Neurocognitive modelling of human decision making

Azadeh Hassannejad Nazir

Faculty of Natural Resources and Agricultural Sciences

Department of Energy and Technology

Uppsala

Licentiate thesis
Swedish University of Agricultural Sciences
Uppsala 2019

Licentiate thesis/Report 103
ISBN (print version) 978-91-576-9645-8
ISBN (electronic version) 978-91-576-9646-5

Print: SLU Service/Repro, Uppsala 2019

Neurocognitive modelling of human decision making

Abstract

A central issue related to climate change and the path to a low carbon society is how we can change our attitudes and associated behavioral patterns. This type of decisions is concerned with how complex systems can be dealt with, conceptually, psychologically, as well as socially. In order to transform our society, we need to consider the relationship between brain, mind and behavior. One of the approaches to address this problem is to design computational models that can be used for simulations and scenario building.

This thesis concerns the development and application of a neurocomputational model of the decision making process of an individual at experiential and social levels, considering both emotional and rational aspects. It is an attempt to bridge the gaps between micro (neuronal), meso (brain areas) and macro (cognition/behavior) levels with a focus on the mesoscale neurodynamics of cortical structures. The model is intended to link neural structures, functions, and includes effects of internal and environmental factors.

The thesis is divided into two parts, corresponding to the two kinds of decision making: 1) experience-based and 2) social-based decision making. At an individual level, a final decision is the result of an integration of rational and emotional processes. The neural structures involved in cognition valuate the potential options regarding internal attitudes and rules, as well as external contexts. Decision values are based on neural properties of activity patterns associated with different actions. The option with the highest value is selected for in the decision making process. Human behavior is guided not only by subjective values and attitudes, but also by the perceived behavior of others. Learning from/about others through observation shapes our thoughts and behavioral patterns. The second part of the thesis deals with this social adaptive characteristic of an individual, where the dynamic changes of her behaviors are connected with trust. Traces of social influences on an individual's decisions and social expectations (e.g. trust) have been observed in the rational and emotional brain structures and their functions.

While the neurocomputational model is based on anatomical and physiological data of the modeled brain structures, no real world data have been available for model validation. Yet, simulation results mimic EEG and fMRI readouts, which could be compared with experimental/clinical data, when available. Future work intends to provide such data, but currently the modeling can only provide insights in the neurodynamic interactions between brain areas involved in decision making.

Keywords: Decision making, Observational Learning, Anterior cingulate cortex, Amygdala, Orbitofrontal Cortex, Lateral prefrontal cortex, trust, climate change.

Author's address: Azadeh Hassannejad Nazir, SLU, Department of Energy and Technology, P.O. Box 7032, 75007 Uppsala, Sweden

Neurokognitiv modellering av mänskligt beslutsfattande

Abstract

En central fråga i samband med klimatförändringar och vägen till ett fossilfritt samhälle är hur vi kan ändra våra attityder och beteendemönster. Denna fråga är besläktad med hur ett komplext system kan hanteras, konceptuellt, psykologiskt och socialt. För att omvandla vårt samhälle måste vi bl.a. betrakta förhållandet mellan vår inre och yttre värld. En metod för att lösa denna typ av problem är att utveckla datormodeller som kan användas för simulering och scenario-generering för beslutsstöd.

Denna avhandling behandlar utvecklingen och tillämpningen av en neurokognitiv datormodell av beslutsprocessen hos en individ på såväl erfarenhetsmässig som social nivå, som innefattar både emotionella och rationella aspekter. Det är ett försök att överbrygga gapen mellan mikro- (neurala), meso- (hjärnområden) och makro- (kognition/beteende) –nivåer, med fokus på mesoskopisk neurodynamik hos vissa kortikala strukturer. Vår datormodell bygger på neurala strukturer, dynamik och funktioner som är inblandade i beslutsprocessen, och inkluderar effekter av både individuella och miljömässiga faktorer. Beslutsprocessen kan betraktas både som en individuell och en social process, där vi främst beaktar individens kognitiva funktioner, särskilt inlärning, planering, beslutsfattande och handlande.

Inriktningen i den första delen av denna avhandling ligger på den erfarenhetsbaserade beslutsprocessen. På individnivå är ett beslut resultatet av en integration av kognitiva och emotionella faktorer, där olika neurala strukturer är involverade i respektive processer. De neurala strukturer som är inblandade i kognition beräknar värdet av olika alternativa beslut/handlingar, baserat på inre och yttre omständigheter. Beslutsprocessen innefattar en värdering av de olika alternativa handlingarna, och alternativet med det högsta värdet är i allmänhet beslutsprocessens slutresultat. Mänskligt beteende styrs inte bara av subjektiva värderingar och attityder utan också av andras beteende. Att lära av och om andra genom att observera deras beteende påverkar våra tankar och beteendemönster och beror på graden av förtroende. Den sociala påverkan på en individs beslut har även observerats i de emotionella och kognitiva hjärnstrukturerna. Den andra delen av denna avhandling fokuserar på dessa sociala adaptiva aspekter hos en individs beslutsfattande.

Medan vår datormodell baseras på anatomiska och fysiologiska data från relevanta hjärnstrukturer, har vi inte haft tillgång till några data för modellvalidering. Dock kan modellsimuleringarna, som efterliknar data från EEG och fMRI, jämföras med experimentella sådana då dessa finns tillgängliga. Framtida arbete ämnar förse oss med sådana resultat, men för närvarande kan modellen endast ge insikter i hur neurodynamiken i de olika hjärnstrukturerna samverkar under en beslutsprocess.

Nyckelord: Beslutsfattande, Orbitofrontal cortex, Lateral prefrontal cortex, Anterior cingulate cortex, Amygdala, förtroende, observationslärande, klimatförändringar.

Author's address: Azadeh Hassannejad Nazir, SLU, Department of Energy and Technology, P.O. Box 7032, 75007 Uppsala, Sweden

Dedication

To my beloved husband, Ehsan.

Contents

List of publications **9**

Abbreviations **11**

1 Introduction **13**
1.1 Purpose and aims 13
1.2 Background 17
1.2.1 The impact of decision making on climate change 17
1.2.2 Cognitive aspect of decision making process 17
1.2.3 Neural basis of decision making 21
1.3 Boundaries of the project 24

2 Methods **25**
2.1 Decision making in choice of transport 25
2.2 Experience-based decision making 27
2.2.1 Behavioral aspect of experience-based DM 27
2.2.2 Neural aspect of experience-based DM 28
2.3 Social-based Decision Making 33
2.3.1 Behavioral aspect of social-based DM 33
2.3.2 Neural aspect of social-based DM 35

3 Simulation and results **39**
3.1 Experience-based decision making results 39
3.1.1 Results from Paper I 39
3.1.2 Results from Paper II 45
3.2 Social-based decision-making results 49
3.2.1 Results from Paper III 50
3.3 Sensitivity analysis 55

4 Discussion **57**

5 Conclusion and future work **61**

References **63**

Popular science summary **69**

Populärvetenskaplig sammanfattning **71**

Acknowledgements **73**

Appended Papers **75**

List of publications

I Azadeh Hassannejad Nazir, Hans Liljenström (2015). A cortical network model of cognitive and emotional influences in human decision making. BioSystems 13, pp.128–141.

II Hassannejad Nazir, A. & Liljenström, H. (2016) A Neuro-Cognitive Model for Decision Making in Everyday Travelling. In: "Towards a Fossil-Free Society - In the Stockholm-Mälar Region" (H. Liljenström & U. Svedin, Eds.),COMPLEX WP4 Final Scientific Report, Human Nature Series. Sigtuna: Sigtunastiftelsen, ISBN 978-91-976048-4-0. doi: 10.13140/RG.2.2.36656.97284.

III Azadeh Hassannejad Nazir, Hans Liljenström. A Neurocognitive model of observation-based decision making with a focus on trust (manuscript)

Paper I-II are reproduced with the permission of the publishers.

The contribution of Azadeh Hassannejad Nazir to the papers included in this thesis was as follows:

I Major part of concept, most planning, modelling and evaluation.

II Major part of concept, most planning, modelling and evaluation.

III Most part of concept, planning, modelling and evaluation.

Abbreviations

ACC	Anterior Cingulate Cortex
DM	Decision making process
LPFC	Lateral Prefrontal Cortex
OFC	Orbitofrontal Cortex
PE	Prediction error

1 Introduction

1.1 Purpose and aims

The planet is currently experiencing a climate change, evidently caused by human activities of various sorts, primarily our burning of fossil fuels. How can we, as humans, change our behavior, in order to mitigate (or adapt to) climate change? What determines our behavior and way of living, and what could be the main causes for changing this? How do our decisions (in everyday life) affect our behaviors, and what are our decisions based on?

Human behavior is guided not only by subjective values, but also by the perceived behavior of others, in particular by social norms. Therefore, the decision making process can be regarded as an individual as well as a collective process. This is obvious when e.g. observing our neighbors recycle their waste, or commuting to work by public transport rather than by their own cars.

The overall goal of this thesis is to make a connection between the micro (neuronal), meso (brain areas) and macro (behavior and social influences) levels. However, the main focus is the neurodynamics of some cortical structures underlying the decision making process (DM). My sub-goals in support of this goal are to elucidate the neural pathways and processes associated with the emotional-rational decision making process in an adult individual and how this is influenced by others. The aim of my work is to find out the relative importance of various internal and external factors influencing our decisions. In this regard, the thesis is divided into two parts: 1) experience-based and 2) social-based decision making.

In the first part of the thesis, the main focus is on an individual's perception of the environment and its direct influence on her emotional-rational reasoning and decisions. An individual's attitude, preferences, and mood are some self-related examples of factors impacting on the individual's decisions. I present and discuss a model of the neural processes associated with experiential DM, applied to semi-realistic societal choices with consequences for climate and environment. I base the modelling approach on the notion that DM is influenced by rational, as well as emotional considerations, as discussed by e.g. Kahneman and colleagues(Kahneman, 2011, Kahneman and Tversky, 1979). The aim of this part is to elucidate the interaction between the neurodynamics of the brain areas involved in rational and emotional aspects of DM and suggest mechanisms for how the brain-mind may evaluate influencing factors.

In spite of the impact of an individual's experiences on DM, a successful decision is also an adaptive process based on social interactions. In the second part of this thesis, the focus is on social cognition and its influence on DM. Here, the individual decision making is based on what is being learnt by observing the behaviors of others.

I focus on the behavior change of an individual influenced by the observation of an action-outcome association of another individual, whose behavior can be seen as more or less trustworthy. This serves as a basis for further developing our neurocognitive model to study an adaptive brain mechanism underlying social-based decisions. One of the social influences of observational learning is trust between the observing and the observed individual.

In this regard, the central premise of this part is that an individual observes the behavior and its subsequent outcome of the other (such as taking public transport, rather than car, or eating vegetarian food, rather than meat), and eventually may adopt that behavior. The decision of an individual is supposedly influenced by observing the action-outcome association of the other, which may build trust in the other person(s). A changed behavior could also be a result of following the advice of an expert or a politician, or someone else we may trust, to various degrees.

I aim to study an individual behavior following the observation of the action-outcome association, depending on the observer's trust in that observed person. The attitude change of the observer from an emotional to rational influenced by rational trust will be studied in this part. Here, two aspects of rational trust, consistency and competence, are taken into account.

The major goal of this part is to examine the interaction between observational learning and trust as well as their influence on decision making.

To achieve the goal discussed here, I have developed individual-social neurocognitive models, which I simulate for a large number of trials, in order to test many combinations of influencing factors in the DM. I model and study the neural activities of the structures thought to be involved in the emotional and rational observation-based decision-making process. To concern the reduction of CO_2 emissions with regard to individual behavior, I deal with socially embedded decisions in particular the choice of transport between home and work. In order to attain the objectives of this research, an extensive study has been conducted as outlined in the work flow diagram in Figure 1. I have tried to address the goals of this project in three papers.

Paper I presents the neurocomputational model of the experience-based decision making process. In this paper, I investigate the emotional-rational oscillatory neural activities in the experiential context.

Paper II studies the behavior change of an individual who makes a decision in the individual context. This study is based on the model developed in the first paper concerning the influence of environmental factors (e.g. traffic jam, policies, weather, etc.) on an individual's decisions.

Paper III studies the behavior change of an individual, in the social context by developing a social-based neurocomputational model. This model has been developed based on the previously developed model in Paper I. Here, I study the impact of others' behaviors on an individual's decision.

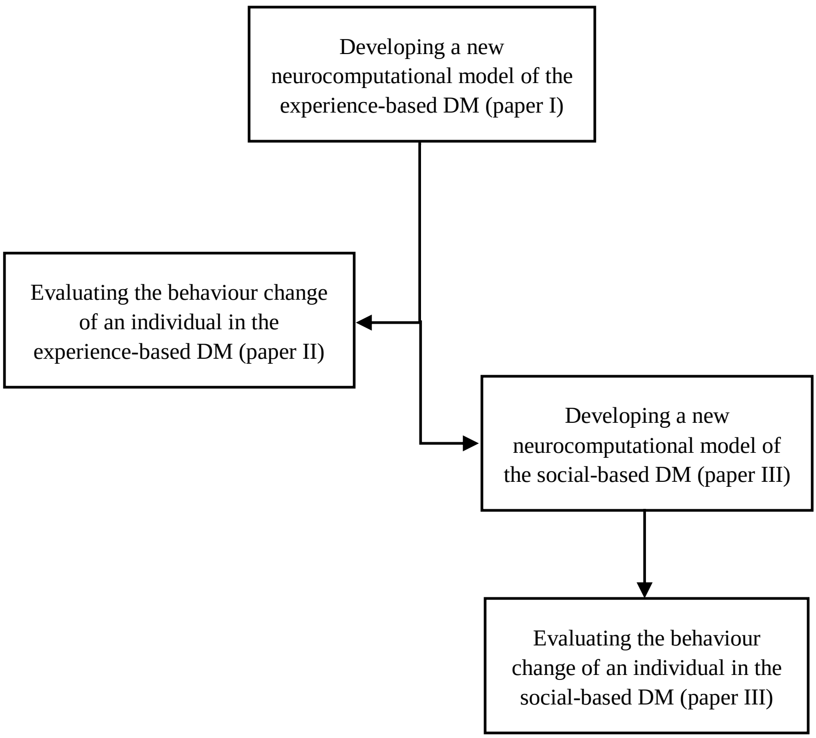


Figure 1. The work flow of the thesis.

