lead to reduced retrospective ownership states, for example, in persons suffering from schizophrenia. This can explain why sometimes the own actions are attributed to others or actions of others are attributed to oneself.

Chapter 9 addresses how in social interaction between two persons usually each person shows understanding of the other person. This may involve both nonverbal and verbal elements, such as bodily expressing a similar emotion and verbally expressing beliefs about the other person. Such social interaction relates to an underlying neural mechanism based on a mirror neuron system. Differences in social responses of individuals can often be related to differences in functioning of certain neurological mechanisms, as can be seen, for example, in persons with a specific type of Autism Spectrum Disorder (ASD). This chapter presents a temporal-causal network model which, depending on personal characteristics, is capable of showing different types of social response patterns based on such mechanisms, adopted from theories on the role of mirror neuron systems, emotion integration, emotion regulation, and empathy in ASD. The personal characteristics may show different variations over time. This chapter also addresses this adaptation over time. To this end it includes an adaptive temporal-causal network model capable of learning social responses, based on insights from Social Neuroscience.

Chapter 10 addresses joint decision making. The notion of joint decision making as considered does not only concern a choice for a common decision option, but also a good feeling about it, and mutually acknowledged empathic understanding about it. In this chapter a temporal-causal network model for joint decision making is presented addressing the role of mutually acknowledged empathic understanding in the decision making. The model is based on principles from recent neurological

theories on mirror neurons, internal simulation, and emotion-related valuing. Emotion-related valuing of decision options and mutual contagion of intentions and emotions between persons are used as a basis for mutual empathic understanding and convergence of decisions and their associated emotions.

In Chap. 11 it is discussed how adaptive temporal-causal network models can be used to model evolving social interactions. This perspective simplifies persons to just one state and expresses the complexity in the structure of the social interactions, modeled by a network. The states can represent, for example, a person's emotion, a belief, an opinion, or a behaviour. Two types of dynamics are addressed: dynamics based on a fixed structure of interactions (modeled by a non-adaptive temporal-causal network model), and dynamics where the social interactions themselves change over time (modeled by an adaptive temporal-causal network model). In the case of an adaptive network model, the network connections change, for example their *weights* may increase or decrease, or connections are added or removed. Both types of dynamics can also occur together. Different types of adaptive social network models are addressed, based on different principles: the *homophily principle* assuming that connections strengthen more when the persons are more similar in their state (the more you are alike, the more you like each other), and the *more becomes more principle* assuming that persons that already have more and stronger connections also attract more and stronger connections. Moreover, it is discussed how dynamics of social interactions can be modeled when (empirical) information over time is available about *actual interaction* between persons (both in the sense of frequency and of intensity), for example, as visible via social media. Based on such information connection weights can be modeled in an adaptive manner: the weights are adapted to the actual interaction.

Part IV Analysis Methods for Temporal-Causal Network Models

Models can be analysed by performing simulation experiments in a systematic manner. For example, it can be found out that under certain conditions a certain state always gets a certain activation level. Moreover, during such experiments values for the parameters of a model can be identified by hand such that for these parameter values the model shows a certain type of behavior. For more complex models such processes may be difficult. In this part some techniques are discussed to achieve this by analysis of the model in different ways.

Chapter 12 addresses the analysis of some types of properties of a temporal-causal network model in an analytical mathematical manner. Properties addressed describe whether some values for the variables exist for which no change occurs (stationary points), whether these variables converge to such a value as a limit value (attracting equilibria), whether variables will show monotonically increasing or decreasing values over time (monotonicity), and whether situations occur in which no convergence takes place but in the end a specific sequence of values is repeated all the time (limit cycle). It is discussed how such analyses can be used for verification of the (implemented) model. Any discrepancies found, suggest there is something wrong in the implementation of the model. In this chapter some methods to analyse such properties of adaptive temporal-causal network models will be

described and illustrated for the Hebbian learning model, and for adaptive connection weights in social network models.