While the neurocomputational model is based on anatomical and physiological data of certain brain structures, no real world data have been available for model validation, including input and output signals. Yet, simulation results mimic EEG and fMRI readouts, which could be compared with experimental/clinical data, when available. Future work intends to provide such data, but currently the modeling can only provide insights in the neurodynamic interactions between brain areas involved in decision making. Inputs are randomly generated sensory-like stimuli simulating the neuronal input to some cortical structures.

1.2 Background

1.2.1 The impact of decision making on climate change

In our everyday life, we make different decisions with various forms of consumption patterns, in particular the choice of transport. Transport is one of the largest contributors to CO_2 emissions and climate change. In order to reach a low carbon society, as has been decided for the EU countries, it is important to change our life styles and habits, including how we travel to work and for leisure (Liljenström et al., 2016). This is the motivation for the current example, where the decision making concerns the choice of transport for an individual who is traveling from home to work at a regular basis. (Our approach is at a later stage intended to be embedded in a social context, where a distribution of individual choices will influence each other and the society/ environment).

1.2.2 Cognitive aspect of decision making process

Learning

We are constantly subject to a huge amount of information received from the environment. Environment is a broad concept encompassing living and non-living phenomena, including society and natural/built environment. Our environment, as well as our biological heritage, are pivotal to sculpt our behaviors. Indeed, bidirectional interactions between our genetic heritage and environment, the gene-culture interaction(Laland et al., 2010) makes this process even more complicated. *Culture* can be defined as a way of life for a certain group of people. This broad concept covers beliefs, morality, norms, customs and many other traits of the individuals' characters. In addition to our genetic and cultural heritage, our behaviors depend on our experiences and social interactions influencing our neural and mental development. Behavior changes caused by environmental influences are the result of our ability to learn. There are different types of learning in terms of the contextual information (Lee and Harris, 2013, Gariepy et al., 2014) resulting in knowledge development: experiential and social learning.

A large part of human behaviors is goal-directed. The causal relation between the action and outcome is the major concern for a goal-directed behavior (de Wit and Dickinson, 2009). Choosing reward seeking and punishment avoidance behaviors is a principle of a goal-directed behavior. Individual experience without any social intervention is the major cause of individual learning (experience-based learning). Experiential learning can be seen as a trial and error-based learning to reach a goal (as obtaining reward or avoiding punishment) (Cohen et al., 2012). Learning emerges, in this context, from the difference between the predicted and actual value of the experience, referred to as the experiential prediction error (PE) (Lak et al., 2014, Schultz, 1998, Wise, 2004).

As human beings we influence the society we live in, but we are in turn also influenced by it. Hence, social interactions play crucial role in our lives. Our brains have to a large extent evolve to deal with various types of social relations (Gredebäck and Melinder, 2010, Lieberman, 2013). The behavior of an individual is defined in a social context by learning from others, i.e. social learning (Gariepy et al., 2014, Bandura, 1977, Campbell-Meiklejohn et al., 2010). Social learning is the consequence of a wide array of behaviors, such as imitation(Heyes, 2001, Iacoboni et al., 1999, Rizzolatti et al., 2001), peer influences (Clark and Dumas, 2015, Stallen et al., 2013), and outright teaching (Biele et al., 2011).

One of the common forms of social learning is known as *observational learning*, i.e. learning as a result of observing other people's behaviors (Bandura, 1971, Albert Bandura, 1961). Observational learning occurs through observing others experiencing a situation. According to Bandura (Bandura, 1965), there are four keystone parameters of observational learning: attention, retention, reproduction and motivation. Learning about the consequence of an action is crucial for all living creatures. At the experiential level, individuals associate their experienced actions with the subsequent outcomes, while at a social level, the individual may associate the observed action performed by others with its consequence.

At the experiential level of the DM, the difference between an individual's prediction and the experienced actual value of the action generates a PE. Similarly, humans predict the actions and their associated outcomes of other individuals. The difference between their predictions and reality leads to individual learning about and from the observed person. There are two types of observational prediction errors: observational action PE and observational outcome PE. The difference between the actual and predicted value of the observed action and its subsequent outcome bring about the observational action and outcome PEs, respectively (Burke et al., 2010, Jones et al., 2011, Hauser et al., 2015, Apps et al., 2015, Monfardini et al., 2013, Chang et al., 2011).

Decision-making process

Decision making is perhaps the most important cognitive ability related to behavior and is crucial for the survival of all higher animals. The DM could be regarded as the result of five subsequent steps (Doya, 2008, Bedia and Di Paolo, 2012), as illustrated in figure 2 and described as follows:

1. *Representation*: An individual faces decision problems, including the identification of the internal state, the external state and the potential course of action.
2. *Valuation*: The value of the decision alternatives are analyzed and valuated based on the individual attitude and experiences.
3. *Action selection*: Comparing the valuated alternatives, the one with the higher net value is selected.
4. *Outcome evaluation*: The desirability of the selected action (the actual outcome) is measured.
5. *Learning*: Based on the difference between the predicted and actual value of the selected alternative (prediction error), the stored information about the values and attitudes are updated to improve the quality of future decisions.

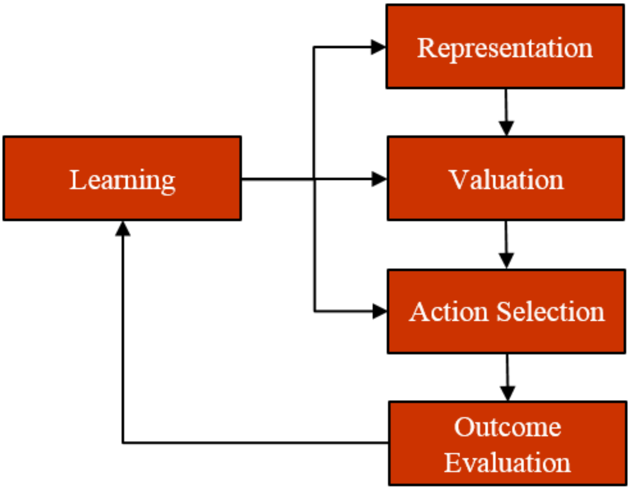


Figure 2 Decision-making process includes five cognitive processes. An individual predicts the values of the decision options based on the received internal and external stimuli. The final decision is the result of the comparison between the options. The one with the higher value is considered as the final decision. The difference between the perceived actual value of the decision and the predicted one results in learning in the individual who makes a decision.

The evaluation of the decision options is supposedly based on both emotional and rational processes (Mukherjee, 2010, Evans and Stanovich, 2013, Evans, 2008). Daniel Kahneman propounds the theory of “dual thinking” in his book “Thinking, Fast and Slow” (Kahneman, 2011). Emotion and rationality are two major components of reasoning, which correspond to Kahneman’s System 1 and 2, respectively. System 1, representing the emotional aspect of the mental activity, is heuristic and fast. The neural basis of emotion depends upon memory retrieval of associative memory, and could be considered as an automatic process.

System 2 deploys the cognitive control process. The procedure covers different psychological and neurological aspects ranging from an attentional system, mapping stimuli to actions based on the stored rules to the learning process. In contrast to the emotional reasoning, rationality is a slow process. The activity of working memory and interference control (Zilli and Hasselmo, 2008) could be considered a principal part of rational reasoning. Receiving external stimuli about the options, the rational expectancy outcome of the options are valuated by encoding rules and attitudes. The prominent characteristic of working memory is its capability in forming associations. The final decision is the result of the integration of the emotional and rational values so that the rational system modifies the emotional system. Regarding the described process, the rational reasoning is a more complex and time-consuming mental activity than the emotional reasoning (Damasio, 1996, Doya, 2008, Gold and Shadlen, 2007).

Trust

Societal influences have a direct relation with the level of interpersonal trust (Campbell-Meiklejohn et al., 2010). The concept of trust has been studied in different fields of science, e.g. sociology, psychology, and neurology. According to Lewicki et al.(Lewicki et al., 1998), trust is “an individual's belief in, and willingness to act on the basis of, the words, actions, and decisions of another.” Trust is apparently a phenomenon linked to and dependent on all forms of time: past, present and future.

In spite of various connotations of trust, the common aspect highlighted among all the definitions is the role of an individual’s “expectation” in trust related situations (Rotter, 1971). People’s expectancies are rooted in their predictions which is a subjective valuation of the probability of an event and its subsequent outcome. Hence, trust not only reflects the prediction of an individual about the contingency of the actions of others (i.e. consistency) but also is about the desirability of their associated outcomes (i.e. competence). The predictions about an individual's action and its outcome are two cognitive variables for assessing the level of trustworthiness (Baker, 1987, Rompf, 2015). Regarding the definition, the evaluation of the consistency of an individual in taking an action, and the competency in performing a successful action, are the results of action and outcome predictions, respectively. Accordingly, in this study, I define trust as an individual's attribute based on the cognitive valuation of others in a specific context with respect to their consistency and competence levels.

With regard to this definition, to build trust, an individual has to learn about others in a social context. This learning might be based on the observation of their actions and the associated outcome. Hence, the process of trust building includes social perception (evaluating the trustworthiness of other persons), learning and decision making.

1.2.3 Neural basis of decision making

Experimental results indicate that different neural structures are involved in the emotional and rational DM (Kable and Glimcher, 2009). Amygdala, orbitofrontal cortex (OFC) and lateral prefrontal cortex (LPFC) appear to be major neural structures underlying decision making. The interaction of the first two structures plays a particular role in emotion perception and the emotional response, while rational decisions are evolved at the latter structure.

Amygdala, as a part of the limbic system, has since long been associated with emotional processing. It correlates sensory perception and learning, linking the stimulus that provokes the emotional response to its emotional value. Amygdala is important to trigger the autonomic nervous system in response to emotional stimuli, as reward and punishment (Zhang et al., 2013). The projection of internal stimuli to the amygdala makes this structure unique in having access to the internal states of mammals. Internal states such as hunger, anger, and happiness are influential parameters of emotional decisions (Gupta et al., 2011, Baxter and Murray, 2002). With regard to a hypothesis by Damasio (Damasio, 1996), experiments seem to show that amygdala plays a significant role in the expression of the somatic marker. Damage to the amygdala impairs the somatic response to reward and punishment, hindering future decision-making. Amygdala has also been found to be active when subjects choose options associated with large immediate rewards (Smith et al., 2009). The functionality of the amygdala is realized through its connection to OFC, which receives extensive neural afferents from different sensory modalities (Jenison, 2014). The bidirectional connections between OFC and Amygdala are supposedly embodied in an emotional DM, where the perception and evaluation of environmental stimuli constitute the emotional reasoning (Barbas, 2007a, Barbas, 2007b, Rich and Wallis, 2013, Wager et al., 2008).

OFC has a heterogeneous structure, differentiated in its different areas (John et al., 2013): agranular areas with three layers, dysgranular areas with four layers, and granular areas with six layers (Barbas, 2007b, Barbas, 2007a). Amygdala and OFC receive afferent signals from the late sensory processing system. The firing frequency of OFC neurons is interpreted as an expected value of the external stimulus termed "expectancy signal" (Balleine et al., 2011, Rempel-Clower, 2007). This signal demonstrates the context or the contingency of the outcome. The neural basis of emotion is based on the retrieval of associative memory. Hence, this process is heuristic and fast.

On the other hand, rational decisions are evolved at the lateral prefrontal cortex (Pribram, 1987). LPFC contributes to the prediction of the expected rational values. This structure has a homogenous six-layered structure (Petrides, 2005, Figner et al., 2010, Dixon and Christoff, 2014, Koechlin and Summerfield, 2007). Lateral prefrontal cortex is considered as a major neural structure active in self-control and modification of short-term emotional gratification(Christodoulou et al., 2010).The emotionally assessed stimuli in the amygdala-OFC pathway would be modified by LPFC and a final decision would be taken(John et al., 2013, Levine, 2009, Gray et al., 2002, Baumgartner et al., 2011, Sokol-Hessner et al., 2012).

The schematic illustration of the neural flow of information in the DM taking account of the emotional and rational systems is presented in figure 3.

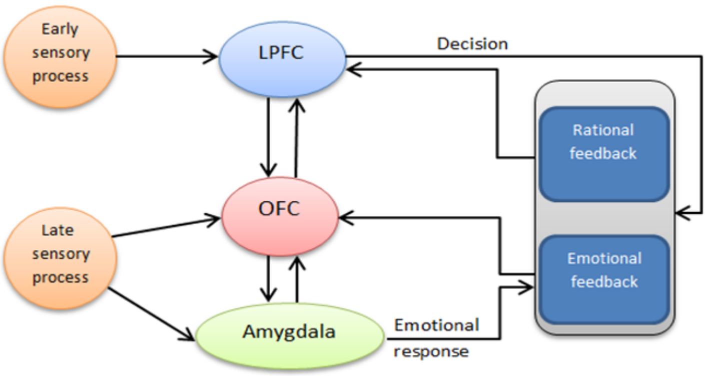


Figure 3 Illustration of the interactions of the three main neural structures in the decision making process. Amygdala and orbitofrontal cortex (OFC) are considered as the main organizations in emotional decision making and lateral prefrontal cortex (LPFC) plays a crucial role in rational analysis. The inputs come from all sensory modalities.

The so-called “social brain” is a network of brain regions implicated in the processing of social information (Gallese et al., 2004, Lieberman, 2013, Lieberman, 2007, Beer and Ochsner, 2006, Adolphs, 2009), including the areas OFC and LPFC. In addition to these two “social structures”, the neural activity of anterior cingulate cortex (ACC) has been observed in social contexts (Lavin et al., 2013). Regarding the unique position of ACC, this structure is connected to the cortico-cortical and cortico-limbic pathways. Hence, ACC is considered to be a social hub contributing to the emotional and rational aspects of human behavior. Cingulate cortex is part of the limbic cortex and is composed of two different histological structures with respect to Brodmann’s classification, as areas 24 and 29, anterior and posterior sections, respectively. The bidirectional connections of ACC with LPFC, Amygdala, and OFC facilitate the flow of social information among these structures (Medalla and Barbas, 2012, Allman et al., 2001, Apps et al., 2016, Hughes and Beer, 2012, Palomero-Gallagher et al., 2008, Bush et al., 2000).

ACC plays an important role in modulating the oscillatory activity of OFC and LPFC, with a mechanism based on a reinforcement learning process (Apps et al., 2013). The sign and magnitude of the prediction error make an impact on the properties of the correlated cell assembly, such as the neural weight strengths and excitabilities. Positive/negative PE signals strengthen/weaken the oscillatory properties of the corresponding neural patterns. The interactions between the ACC, LPFC and OFC constitute an important basis for social learning, as illustrated in Figure 4.

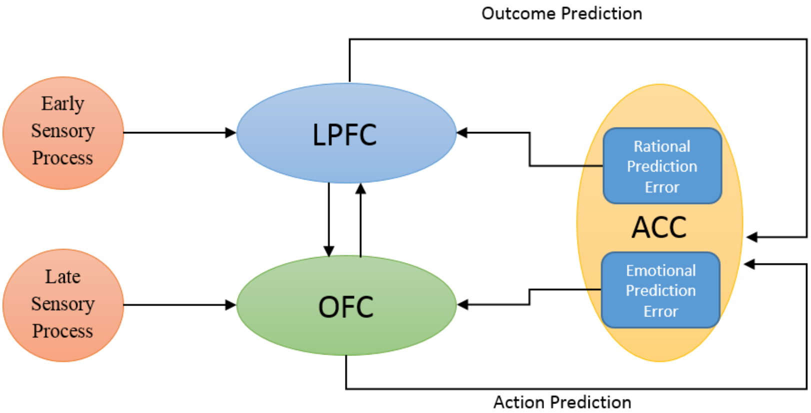


Figure 4 Illustration of the schematic flow of information among neural structures in observational learning. LPFC and OFC are, respectively, subject to early rational and late emotional sensory stimuli projecting the processed to ACC. The difference between the actual and anticipated observed action and outcome signal result in updating the neural oscillatory properties of LPFC and OFC.

1.3 Boundaries of the project

In order to model any system, it is necessary to consider the system boundary and the components relevant to the study purpose. In our case, a comprehensive knowledge about the experience-based and social-based DM is crucial to model these two related systems.

As mentioned above, the DM depends on the interaction between the individual and the environment. “Environment” is a broad concept, encompassing living and non-living systems, including society and the natural/built environment.

For the experience-based decision making, the interaction between an individual and the environment is at the center of my attention. Therefore, at an individual level, the decision making system includes the individual person, her/his attitude and individual experiences, while the natural/built environment (e.g. climate condition, traffic condition) is outside the system boundary.

In a larger contextual frame, our own decisions and actions are in turn influenced by other individuals we interact with in the society. The social influences can be measured based on the distance between individuals for example, geographical distance, a psycho-social distance, and strength of interpersonal ties. Hence, in addition to the components included in the first system, for the experiential DM, the society surrounding an individual is an influential component when defining the system for a social-based DM.

Our model can be analyzed temporally on two time scales. The neural activities of the structures underlying the DM take place at temporal scales of seconds or less, while the social interaction and attitude change can be considered at a scale of hours, months or longer. The spatial modeling of this process can be scaled in the same matter, at a micro and macro scale, respectively. The micro scale here corresponds to the neural networks of the brain structures involved in the DM, while transport behaviors are studied at a macroscopic scale of landscapes.

2 Methods

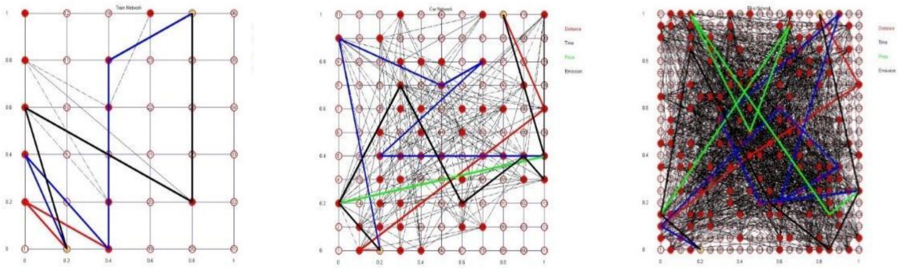
In order for us to change our society with regard to climate change and associated challenges, it is important to understand how humans make decisions and how the following actions impact on climate. Every day, we make many different decisions concerning various forms of consumption patterns, such as eating habits and the choice of transport from home to work. This thesis aims at an increased understanding of the decision making process (DM) at both individual and societal levels, by means of neuro-computational modelling taking the example of transport. In the following, I describe the behavioral assumptions of the developed neural models. Then I will present the scenarios under which the experience-based and social-based DM are studied.

2.1 Decision making in choice of transport

Our actions are influenced by changes in our external environment, but it is also based on a change of perception in our internal environment. We explore our world in a perception-action cycle (Freeman, 2000). This thesis scrutinizes the perception-action cycle at the individual and social levels from the behavioral and neural perspectives. This adaptive process in the social and individual contexts are biased by information. Different inputs might be developed in respect of perceptional, attentional and motivational biases. Considering the sources of information, two different perspectives are defined explaining the experience-based and social-based decision making. The developed neurocomputational models in the first and second parts are applied to semi-realistic societal choices with consequences for climate and environment.

The focus here is on certain external and internal factors that influence our choices and form the basis of our DM. As an example of DM at an individual level, which also has implications at a societal level, we take the choice of transport at an everyday basis. Given a set of options, this has relevance for reaching a climate neutral society (see Liljenström et al., 2014). The impact of individual's attitudes on climate change to fit with the three pillars of sustainable development (SD): Ecological (eco), social (soc), and economic/monetary (mon). The various options are also associated with these three categories of attitudes and values. The choice of action, i.e. which optional means of transport we will take, depends on various environmental (distance, traffic situations, cost etc.), social (others' behaviors) and internal (motivation, attitude, mood etc.) factors. Here, I suggest the different options are to take either bike, car, or public, (where the public transportation could be e.g. bus, train, or metro), which all are considered to be available, albeit with different levels of convenience.

The designed networks of pathways for the mentioned modes of transport are different considering their densities. The road intensity of bike, car and public transport are respectively, high, medium and low. Different colours in the maps illustrated in figure 5 determine the shortest pathways between the starting and final points of travel in terms of time, cost, distance, and CO_2 emission. According to the randomly generated values of coordinated time, cost, distance, and CO2 emission matrices, some of these lines might overlap in some of the maps.



(a) (b) (c)

Figure 5 Roadmaps of three modes of transport; Public transport (a), Car (b) and cycle (c). Four coloured lines illustrate different shortest pathways regarding distance (red), time (blue), price (green) and carbon dioxide emission (black). As is shown, lines determine the shortest distance and lowest amount of CO_2 emission overlap

I also assume that individuals have different preferences, depending on their living conditions and general attitudes with regard to environmental, social, and economic concerns. Accordingly, each option has an ecological/ climate value, a social/temporal value, as well as an economic/ monetary value, but these are considered to be different for different individuals. I consider the emotional and rational priority as based on the individual's personality.

2.2 Experience-based decision making

In this part of the thesis, I highlight the DM from the first-person perspective considering the fact that the environmental contexts (e.g., natural environment and social infrastructures) play pivotal roles in the outcomes of decisions. The context-based decision making process is the spotlight of the experiential DM process. In following, different scenarios are presented from the behavioral and neural perspectives.

2.2.1 Behavioral aspect of experience-based DM

The first step is to estimate the outcomes of different options. In our case example, time, cost and CO_2 emission, are considered as outputs of the options. Considering the “personality” of an individual who makes decision, the order of emotional and rational priorities is defined based on their salience, i.e. one of the three sustainability categories. There is a one-to-one correspondence between the “pro-social” personality and the importance of time, the “pro-economy” and cost, and the “pro-environment” and level of CO_2 emission. Three different scenarios are considered at the experience-based decision making process. The individuals in each scenario has different personalities described below.

Scenario I. In the first scenario, I study the decision making process by developing a neurocognitive model. Here, the individual is exposed to the environmental and the internal stimuli when traveling between home and work. I assume that the individual has an equal tendency to decide emotionally and rationally.

The developed neurocognitive model in this scenario is applied for the next two scenarios to study the behavior change of the individual influenced by different external stimuli.

Scenario II. The individual, in this scenario, has a different personality and is subject to unpredicted events such as accidents, traffic jams, delays, bad weather, etc. The individual is a pro-social person gives, rationally, higher priority to time over the other outputs, whereas she may have different emotional priorities. Therefore, her first priority is to choose car as a means of transport. The model is simulated for 250 trials (e.g. days), divided into five intervals of 50 trials each.

Scenario III. Similar to the second scenario, here, the behavior change of the individual is at the center of my attention. In this scenario, I study the influence of implementing temporary policies on the change in priority order, while there is no unpredictable event. The policies are implemented for a fixed period of time, after which return to initial situation. We ran the simulation for different lengths of time, to study the effect on trust and behavior. At five time intervals, temporary changes are imposed which might influence the DM.

A trial corresponds to an occasion when a relevant decision (of means of transport) is made. For simplicity, we can assume that one such decision/trial is made by the individual once a day, for example when going from home to work.

In addition, the choice of personalities in the aforementioned scenarios contributes to better understanding of the behavior change. However, any other personalities can be applied.

2.2.2 Neural aspect of experience-based DM

The process illustrated in figure 2 is the conceptual basis of the developed neurocomputational model of the experience-based decision making process. The conceptual model is framed by modelling the functionalities of the three neural structures, LPFC, OFC, and Amygdala as the most important constituents of the DM. The first structure underlies the rational reasoning of DM while the last two are the representatives of the emotional decision-making process. Amygdala is stimulated by internal and external stimuli while the other two are subject to external inputs. With regard to different functionalities of structures, the model analyses the impact of different internal and external contexts on the individual's decision.

The DM is modeled at a level of mesoscopic neurodynamics, using attractor neural networks based on the developed cortical neural network model of Liljenström (Liljenström, 1991). Oscillatory rhythms encode information related to perception, rational and emotional associations in this model. The emerged oscillatory activities are the result of interactions between neural populations. The developed model generates the oscillatory neural activity as the local field potentials (LFP) or electroencephalogram (EEG) readouts.

The neural units in the model represents a group of neurons firing in synchrony. At the mesosocopic level, oscillations and irregular chaotic-like behavior of neural units can be generated by the interplay of neural excitatory and inhibitory activity at the network level. Hence, in this model, the network is composed of three layers, two inhibitory and one excitatory layers. The excitatory layer in all the three neural parts is innervated by external stimuli, and the inhibitory effects of GABAergic neurons modulate the activities of the excitatory neurons. This suggests a lumping of the upper layers (I, II&III) as a feedforward inhibitory layer, and the two lower layers (V &VI) as a feedback inhibitory layer, on either side of the excitatory middle layer.

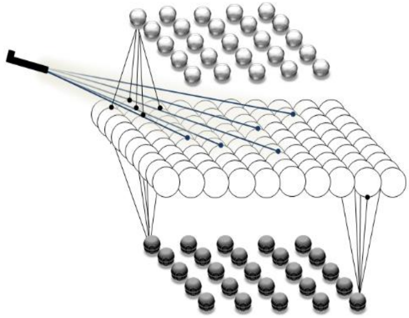


Figure 6 The simplified layered neural structure of three neural organization. The upper and lower layers are composed of 25 inhibitory neurons and the network in the middle is composed of 100 excitatory neurons. The external inputs stimulate (subset of) excitatory neural network. The stimulation of excitatory neurons is the start of activity of the system. Stimulated excitatory neurons excite inhibitory neurons which result in the excitation-inhibition balance.

The excitatory neurons excite the two inhibitory layers. The feedforward and feedback inhibitory layers inhibit the excitatory neurons locally. The excitatory sub-layer of each structure is a network of 100 neural units (populations), while each of the two inhibitory networks is composed of 25 inhibitory units. The excitatory network nodes are connected recurrently, while there is no internal connections among inhibitory units. An excitatory-inhibitory balance results from the bidirectional connectivity of excitatory units with the two inhibitory networks on either side (Fig. 6). The network structure allows for a complex neurodynamics, in particular, oscillations with varying amplitudes and frequencies. The activity of each neural unit can be regarded as the mean membrane potential of the population resulting in a graded, rather than spiking, neuronal output (Liljenstrom and Wu, 1995, Liljenström, 1991).

The external stimuli are driven by afferent neurons (not explicitly modeled) to a subset of the network of excitatory units. The various magnitude of emotional and rational external inputs distinguish different stimuli. The stimulated neural units transmit signals to their excitatory neighbors, as well as to the neighboring inhibitory units, which inhibit all excitatory units.

The formation and update of cell assemblies are the bases of the functionalities of the three neural structures. The oscillatory activity of the cell assemblies in different structures could demonstrate information related to either the stored experiences, attitudes or the associated feelings towards the consequence of the selected action. The excitability of neural units and strength of neural connections represent the value of the above cognitive information. To compute the cell assembly properties, the characteristic magnitude of the neural units should be taken into account.

The time evolution for a network of N nodes (neural populations) is given by a set of coupled nonlinear first order differential delay equations for all the N internal states, ui. With external input, I(t), time constant, τi, and connection weight wij between nodes i and j, separated with a time delay δij, the neural activity of each unit, ui, would be measured (Eqn. 1).

$$du_i/dt = -u_i/\tau_i + \sum_{j\neq i}^{N} w_{ij} g_j\big(u_j\,(t-\delta_{ij})\big) + I_i(t) + \xi\,(t) \qquad (1)$$

The input-output function, $g_i(u_i)$, a continuous sigmoid function, is determined by Freeman (Freeman, 1979) as follows.

$$g_i(u_i) = CQ_i(1 - exp[-exp(u_i)\,/Q_i]) \qquad (2)$$

Where Q is an intrinsic motivation taking different values in the emotional ($Q_{emo.}$) and rational ($Q_{rat.}$) structures. The larger value of Q indicates the higher motivation and neural arousal for choosing a particular option. An individual's motivation to make a decision is a function of her experiences and environmental factors. The changes in the environmental/societal and individual conditions make an impact on the value of Q.