Chapter 13 discusses dynamic properties of processes describing patterns that emerge over time, and how they can be identified and verified in a systematic manner. A process often generates patterns over time that can be described in a temporally more global manner, by expressing temporal relations over longer time periods, in contrast to temporal-causal network model descriptions that specify local mechanisms over small time durations. Such patterns can be considered as emergent phenomena, and it is often a challenge to analyse whether they occur and if so, how their occurrence relates to the local descriptions of underlying mechanisms and their characteristics. Properties describing them have in common that within them references occur to different time points and order relations between time points such as ‘before’ and ‘after’. Moreover, quantifiers over time are used such as expressed by ‘eventually’, ‘always’, ‘during’, ‘for some time point...’, or ‘for all time points...’. Such dynamic properties can be expressed in informal, semiformal and formal ways. Expressing them in a formal numerical-logical format makes it possible to verify whether they hold in some given empirical or simulated scenario in a systematic or even automated manner. This can be helpful in particular if many of such checks have to be done, for example by analysing the effects of a systematic variation of initial values and/or parameters in a simulation experiment.

In Chap. 14 it is discussed how a personalised temporal-causal network model can be obtained that fits well to specific characteristics of persons, and their connections and further context. A model is a close approximation, but always a form of abstraction of a real world phenomenon. Its accuracy and correctness mainly depend on the chosen abstracting assumptions and the values of the parameters in the model. Depending on the complexity of the model, the number of its parameters can vary from just a couple to thousands. These parameters usually represent specific characteristics of the modeled phenomenon, for example, for modeling human processes person-specific characteristics or social interaction characteristics. No values for such parameters are given at forehand. Estimation of parameters for a given model is a nontrivial task. There are many parameter estimation methods available in the literature. In this chapter a number of these methods are briefly discussed.

Part V Philosophical, Societal and Educational Perspectives

In Part V some wider perspectives are addressed. It is discussed how the Network-Oriented Modeling approach relates to historical and philosophical developments concerning dynamics, how it fits in current trends in societal development, and how such a modeling perspective can play a crucial role in an integrative multidisciplinary academic curriculum.

In Chap. 15 it is discussed how dynamics has been a challenging issue in different disciplines since long ago. This issue has been addressed for different domains, in Physics but also in Mathematics, Cognitive Science and Philosophy of Mind. In the development of Physics it has led to notions such as velocity, momentum, kinetic energy and force that drive motion in mechanics. The issue of

dynamics is still out there today, for example, in the domain of Cognitive Science and Philosophy of Mind concerning the physical realism of assumed but not directly physically observable mental states such as desires and intentions that are supposed to drive (physically observable) behaviour. Four cases of dynamics within different traditional disciplines are discussed in this chapter. Similarly, it is shown how in this way causal graphs and transition systems (often used in AI and Computer Science) can be interpreted from a perspective of dynamics. The chapter provides a unified view on the explanation of dynamics across different disciplines. This view is related to the basic assumptions underlying the Network-Oriented Modeling approach based on temporal-causal networks.

Chapter 16 outlines the strong societal development to the integration of more and more smart devices in all aspects of life. Scientific areas addressing this development have names such as Ambient Intelligence, Ubiquitous Computing, Pervasive Computing, Human-Aware Computing or Socially Aware Computing. This development in society often results in integrated complex systems involving humans and technical equipments, also called socio-technical systems. In this chapter it is discussed how in such systems often not only sensor data, but also more and more dynamic computational models based on knowledge from the human-directed sciences such as health sciences, neurosciences, and psychological and social sciences are incorporated. These models enable the environment to perform in-depth analyses of the functioning of observed humans, and to come up with well-informed interventions or actions. It is discussed which ingredients are important to realize this view in a principled manner, among which dynamical models such as temporal-causal network models, and how frameworks can be developed to combine these ingredients to obtain the intended type of systems in practice.

Chapter 17 discusses the design of a curriculum with main focus on human-oriented scientific knowledge and how this can be exploited to develop support for humans by means of advanced smart devices in the daily environment. The aim for this curriculum was to offer a study path for those students with exact talents but with an interest mainly in human processes and society. The curriculum was designed from a problem-oriented perspective in relation to societal problem areas. From human-oriented disciplines scientific knowledge for human processes in such problem areas was obtained. Computational modeling for such human processes plays a central role as an integrating factor in the curriculum. Elements from Ambient Intelligence, Artificial Intelligence, and Informatics are included for design of smart support systems.

Part VI Network-Oriented Modeling: Discussion

Chapter 18 is a discussion in which some of the main issues addressed in the book are briefly reviewed. In particular, the Network-Oriented Modeling approach based on adaptive temporal-causal networks is discussed and how generic and applicable it is as a modeling approach and as a computational paradigm.

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