It is noteworthy to mention that the developed neurocomputational model focuses more on the functionalities of the three neural areas than their structures. Hence, in spite of the different observed neuroanatomical structures of OFC, LPFC and amygdala, the three-layered network of neural units is applied for all of them. Despite the variation observed in their structures, the laminar structure of the two cortical structures (i.e. OFC and LPFC) and the cytological arrangement of Amygdala supposedly make this model an appropriate approximation of the real structures. Among the different nuclei in amygdala, we model the functionality of the three most prominent nuclei: basolateral (excitatory) amygdala, intercalated cells and the central nucleus (both inhibitory) (Zhang et al., 2013).

Formation of cell assemblies

In our model, an individual's preferences/priorities are determined by the neural activity of cell assemblies in the three brain structures, which represent the individual's attitude and the expectancy value of the decision. To show the function of the three neural structures, the activation of cell assemblies are required. The formation of and updating cell assembly are based on the Hebbian learning rule (Liljenström, 1995).

$$\Delta w_{ij} = \eta g_i[u_i(t)]g_j\left[u_j\left(t - \delta_{ij}\right)\right]\left(w_{max} - w_{ij}\right) \tag{3}$$

Where η is the learning rate. The oscillatory activities encoded in Amygdala and OFC determine the emotional value of the decision options, $V_{emo.}(Opt)$ and the recorded oscillation in LPFC determine the rational value, $V_{rat.}(Opt)$. This value is a function of the size of cell assemblies, mean frequency and signal's amplitude.

$$V(Opt) = \left|s_{opt}\right| \cdot \langle\overline{\boldsymbol{f}_{opt}}, \overline{\boldsymbol{A}_{opt}}\rangle = \left|s_{opt}\right| \cdot \langle\overrightarrow{\overline{f_{opt}}}, \overrightarrow{\overline{A_{opt}}}\rangle, \quad \forall\, opt = 1, \dots, n \tag{4}$$

Where |s| indicates the number of active neural units in the cell assembly, $\underline{f}$ and A are the averaged frequency and amplitude of neural oscillation, respectively.

The final decision is the result of the emotional and rational integration. The Eq.5 shows a simple arithmetic calculation on the emotional and rational values considering the attitude of the individual.

$$\vec{V}_{fin} = \alpha \times \vec{V}_1 + (\alpha - 1)\,\vec{V}_2 \tag{5}$$

The coefficient α determines the weight of emotion in the DM. The higher the α is, the more emotionally the individual would behave.

The formation of emotional and rational cell assemblies serves as the bases for measuring the emotional and rational values of options.

As was discussed in the previous section, the interaction between OFC and amygdala plays a pivotal role in the emotional system. The oscillatory properties of the signals recorded in OFC delineate the expectancy values of the options. The integration of the signals generated in the OFC and amygdala leads to an emotional response. The emotional value is the result of a regulation by OFC of amygdala activity. As mentioned before, in the case of similarity between the output from OFC and amygdala, OFC may either excite amygdala to release an emotional response, or otherwise inhibit it. The similarity between the values of amygdala and OFC is a measure using cosine similarity in our model. We let similarities greater than a threshold value θ result in an excitation, and if less thanθ, it will result in inhibition. For example, if we let θ = 0.9, the values, V1 and V2 of Systems 1 and 2, respectively, can be expressed as

$$similiarity = \frac{\langle\overrightarrow{V_{OFC}}, \overrightarrow{V_{Amy}}\rangle}{\|\overrightarrow{V_{OFC}}\| \cdot \|\overrightarrow{V_{Amy}}\|} \geq \theta \rightarrow V_1 = V_{Amy} \tag{6.1}$$

$$similiarity = \frac{\langle \overrightarrow{V_{OFC}}, \ \overrightarrow{V_{Amy}} \rangle}{\|\overrightarrow{V_{OFC}}\| \cdot \|\overrightarrow{V_{Amy}}\|} < \theta \ \rightarrow V_1 = V_{OFC} \tag{6.2}$$

Amygdala is driving emotional response if the similarity is higher than 90% (Eq. 6.1) otherwise, OFC's neural activity determines the emotional response (Eq. 6.2).

The neural activity of LPFC has been recorded during the temporarily maintenance and manipulation of data from working memory (WM) (Zilli and Hasselmo, 2008, Collins et al., 2017). To model the involvement of LPFC in WM, I have adopted the cognitive theory of Adaptive Control of Thought—Rational (ACT-R)(Anderson and Matessa, 1997) . According to the ACT-R, declarative and procedural memories are the main building blocks of the cognitive analysis in WM. (In this model, declarative memory is modelled based on the semantic memory disregarding the episodic memory).

Declarative memory establishes facts and experiences while procedural memory involves in the collection of if-then rules. Attitudes, social norms and rational values are portrayed and maintained as a set of rules in this memory. The association between the concepts/contexts and the outcome can be stored as if-then rules in procedural memory.

The reciprocal interaction between these two memory systems (declarative and procedural) provides the basis for the cognitive analysis. The oscillatory activity of the neural pattern in LPFC rational predicted values of the options is regarded as the result of the interaction between the procedural and declarative memories. The option with the highest rational value is the final rational decision of the individual.

Final decision and system update

As mentioned before, the final decision is the result of the integration of the emotional and rational value. The individual is subject to the actual outcome of the selected action. The difference between predicted and actual action generates prediction error signal in the OFC and LPFC. The schematic illustration of the developed experience-based DM model is presented in figure 7.

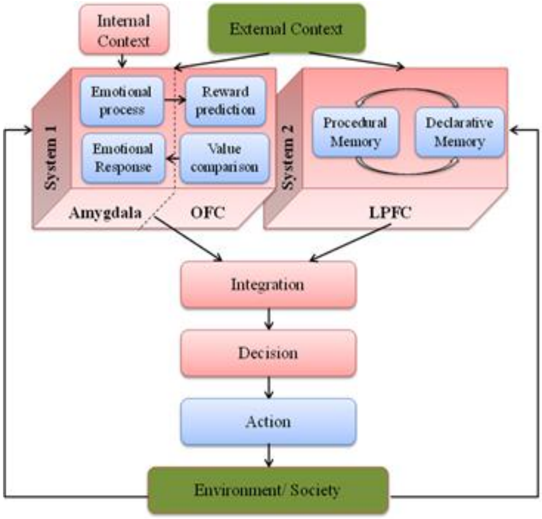


Figure 7 Schematic flow chart of the subsystems and information flow in the modelled decision making process. System 1 is an automatic and emotional system. In this system, OFC and amygdala involved in encoding emotional expectancy signals. System 2 is a controlled and rational system represented by the activity of LPFC.

The properties of the cell assemblies determine the significance of the options. To update the stored emotional and rational attitude, these properties are modified according to the sign and magnitude of the prediction error. A positive/negative prediction error strengthens/weakens the properties of the cell assembly, i.e. here, the strength of neural connections and Q value, associated with the selected option.

2.3 Social-based Decision Making

In this part of the thesis, I highlight the decision making process from the third-person perspective considering the fact that the social contexts (e.g., others' behaviors) play pivotal roles in an individual's decisions. In following, the behavioral scenario and the neural representation of the social-based model is presented.

2.3.1 Behavioral aspect of social-based DM

Human beings are part of a society which would affect their decisions. Social impact on an individual's decisions is an inseparable part of the DM. The probability of being influenced by others through observing their behaviors or hearing their advice is associated with some parameters: interpersonal trust between the individual who makes a decision and the others, the personality similarities between the individual and the others, as well as the history of the observed individual in providing useful advice or being consistent/competent in their actions/outcomes.

In continuation of the previous scenarios in the experiential context, here, I want to study the impact of society on the behavior of an individual. In this thesis, the social influences are confined to what the individual learns from and about the others through observing their actions and the subsequent outcomes.

Scenario. Among the various categories of people we interact with every day, our friends influence our decisions, depending on the psycho-social distance (trust). This influence may be informational, by adopting the decisions/behaviors of our trusted friends through observing their daily decisions. As mentioned in the previous section, considering the case of traveling, the options have three different outcomes, in terms of time, cost and the amount of CO_2 emission. The outcome of the friends' actions in this case example can be observed by the individual. The individual (observer) might associate the social, economic or health condition of the observed person (friends) with their choice of action (travelling). Observing friends who are on time, wealthy or looking healthy might lead the individual to make a deduction about the association between their decisions (i.e. car, public transport and bike, respectively) and the mentioned outcomes. The impact of taking bike on climate is not immediate and cannot be recognized at the personal scale. Hence, here, I consider that an individual's health is the outcome of choosing bike for traveling between work and home.

To have a better understanding of an individual observer's behavior change in a social context, the scenario is defined based on a specific personality of the observer. However, different scenarios with different individual personalities can be applied in this model. In this part, I intend to show how an emotional decision changes into a rational one. In this regard, the individual is considered to be an emotional person who puts a high emotional value on car. However, she is rationally a pro-economy person. Her rational priority is public transport but still has a lower value than the emotional value of car.

The observed individual (i.e. the individual's friend) is expert in climate. Therefore, it is generally assumed that an expert in this field rationally prefers to take public transport to travel between home and work. The degree of predictability (action and outcome) of the expert is chosen to be high (80%). The individual observers the action and the subsequent outcome of the expert for 80 days while she is traveling between work and home. In the same day, she also makes a decision which might be influenced by her attitude and social influence.

2.3.2 Neural aspect of social-based DM

The conceptual framework of this part is based on the notion of the interplay between observational action-outcome learning and decision making. In addition, as mentioned before, trust has an undeniable impact on an individual’s decisions. The prediction of an action-outcome of the observer makes an impact on the observer’s trust in the expert. In this regard, the neurocomputational model investigates and predicts the behavioral pattern of the observer following the observation of the action-outcome association of the alleged expert.

In spite of the differences between the individual and social neural structures, the cognitive processes behind individual and social learnings are the same and can be explained by ‘associative learning’ theory (Heyes, 2012). With regard to the recently developed knowledge around the neural mechanism of social learning(Behrens et al., 2008), illustrated that social reward-learning mechanism is also based on associative learning. Nevertheless, different input mechanisms are the divergence point of these two systems. Different input mechanisms might be developed in respect of perceptional, attentional, and motivational biases phylogenetically, ontogenetically or due to some other experiment-dependent neural development. In the social learning, the observer not only predicts the values of the environmental contexts but also the valuation of the observed individual's behaviors is principal.

Similar to experiential learning, reinforcement learning and associative learning are critical in the observational learning process. These two processes are vicariously involved while the observer observes the behavior of another individual. Social learning, likewise the experiential learning, is the corollary of Hebbian Learning. Hebbian learning can explain the adaptive process of social-based DM. Hence, the Eq. 3, describing the formation of cell assembly based on Hebbian theory, can be applied in the social context, as well. However, the impact of social variables, e.g. trust, on individual learning shouldn’t be disregarded. The effect of trust on behavior change, in this model, is considered by adding a variable to the Eq. 3 (i.e., Tr) proportional to the level of trust.

$$\Delta W_{ij} = \alpha g_i g_j (W_{max} - Tr.W_{ij}) \tag{7}$$

Allowing for the action and outcome predictions, two crucial determining factor of trust, Tr variable is contingent on the level of trust. The initial value of Tr is equal to 1 follwoing the general Hebbian learning rule.

As described in the experiential-based DM, OFC and LPFC are involved in goal-direct behaviors. These structures mainly participate in the emotional and rational valuation of the external stimuli, respectively. These two structures are also categorized as “social structures”, even though their oscillatory activities have also been observed in the individual contexts. In addition, the oscillatory activity of the LPFC’s neural units during the observation of others’ behaviors indicate the activities of mirror-like neurons in this neural part.

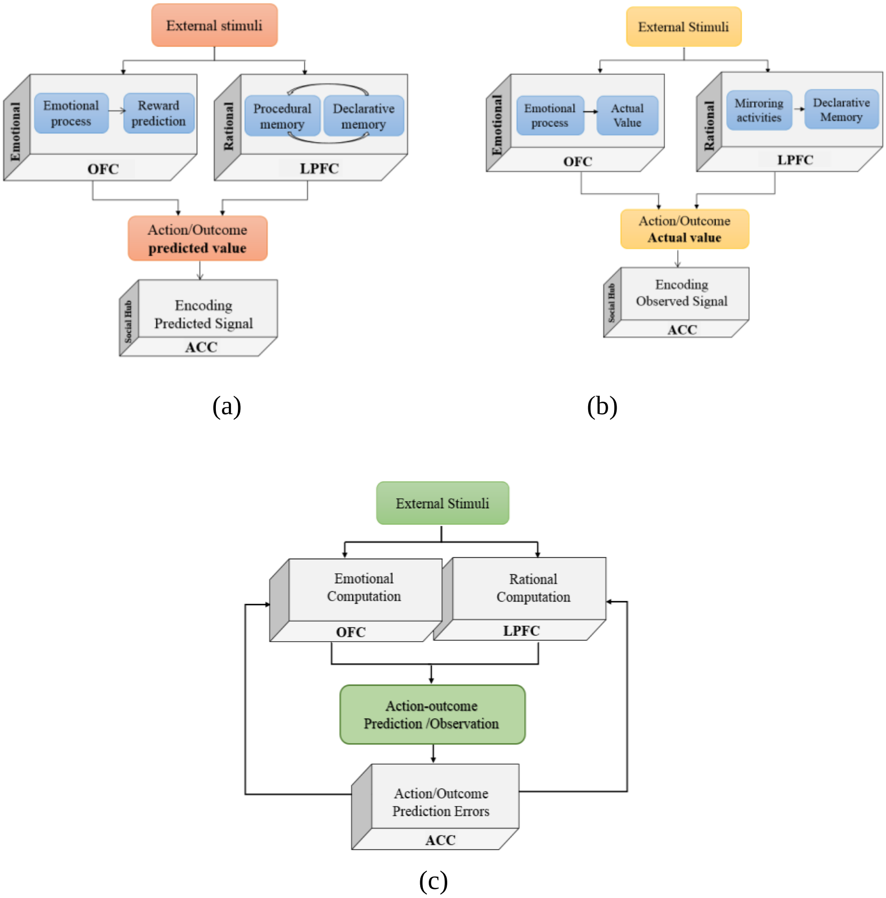


Figure 8 illustrates the schematic flow of information between neural structures involved in the observation-based DM. The oscillatory activities of neural units in OFC and LPFC represent the emotional and rational values of the observed action and outcome. ACC is a social hub in this model and receives the encoded predicted and actual (observed) values of the action/outcome projected by OFC and LPFC. The observed neural activities in ACC is the result of the difference between these values (i.e. action and outcome PE). These PE signals are projected to OFC and LPFC and update the emotional and rational cell assemblies corresponding to the observed action.

The described model in the first part is a basis for the DM in the social context. To simulate the impact of observational learning on the DM, the ACC and the mirror neuron system as the complementary social components have been added to the previous developed model. In this model, for the sake of simplicity, the amygdala is also excluded from the previous model.

ACC, as a social hub, plays a pivotal role in processing the social-based PE signals and updating the social values of OFC and LPFC. ACC receives the predicted and actual values of observed action-outcome from OFC and LPFC, integrates them and generates the prediction error signals, and projects them into OFC and LPFC to update the emotional and rational values of the observed action. This process makes it possible for the observer to learn from/about others through observing their actions and outcomes. Figure 8 illustrates the interaction between neural structures underlying observation-based decision making process. The action and outcome prediction process are illustrated in the figure (8. a) and (8. b), respectively. The emotional and rational updating processes based on the received PE signals from ACC is shown in figure (8. c).

The acquired knowledge from/about the alleged expert through observational learning influences the oscillatory properties of the neural patterns associated with the observed action as well as the trust level. The updated value of the trust level influences how the observer evaluates the decision options in the next decisions/day. Although interpersonal trust can be analyzed emotionally and rationally, here, this model only studies rational trust. Therefore, in this model, LPFC is the sole structure that contributes to trust formation.

The cell assembly presenting the observed individual (here, considered an expert to be followed) is associated with the cell assemblies representing the action-outcome association. Therefore, updating the action-outcome association leads to a change in the properties of the expert's associated cell assembly. Here, ACC plays an important role to update this system. Therefore, the projected signal from ACC to LPFC updates the cell assembly representing the action-outcome association which subsequently updates the oscillatory properties of the expert's associated cell assembly. In this regard, trust will change.

The way that probability is encoded in the brain, the neural representation of probability, is a key issue in neuroscience. It is generally assumed that the neural activities in an uncertain environment can appropriately be modeled by Bayesian theory (Doya, 2007, Knill and Pouget, 2004, Schultz and Dickinson, 2000, Rich et al., 2015).

Regarding the importance of the history of the action/outcome of the expert in the decision making process, the observational action and outcome predictions not only depend on the frequency of actions' selection but also the conditional probability of action-outcome association should be considered. In contrast to

Markov chain properties (Eq. 8.1), considering the recent state, Dynamic Bayesian Probability (DBP) takes the advantages of history of the actions and outcomes (Eq. 8.2). The equation (8.2) represents the probability of occurrence of an action at time n+1,X_{n+1}, given the past actions based on DBP

$$Pr(X_{n+1} = x|X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) = \Pr(X_{n+1} = x|\, X_n = x_n) \tag{8.1}$$

$$Pr(X_{n+1} = x|X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) = Pr(X_{n+1} = x|\, X_n = x_n) \times \Pr(X_n = x|\, X_{n-1} = x_{n-1}) \times \dots \times \Pr(X_2 = x|\, X_1 = x_1) \tag{8.2}$$

In this thesis, the neural excitability, strength of neural units' connections and strength of associative connections are central variables indicating the probability and likelihood of action/outcome happening.

The approach and attitude of the expert can be modeled by a sequential dependent probability distribution. Hence, here, DBP is deployed to adjust the neural oscillatory activities during observations. The predictive signals properties (i.e. mean peak value and frequency) is measured considering the observed actions/outcomes probabilities.

$$DBP = Pr(AO_{n+1} = r|AO_1 = r_1, AO_2 = r_2, \dots, AO_n = r_n) \tag{9}$$

where AO represents the action-outcome association and r_n indicates the desired rewarding outcome at time *n*. In this regard, the degree of consistency and competence of the observed expert can be measured with the help of DBP in the DM. The expert's consistency and competence determines the likelihood that the observer follows the expert.

Considering the uncertainties about the expert's actions and the subsequent outcomes, the oscillatory properties of the cell assemblies associated with the expert are measured based on the signal energy, E_s, dynamic probability, DBP and motivation to follow the observed individual $Q_{individual}$, (i.e. trust to the observed individual)

$$Signal\ value = E_s \times Q_{individual} \times DBP \tag{10}$$

The measured signal value is the magnitude of the prediction signal indicating what an observer has learned about the expert.

3 Simulation and results

As described in the previous section, under different scenarios, I intend to scrutinize the individual the DM at the experiential and social levels. In the following, the neural and behavioral results of the developed models will be presented in the order of the described scenarios.

It is important to mention that the presented results are not based on real-world behavioral data. However, the external inputs are defined in a reasonable range of visual stimuli. Therefore, the results illustrating the oscillatory neural activity are sensible within a realistic neural range, but the absolute numbers do not transfer any message. Undoubtedly, presenting exact numbers showing the required time to form an attitude or a habit depends on real behavioral data. The major message of the following results are the relative changes of behavioral pattern with regard to the neural changes.

3.1 Experience-based decision making results

Decision making is a value-based process influenced by internal and external circumstances (context). Therefore, measuring the values of the options is arguably the first step in studying the value-based DM.

3.1.1 Results from Paper I

Considering the role of the underlying neural activities in action selection, the intensity and excitability of the cell assemblies indicate the salience of the corresponding options. The number of cell assemblies associating the different responses to external stimuli corresponds to the number of options. In addition, as mentioned in Section 2, the Q value represents the level of neural arousal and motivation of the individual. Therefore, the larger Q value brings about the more excitable neural structure.

The emotional and rational values of the options (e.g. car/public/bike) are taken as the normalized magnitude of the product of the size, the (mean) amplitude and (dominant) frequency of the corresponding cell assembly, based on Eqn. (4). The detailed information about the measured values and the final decision based on the integration of the emotional and rational values in a sample situation can be found in Paper I.

$$V_{AMY=} [|s_{car}| \cdot \langle \overline{\boldsymbol{f}_{car}}, \overline{\boldsymbol{A}_{car}} \rangle, |s_{public}| \cdot \langle \overline{\boldsymbol{f}_{public}}, \overline{\boldsymbol{A}_{public}} \rangle,$$

$$|s_{bike}| \cdot \langle \overline{\boldsymbol{f}_{bike}}, \overline{\boldsymbol{A}_{bike}} \rangle]$$

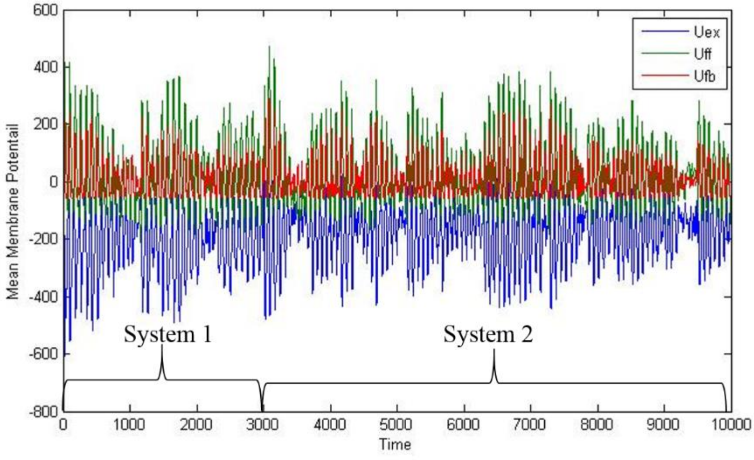
Similarly, the expectancy signal generated in OFC is measured. Following Eq. (6), the degree of similarity between the value of OFC and amygdala determines the final emotional value.

$$similiarity = \frac{\langle \overrightarrow{V_{OFC}} \,,\ \overrightarrow{V_{Amy}} \rangle}{||\overrightarrow{V_{OFC}}|| \cdot ||\overrightarrow{V_{Amy}}||}$$

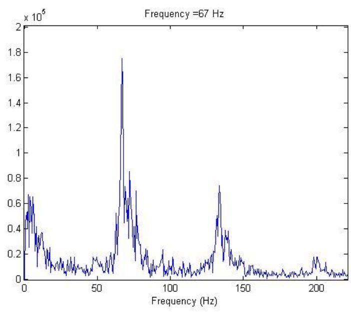
The final value of the options are the result of emotional and cognitive signal integration computed mathematically as follows. Taking account of the initial assumption, the individual has the same emotional and rational tendencies. Hence, the coefficient, is equal to 0.5.

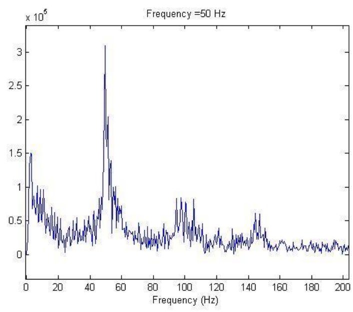
$$\vec{V}_{fin} = \ 0.5\vec{V}_1 + \ 0.5\vec{V}_2$$

The measured values (more details in Paper I) determine the strength of the correlating cell assemblies, for one simulation with a specific set of parameter values. The recorded EEG-like oscillatory activities of the neural patterns (i.e., car, bike, and public transport) are in the gamma range, i.e. around 40-90 Hz. Figure (9.a) shows the emotional and rational oscillatory activities of one of the options (i.e. car) in one frame. The simulated neural activity demonstrates the balance between excitation and inhibition in the network structure. The activity of excitatory neural units is shown with blue and the inhibitory activities at the feedforward and feedback layers are shown with green and red, respectively. The first 3000 ms illustrates the oscillatory activity of the cell assembly in system 1, and the following period, 3000-10000 ms, displays the activity of system 2. Different frequencies (Figs 9.b and 9.c) correspond to different preferences given to any of the options. The dominant frequency of a signal demonstrates the highest signal energy level. Therefore, a pattern with a higher dominant frequency has a higher excitability. The emotional and rational neural patterns oscillate with different excitabilities (figures 9.b and 9.c). The dominant frequencies of the emotional and rational oscillations in this particular example simulation are 67 Hz (fig 8.b) and 50 Hz (fig 8.c), respectively. The higher dominant frequency shows that the “emotional” excitability of cell assembly corresponding to car is higher than its rational value, in this particular case.



(a)

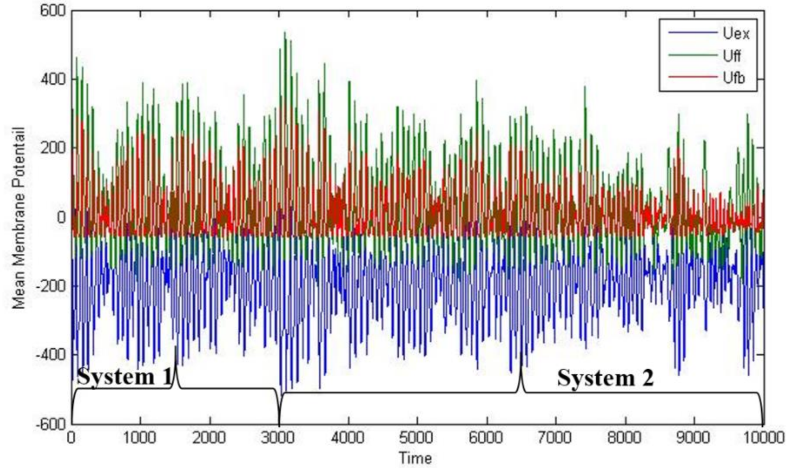




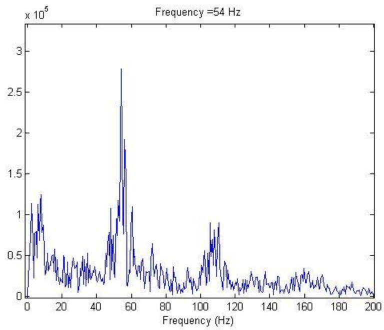
(b) (c)

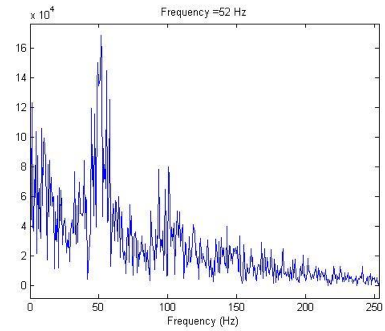
Figure 9 The balanced inhibitory and excitatory oscillatory activities of the OFC and LPFC structures representing the emotional and rational values of car. The value of the emotional dominant frequency (67 Hz) is higher than the rational dominant frequency (50 Hz), which shows that the emotional priority of this option is higher than its rational value.

The neural activity of the cell assemblies associated with public transport and bike are shown in Figures 10 and 11, respectively. These two figures show the corresponding emotional and rational activities of the mentioned options, respectively.



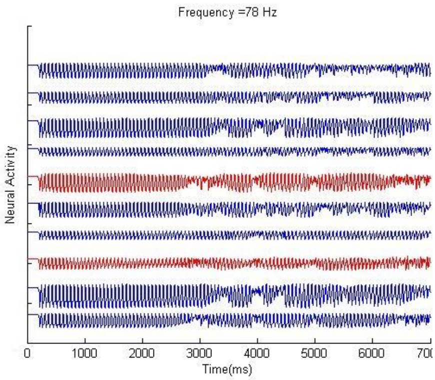
(a)

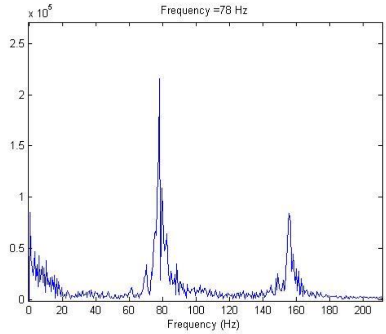




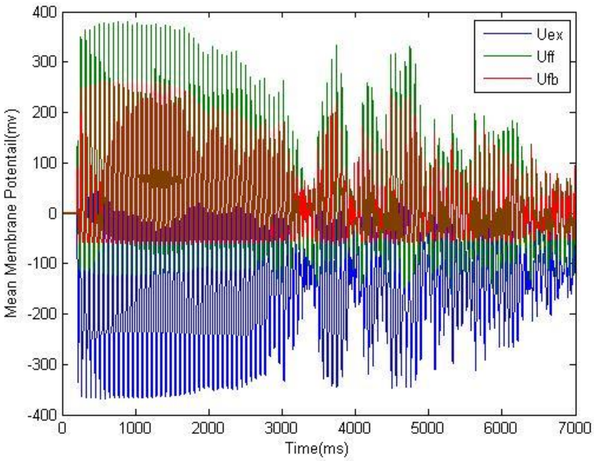
(b) (c)

Figure 10 The balanced inhibitory and excitatory oscillatory activities of the OFC and LPFC structures representing the emotional and rational values of public transport (a). The higher value of (b) the emotional dominant frequency (54 Hz) than (c) the rational dominant frequency (52 Hz) depicts that the emotional priority of this option is higher than its rational value.





(a) (b)



(c)

Figure 11 Cell assembly activity in System2, representing the rule-based goal in procedural memory. In the upper left frame (a), the activity of ten randomly chosen network nodes are depicted. The upper right frame, (b), shows the FFT frequency distribution of the network activity with the highest peak around 78Hz. The "mean membrane potential" of the feedforward and feedback inhibitory nodes, Uff and Ufb , are illustrated in the lower frame by green and red traces, respectively (c). The red traces represent the mean membrane potential, Uex, of the stimulated excitatory nodes and the blue ones are non-stimulated excitatory nodes.

The dominant frequencies of the above three neural assemblies show the rational priority orders of the three available means of transport. The illustrated rational dominant frequencies of car, public transport and bike are 50 Hz, 52 Hz and 78 Hz, respectively. On comparison, car has the lowest rational priority and bike has the highest rational value. Accordingly, the individual is (rationally) more prone to choose bike as a means of transport to travel between work and home. The above results illustrate the direct relationship between the value of the options and the excitability of the corresponding neural patterns. The neural pattern with the highest excitability and strength would be considered to be a final decision. Then, the individual experience the actual value of the decision. The difference between the predicted and actual value is a ground for the generation of the PE signal. The sign and the magnitude of the PE updates the stored emotional and rational attitude and its correlating neural excitabilities. A negative PE results in a decline of motivation in taking that option again in the future, while a positive PE increases the probability that the previous final decision will be selected once again in the next DM.

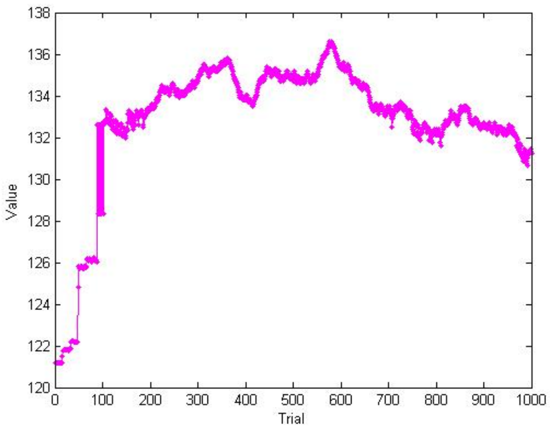


Figure 12. The illustration of fluctuations in the values of car resulting from the signaled prediction errors. The values of the y-axis denote the final values of the decision made in any trial. The difference between actual and predicted values yields a prediction error, which updates of the corresponding neural patterns in the OFC and LPFC. The sign of the prediction error affects the learning process in these two structures. A positive PE results in an increase in the neural excitability of associated patterns, while a negative sign makes the cell assembly weaker. The updated neural structures signal new prediction values of the options.

Figure 12 shows the changes of the final decision value in a particular example during 1000 trials/days. The variation of the value demonstrates the impact of the sign of PE on the increase/decrease of the value. As described above, the increased/decreased values show the increase/decrease in the neural excitability of the cell assembly associated with the made decision.

3.1.2 Results from Paper II

The developed neurocomputational model in the Paper I, serves as a ground for further studies about the behavior change of the decision maker influenced by the environmental contexts. The behavior/decision is based on the personal attitude, but can be modified depending on environmental conditions and internal state.

Based on the assumptions and underlying factors in our model, I could formulate a *hypothesis* concerning the role of negative *PE*:

As long as there is no negative prediction error, there is no behavior change, at least not in a short time.

To test this propositions, the following two scenarios are designed and simulated.

Scenario II. I study the influence of unpredicted events on the behavior of the individual who makes decision behavior. In continuation of Scenario I, the decision maker is considered to have a rational character, implying that the motivation to satisfy the rational attitudes is higher than for the emotional ones.

Throughout the simulation, the number of unpredicted events such as accidents, traffic jams increases, and accordingly the number of times that the individual experiences this, the negative PE increases. There is a relation between the number of negative PEs and the sign and magnitude of the slope of the motivational change. A lower frequency of unpredicted events, e.g. accident, results in a steeper slope of motivational change. An increase or decrease of motivation in selecting an option might lead to a change in priority order and subsequently in the decision.

The simulations show that a lack of sufficient negative external feedback (environmental) is the main cause of increasing the motivation for taking the car, instead of any other option. The higher frequency of unpredicted events reduce (the slope of) rational/emotional motivation for taking the car, while the motivation for taking public transport increases with a steeper slope. Increase of rational motivation for taking the *bike* is here due to the advice of those who are pro-environment, with a high trust level. The process of emotional motivation changes is the same as the rational one, except that motivation for taking the *bike* is constant. Emotional and rational motivation changes might result in a change in priority order. Generating sufficient negative prediction error causes priority order to be changed.

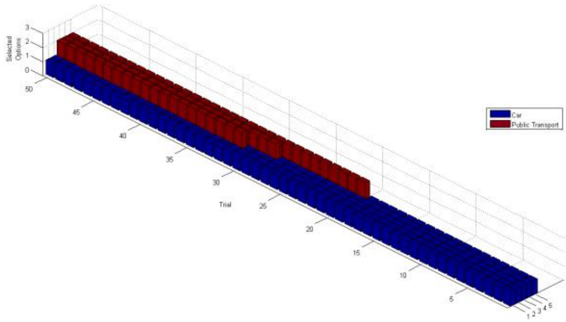
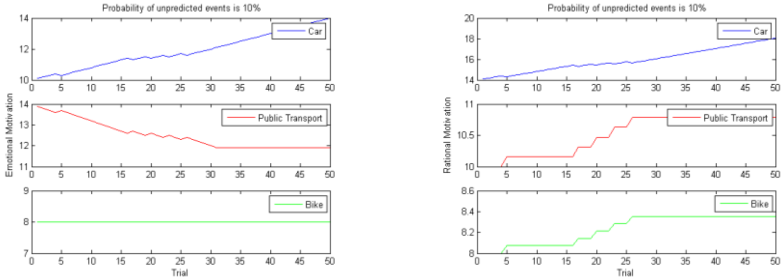


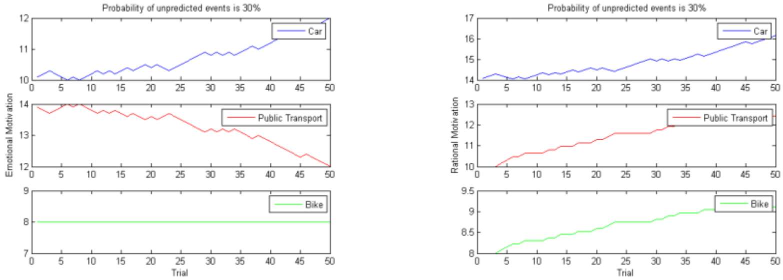
Figure 13 Priority order change while an individual is exposed to different levels of unpredicted events. The bars in blue represent the situation where the selected option is car, and the bars in red are the representation of public transport. The final decision changes during the third time interval while the probability of unpredicted events increased to 50 percent.

In the example of Fig. 13, the individual is in 5 different decision conditions. The probability of unpredicted events changes in different conditions. The probabilities are 10, 30, 50, 70 and 90 percent, here specified with the numbers 1, 2, 3, 4, and 5 frames respectively. As the figure shows the priority of the individual changes from car to public transport in the third condition after some days (here, 31 days) when the probability of unpredicted events is 50%. The number of days for behavior change depends on the importance of the event. Therefore, this value (31 days) does not necessarily simulate any real situation. What is important here is that the time required for the individual to change her priority order shortens with increase in frequency of unpredicted events. This is an example of a "system flip" of individual behavior that can result in a system flip at a societal level, if a large enough set of individuals are involved.

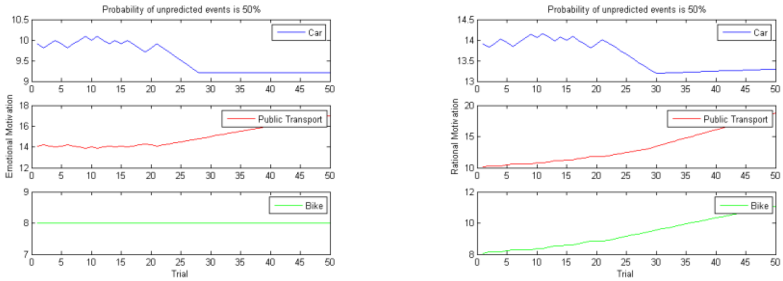
Another impact of unpredicted events is on the emotional and rational motivation of the individual for choosing a means of transport. The difference between the emotional and rational motivation is the result of a difference between the OFC's and LPFC's neural excitability. Therefore, the Q values in the emotional and rational structures, $Q_{emo.}$ and Q_{rat} respectively, are different. For example, the motivation to take the car is subject to negative influence of unpredicted events. During the first two frames, while the probability of unpredicted events is 10 and 30 percent, respectively, the level of motivation to take the car is greater than the motivation to choose public transport. In this case, an increase of the unpredicted event probability to 50% would provide a suitable base for changing the priority order.


Probability of unpredicted events is 10%
Car
Public Transport
Bike
Emotional Motivation
Rational Motivation
Trial

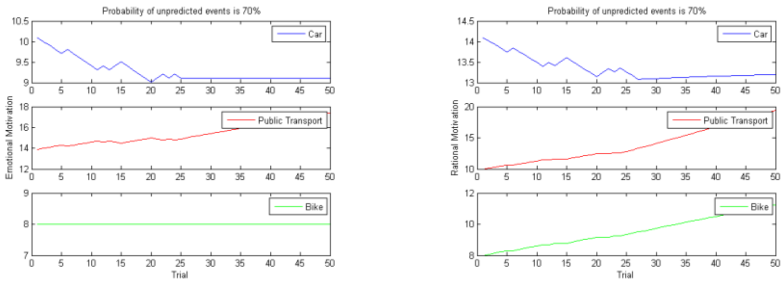
(a)


Probability of unpredicted events is 30%
Car
Public Transport
Bike
Emotional Motivation
Rational Motivation
Trial

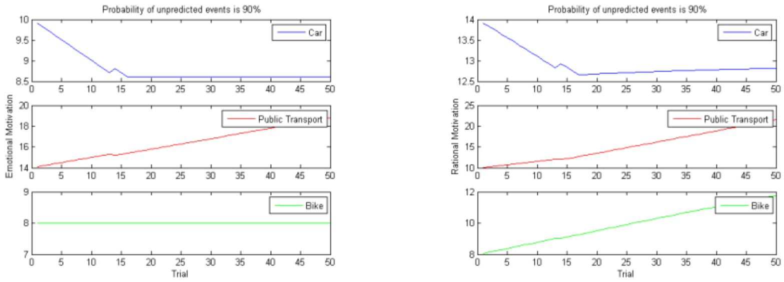
(b)


Probability of unpredicted events is 50%
Car
Public Transport
Bike
Emotional Motivation
Rational Motivation
Trial

(c)


Probability of unpredicted events is 70%
Car
Public Transport
Bike
Emotional Motivation
Rational Motivation
Trial

(d)



(e)

Figure 14 Rational and emotional motivation changes during five time intervals. The probability of the occurrence of the unpredicted events varies from 10, 30, 50 to 90 percent shown in figures (a), (b), (c), (d), and (e), respectively. Blue lines are for car, red for public transport, and green for bike. The emotional and rational motivation, $\mathrm{Q}_{\mathrm{emo.}}$ and $\mathrm{Q}_{\mathrm{rat.}}$ varies in different decision conditions. The increase in the probability of the occurrence of the unpredicted events leads to an increase in the emotional and rational motivation to choose public transport.

It is important to mention that changes in priority order should not be interpreted as a change of personality or attitude. Due to negative external feedback, the decision maker decides to change her behavior but not necessarily his attitude. As is illustrated in Fig. 14, after some trials the decision maker decides to change the means of transport, but not his attitude. The shortest line depicts the shortest path, with respect to required time to reach the goal.

Scenario III. In the second scenario, as in the first one, generating negative PE is the basis for changing the behavior and attitude of an individual. I study the impact of temporary policies on the behavior of the decision maker. An example of a temporary policy is an experiment made in Uppsala municipality, where car drivers could get a free bus ticket for one month, if taking the bus rather than their car to work. The policies lasts temporarily for 10, 30, 50, 70, or 90 days, respectively. The number of days a policy lasts has an impact on the emotional motivation of the individual for choosing a means of transport. As figure 15 shows the individual has a higher emotional motivation, $Q_{emo.}$, to choose public transport while the number of days the temporary policy implemented is higher.

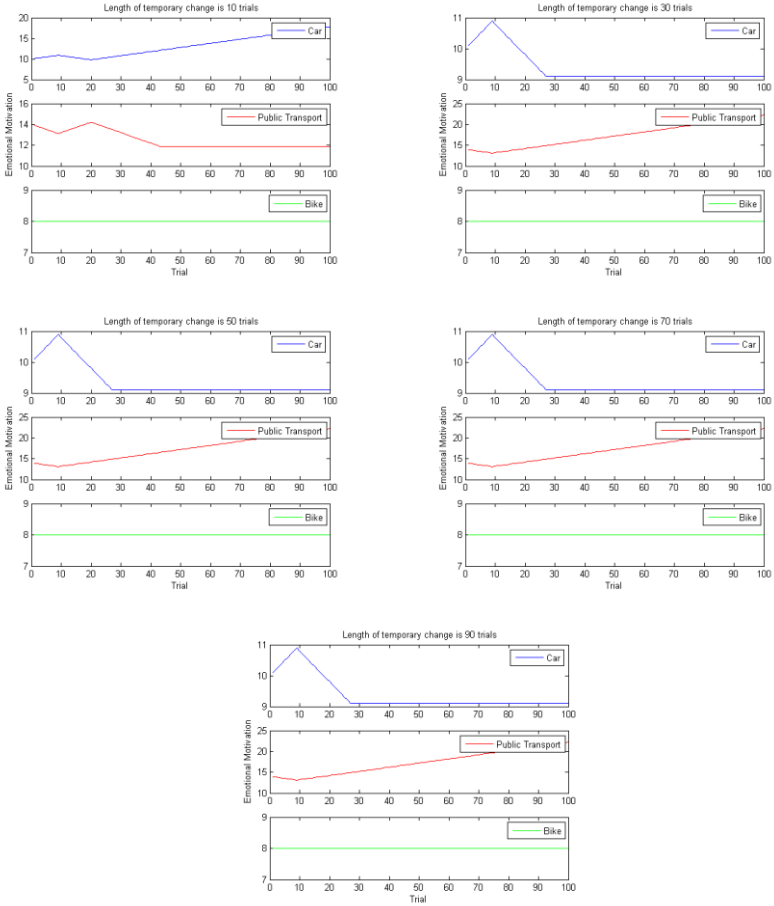


Figure 15. Emotional motivation changes during five time intervals. The length of implementing policies varies from 10, 30, 50 to 90 days, respectively. Blue lines are for car, red for public transport, and green for bike. The emotional motivation is based on the levels of $Q_{emo.}$ of the OFC's cell assemblies representing different means of transport. Increasing the length of temporary changes will increase the emotional motivation of the individual for choosing public transport to travel between work and home.

3.2 Social-based decision-making results

The idea behind the neurocomputational modeling of social-based decision making has been developed in continuation of the first two papers in this thesis, with transport as the same case example.

3.2.1 Results from Paper III

Social value is likewise considered a core aspect of the DM. In addition to the importance of the option to an individual, she should also decide about the value of other determinants (e.g. trust).

The scenario described has been simulated many times for one observer with different initial levels of emotional and rational neural properties. The illustrated results in this section represents one of the obtained results.

Influence of observational learning on trust in expert

The observation of the action and the subsequent outcome of an "expert" (e.g. friend/neighbor) might make an impact on the observer's trust in the observed person. Here, I assume trust to others is based on rationality. The presented definition of trust indicates that the rational trust would be raised in the wake of (action and outcome) consistency and competence of an observed person in

Based on the scenario, the observer observes her friend who is considered more of an "expert", taking public transport almost every day. She is almost always on time, and of course wealthy. The observer is supposedly pro-social. Hence, time, i.e. the outcome of choosing a means of transport, is important to her.

As mentioned, the concept of associative learning is strongly connected with the concept of goal-directed behavior. The observer makes an association between frequently observed action and the desirable outcome. In addition, the associative learning is a part of the social learning so that the observation of the expert who frequently makes one specific decision brings about an association between the expert and the observed action.

The neural oscillatory activity representing trust depends on the level of the arousal, which is determined by the quantity Q in Eq. 3. The observation of the desirable goal-directed behavior results in a change of the trust level. The changes in trust level corresponds to the changes in the neural excitability and strength of neural connection caused by augmented motivation (i.e., Q value). The neural oscillation representation of trust is analyzed the same as the neural activities of options. The dominant frequencies of the neural oscillations during a period of time that the observer observes the expert's action/outcome demonstrate different levels of trust. The more plausible the action-outcome association is, the more trustworthy the demonstrator and the higher neural excitability would be. To study the impact of trust on the neural arousal, a small $Q = 6$ value is set as an initial level of neural arousal of the LPFC's cell assembly associated with the observed individual. The oscillatory activity representing initial trust is shown in Figure 16. a. As Figure 16.b shows, the dominant frequency of neural pattern of trust equals to 50Hz.

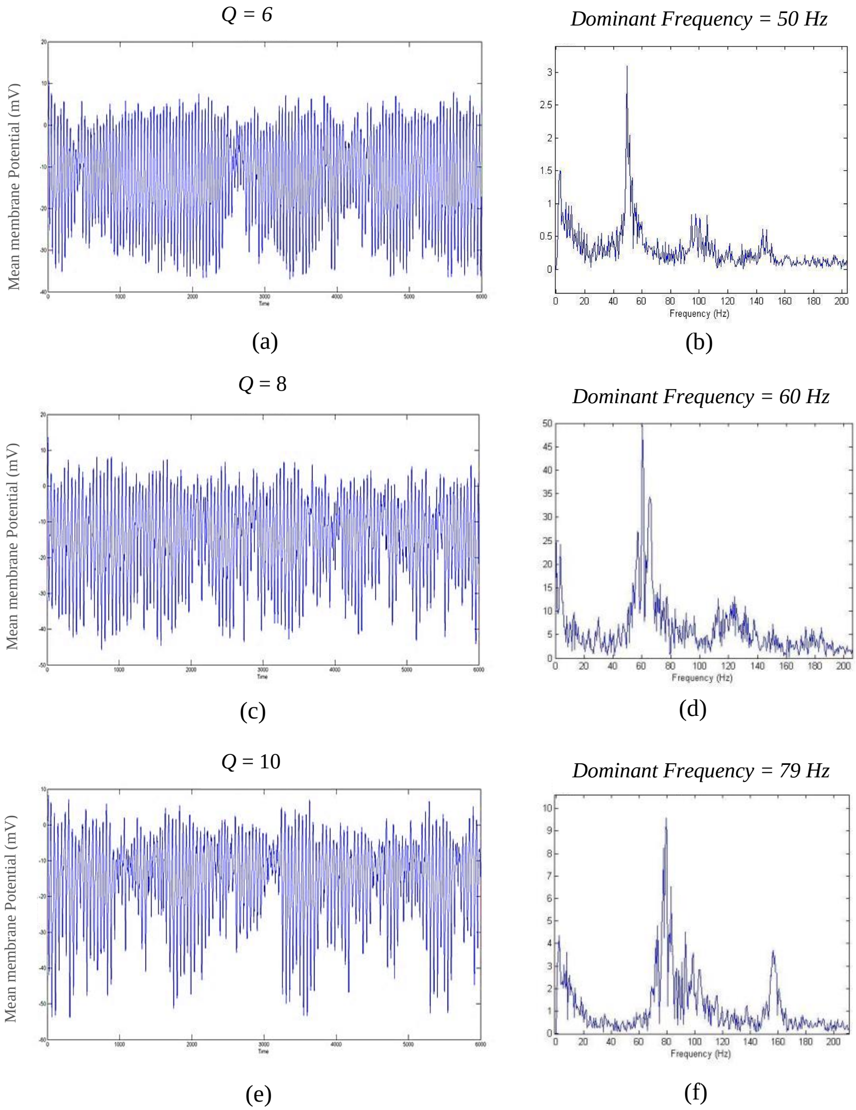


Figure 16 Oscillatory representation of trust. Different levels of trust are illustrated based on different levels of $Q_{rat.}$ values. The higher value of Q leads to the higher level of dominant frequency. Therefore, the neural oscillations representing the higher level of trust have higher energy and are more excitable.

The observation of the expert's action/outcome with high level of consistency and competence increases the Q value and subsequently the excitability of neural pattern corresponding trust in the expert (Figs. 16.c and 16.e). The increased dominant frequencies in figures 16.d and 16.f show the increased level of observer's trust and motivation to follow the observed action. The illustrated EEG-like data in figure 16 is simulated for the first, 20th and 40th observations of the expert's action and outcome.

The increase in the neural excitability reflects the changes in the neural connections weight. The figure 17 illustrates the changes of the neural weight connections of the pattern associated with trust.

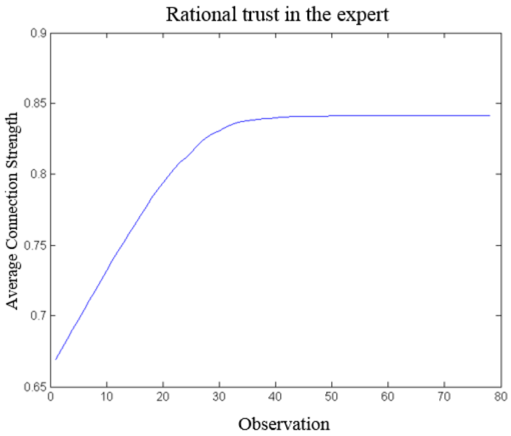


Figure 17 Illustration of changes in the trust level during observing the action-outcome of an expert. The high level of predictability of the expert (predictable rewarding action-outcome association) increases the strength of neural assembly representing the expert.

Figure 17 shows that the rate of changes in the neural connection weights decreases during the observation of the expert and connection will be saturated which determines the stability of the observer's trust in the expert. The increase in the strength of neural connections demonstrates an increase in the excitability of the cell assembly associated with the observed individual.

Influence of trust in expert on observational learning

Trust might have emotional and rational impacts on what an observer learns from others and can be manifested in the observer's prioritization in the decision making process. Here, I study the influence of the augmented trust on the observer's emotional and rational valuations.

Regarding the mentioned expert-action association, the increased excitability of neural patterns corresponding to the trusted expert results in an increase in the oscillatory activity of the associated action (i.e. public transport). The changes in the rational trust directly influences the rational value of the observed action (public transport) to the observer. Taking into account the modified Hebbian learning rule (Eq. 7), the rate of learning about the observed action changes. The learning process, is here based on the changes in the value of Tr. The variable Tr linearly changes when the trust level changes. The increase in the value of Tr results in the decreases in the learning rate.

In addition, regardless of the direct impact of rational trust on rational learning, the generated positive observational PEs have increased the excitability of the emotional and rational cell assemblies corresponding to public transport. Given the contextual information, with the help of the dynamic Bayesian probability, the observer estimates the contingencies of the expert's action and its outcome. According to the assumption, the expert has a high level of action and outcome predictability.

The predicted/observed actual emotional and rational signals are projected from OFC and LPFC into ACC. The result of the integration of the predictions and observed actual values is projected by ACC to OFC and LPFC. The projected positive/negative PE from ACC to LPFC and OFC, increases/decreases the emotional and rational neural arousal, $Q_{emo.}$and $Q_{rat.}$ respectively. Therefore, the OFC's and LPFC's oscillatory activity of the neural patterns corresponding to the selected option by the expert (here, public transport) increases.

Figure 18 shows emotional and rational learning curves. The orange curve in this figure illustrates the sigmoid-shaped rational learning rate of the cell assembly associated with the public transport. The illustrated increase in the level of rational trust in figures 16 and 17 positively changes the rational learning.

Considering the relationship between LPFC and OFC, LPFC is able to modify the activity of OFC. As a result of the LPFC's modification, the oscillatory activity of orbitofrontal cortex increases gradually but with lower learning rate.

During the illustrated process, the rational and emotional motivations of the individual to take public transport take different values. The OFC's and LPFC's neural oscillatory activities change during the observational learning process illustrated in figure 18.b, 18.c, and 18.d. The rate of increase in the rational connection weights (Fig 18.a, orange curve) is higher than the rate of increase in the strength of emotional pattern (Fig 18.a, blue curve).

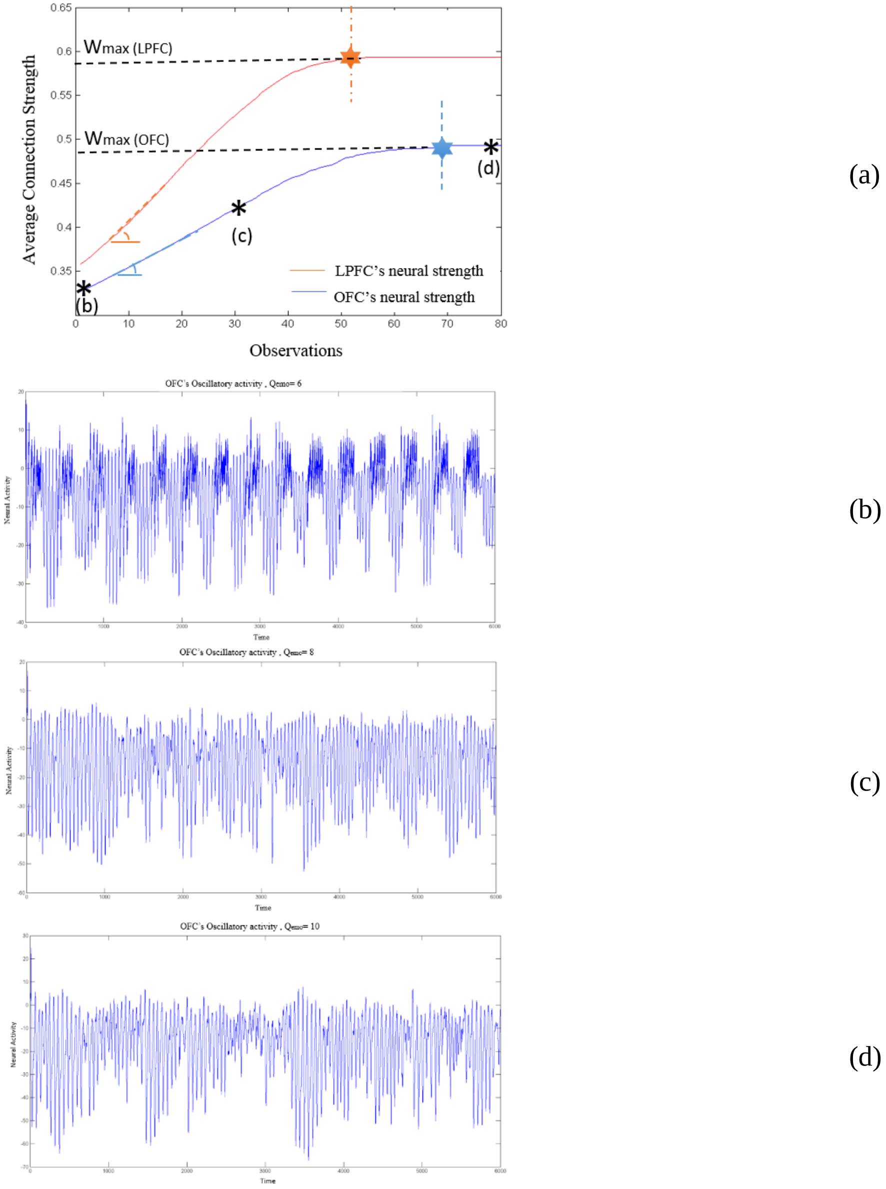


Figure 18 The illustration of the changes in the strength of neural connections in OFC and LPFC structures. The changes of the neural weights follow the sigmoid curve. The rational neural weight connections increases with a higher rate than the rate of emotional changes. The observation of the action and outcome of the expert makes an impact on the emotional preference of the observer. Her preference changes from car to public transport.

Thus, the rational neural connections become saturated (Fig. 18 orange dotted line) before the emotional neural pattern. In addition, the saturation level of LPFC's neural pattern is greater than the maximum strength of the OFC's corresponding pattern. In following, the properties of the emotional and rational cell assemblies associated with public transport during the observation of the expert's actions and outcomes are measured.

The excitabilities of the OFC's and LPFC's cell assemblies before the decision maker start observing the action and outcome of the expert is:

$$\vec{V}_{Emo.,t=1} = [\,Car, Public\ transport, Bike] = [0.2\ ,0.1, 0.08]$$

$$\vec{V}_{Rat.,t=1} = [\,0.1, 0.2\ , 0.05]$$

$$\vec{V}_{final.,t=1} = [0.4, 0.3, 0.1]$$

Based on my initial assumption, the decision maker is an emotional person. She is initially more prone to choose car. However, her rational preference is to take public transport. With regard to initial assumption, the initial emotional value of the public transport is less than its rational value. Hence, the mean neural weight of the emotional pattern of the public transport is less than the rational neural weight of this option. The strength of the cell assembly corresponding to public transport after observing the action-outcome association of the expert for 32 times is measured:

$$\vec{V}_{Emo.,t=30} = [\,Car, Public\ transport, Bike] = [0.223\ ,0.256, 0.089]$$

$$\vec{V}_{Rat.,t=30} = [\,0.15, 0.332\ , 0.051]$$

$$\vec{V}_{tot.,t=30} = [\,0.373, 0.588\ , 0.19]$$

The result shows that the increase in the excitability of rational neural pattern make a positive impact on the increase of emotional neural activities, but with lower changing rate.

3.3 Sensitivity analysis

The parameters in our system have been chosen based on what is known from the literature. Within reasonable ranges, they have been tuned to give plausible results. As with any biological system, the functioning depends on variables and parameters that have been tuned by evolution, perhaps to result in some kind of optimal solutions. Regardless, we have explored the sensitivity of our model system by changing the parameter values chosen, and tested the effect on system behavior. Typically, we changed the parameters by 10%, but in some cases even more, trying to push the system out of stability. The system is shown to be quite stable to variations in these (“natural”) ranges.

4 Discussion

In this thesis, I have pursued the aims of broadening our knowledge about the decision making process in individual and social contexts, as well as studying the impact of social and environmental variables on an individual's decision. I have done so by modelling parts of the neural systems playing major roles in the experiential and social-based DM. The results of my three papers can be discussed from the behavioral and neural perspectives. As mentioned in the previous sections, the obtained results demonstrate the relative correlation between the mesoscale neurodynamics of some neural structures and the subsequent macroscale cognitive process (i.e. decision making process). Given that the environmental and social inputs to the neural structures are not based on real-world data, specific conclusions about the detailed behavioral approach (e.g. required time to form an attitude or change a decision) cannot be inferred from the measured values shown in the figures.

In Paper I, I have modeled three neural parts involved in the experiential DM: Amygdala, orbitofrontal cortex and lateral prefrontal cortex. This model encompasses an input-procedure-action-feedback process from the first-person perspective. With the developed neuro-cognitive model, the main finding of the first paper is describing the emotional and rational structures involved in this flexible process. With the help of these two systems, the first model may predict the experience-based decision of an individual based on the external and internal context. The importance of considering the emotional and rational neural structures can be easily noticed based on the measured activities of OFC, amygdala and LPFC.

The significance of the emotional system has been highlighted with the modeling of Amygdala, which in contrast to LPFC and OFC, is exposed to the internal stimuli. Hence, the final decision in this model is a result of the influence of external as well as internal contexts. In fact, context could be considered as the combination of internal and external context.

In addition, taking OFC-amygdala interactions into consideration, modeling of OFC seems to be necessary for controlling final emotional values and responses. The difference between the projected emotional signals by OFC and amygdala illustrated in the first paper, clearly demonstrates this necessity.

The importance of modeling LPFC is not limited to its involvement in the rational valuation. The result of combining emotional and rational values draws special attention to the LPFC-OFC interaction as a major determinant for the final decision. This is the highlight of the contribution of LPFC in the DM by its role in modulating the OFC's activity. Accordingly, the final values for different options (e.g. car, public, and bike) show the attitude of the decision maker in specific contexts.

The discussion above describes the first three steps of the input-procedure-action-feedback process. The last step can be discussed with regard to the neural activity underlying the DM.

Taking the neural scale into account, this paper shows how differently cell assemblies, representing different optional choices available to an individual, may compete depending on their activity levels. This level, or intensity, of the activity was suggested to be a combined measure of the size of the cell assembly (number of network nodes), and the frequency and amplitude of the oscillatory activity of the nodes. The "winning" assembly is simply the one with the strongest neural activity, measured as the product of the three assembly characteristics (number, frequency, amplitude) and it determines the option that will be taken. The different options get different values, depending on internal and external factors. Internal factors could be attitudes, values, mood, while the external factors include traffic situations, availability, distance, etc. The neural connectivity and the excitability of the patterns determine the probability of selecting an option as the final decision. The more excitable a neural pattern is, the more valuable the corresponding option will be, hence increasing the probability of that option selection. The excitability of neural patterns not only depends on the external/internal states but also the actual value of the decision and its difference with the predicted ones. The excitability and strength of cell assemblies associated with the options change based on the feedback the decision maker receives from the environment. As a conclusion, the activity of cell assemblies associated with the options comprehensively reflect all the steps of the decision making.

The findings in this paper provide a basis for deeper studies about the influence of environmental variables on an individual's decisions.

Based on the first paper, the negative PE results in changing the value of the options. Considering this experience-based neural activities, in paper II, I have applied a broader environmental situation to scrutinize the changes in behavior.

The results show that there is an inverse relation between the number of unpredicted events and the time required to change the priority order. The higher probability of unpredicted events causes the decision maker to step across the threshold of behavior change faster. The higher probability of unpredicted events increases the magnitude of the negative prediction error, hence, the probability of behavior change is higher and the required time for this change is shorter.

In the second scenario, I have studied the direct relationship between the policy framework and an individual's decision. In this scenario, as in the first one, generating negative prediction error is the basis for changing the behavior and attitude of the individual. The results demonstrate that the mere implementation of policies is not enough, but the required time for implementing the policy is equally crucial to influence change of behaviors. Based on the results, a minimum length of implementation is required to change attitudes, and longer time does not make any difference.

Simulation results confirm the mentioned hypothesis related to the role of negative prediction error. The main finding of the scenario II and III is that a negative PE results in a decline of motivation in taking the associated option. In cases with low probability of negative prediction error, a changed behavior does not happen or will take a long time to occur. In the third scenario, I have found that there is a direct relationship between policy framework on higher costs/longer time and negative PE of taking car as a decision. Therefore, when implementing policies for, in this case, everyday traveling the outcomes of the various options (time and cost) should be a special target.

I have continued studying the behavior change of the individual making decision in a larger frame of context while the society is the influential variable.

In paper III, the social influences are confined to what an individual learns through observing an expert. Therefore, the mentioned input-procedure-action-feedback process has been studied from the third-person perspective. The decision maker observes the contingencies of the action-outcome of the expert. As the results show, the high degree of consistency of an expert's action and his competence considering the likelihood of the occurrence of the rewarding outcome make the observed expert trustworthy and the observed action worthy of following. The first result achieved in this paper shows that the more an individual observes a person with high level of predictability, the higher the level of trust in that person will grow.

An increase in level of trust in the expert is an evidence of the increase of the excitability of the neural pattern corresponding the expert. It was shown that the increased excitability of the neural units can be explained with respect to the increased neural weight connections and the Q variable. The higher the level of Q, the more excitable the neural units will oscillate. Hence, the changes in level of trust is proportional to the changes of Q value, and in addition, the higher level of trust is the result of more regular and less chaotic neural activity. The results also show that increased rational trust in an individual has a direct impact on how decision options are evaluated. The increased rational trust level has a positive impact on the rational and emotional preferences of the observer for the expert's action. As the trust level in the expert grow higher, the observer will become more motivated to change their action according to the expert's decision. The rational excitability of the correlating neural structure of the expert's decision (i.e. public transport) also increases but with the lower learning rate than the trust formation rate. Concurrently, the emotional excitability of OFC's neural pattern correlating to public transport will increase.

5 Conclusion and future work

Improving knowledge about the decision-making process has a positive impact on the quality of life at the individual and social level. Our bottom-up approach, from the neural oscillatory activities to the behavioral pattern, assists us to predict and generalize the individuals' behavioral patterns considering the internal and social states.

If we consider a human as an isolated person, the environmental and internal states, prior experiences, and their attitude sculpt their behavior. At the individual level, the levels of contribution of emotions and rationality to decision making, determine how an individual exploits the potentialities effectively. Climate change is one of the most critical issues that people around the world is struggling to control. Controlling our emotional and short gratified decisions influences our consumption style and climate. The more emotionally an individual reasons, the more their decisions will negatively impact climate change.

In addition, social learning plays a significant role in shaping human attitudes. A host of behaviors, from simple avoidance to complex skills, are acquired through social processes. The development of our cognitive and conscious abilities is largely influenced by our social interactions and also depends on trust in various forms. From this study, based on the described assumptions, the following conclusions can be drawn:

- The function of OFC and LPFC not only determines the emotional and rational individual's attitude in an isolated environment but also these structures are the essence of the decision-making process, enacting in a more complicated social context.
- The individual preferences and the probability of making a decision reflects the level of neural excitability and strength of emotional and rational neural patterns corresponding with the environmental and social variables.

- The experiential and observational reinforcement learning are the bases for individual learning either in the experiential or in the social contexts. The negative experiential/observational prediction errors give rise to the behavior change, while the positive prediction errors boost the value of an action.
- The changes in the level of trust in the observed person make an impact on the observer's valuation of the observed person's action emotionally and rationally.
- The changes in the rational valuation of options have a direct relation with the emotional value changes, based on the modulating role of LPFC.
- The rational process changes with the higher rate than the changes in the emotional processing. In this regard, the long gratified decisions as decisions on climate change would not be permanent as long as the changes in the emotional attitude have not been internalized.
- The observation of an expert with high level of consistency and competence engender trust in the observer. The increased trust in the observed expert increases the rational and emotional values of the selected option by the expert. These changes prompt the observer to change their decision.

There are many simplifications and assumptions made in our modeling. Given the proposed models and assumptions, and based on computer simulations, the preliminary conclusions need to be confirmed by empirical data to be fully appreciated. In a future development of our decision making model, I would like to include more biological, psychological, and social facts that to make the results even more realistic. Regarding the specific focus of the second part of this thesis, my intent for future research is to scrutinize the behavior of an individual in a social context, where the behavior and the subsequent outcome of an alleged expert/non-expert are evaluated by an observer. I have already designed a psychological experiment based on the described premise at the Emotion Lab at Karolinska Institutet. The preliminary results obtained from a pilot study seems promising. In a near future, this experiment will be run for a larger group of participants, and the obtained empirical data will be used for validation of our developed neurocomputational model.

References

ADOLPHS, R. 2009. The social brain: neural basis of social knowledge. Annu Rev Psychol, 60, 693-716.

ALBERT BANDURA, D. R., SHEILA A. ROSS 1961. Transmission of aggression through the imitation of aggressive models. Journal of Abnormal and Social Psychology, 63, 575-582.

ALLMAN, J. M., HAKEEM, A., ERWIN, J. M., NIMCHINSKY, E. & HOF, P. 2001. The anterior cingulate cortex. The evolution of an interface between emotion and cognition. Ann N Y Acad Sci, 935, 107-17.

ANDERSON, J. R. & MATESSA, M. 1997. A production system theory of serial memory. Psychological Review, 104, 728-748.

APPS, M. A., GREEN, R. & RAMNANI, N. 2013. Reinforcement learning signals in the anterior cingulate cortex code for others' false beliefs. Neuroimage, 64, 1-9.

APPS, M. A., LESAGE, E. & RAMNANI, N. 2015. Vicarious reinforcement learning signals when instructing others. J Neurosci, 35, 2904-13.

APPS, M. A., RUSHWORTH, M. F. & CHANG, S. W. 2016. The Anterior Cingulate Gyrus and Social Cognition: Tracking the Motivation of Others. Neuron, 90, 692-707.

BAKER, J. 1987. TRUST AND RATIONALITY. Pacific Philosophical Quarterly, 68, 1-13.

BALLEINE, B. W., LEUNG, B. K. & OSTLUND, S. B. 2011. The orbitofrontal cortex, predicted value, and choice. Ann N Y Acad Sci, 1239, 43-50.

BANDURA, A. 1965. INFLUENCE OF MODEL'S REINFORCEMENT CONTINGENCIES ON THE ACQUISITION OF IMITATIVE RESPONSES. J Pers Soc Psychol, 1, 589-95.

BANDURA, A. 1971. Vicarious and self-reinforcement processes.

. In R. Glaser (Ed.), The nature of reinforcement. New York: Academic Press.

BANDURA, A. 1977. Social learning theory, Prentice Hall.

BARBAS, H. 2007a. Flow of information for emotions through temporal and orbitofrontal pathways. J Anat, 211, 237-49.

BARBAS, H. 2007b. Specialized elements of orbitofrontal cortex in primates. Ann N Y Acad Sci, 1121, 10-32.

BAUMGARTNER, T., KNOCH, D., HOTZ, P., EISENEGGER, C. & FEHR, E. 2011. Dorsolateral and ventromedial prefrontal cortex orchestrate normative choice. Nat Neurosci, 14, 1468-74.

BAXTER, M. G. & MURRAY, E. A. 2002. The amygdala and reward. Nat Rev Neurosci, 3, 563-73.

BEDIA, M. G. & DI PAOLO, E. 2012. Unreliable gut feelings can lead to correct decisions: the somatic marker hypothesis in non-linear decision chains. Front Psychol, 3, 384.

BEER, J. S. & OCHSNER, K. N. 2006. Social cognition: a multi level analysis. Brain Res, 1079, 98-105.

BEHRENS, T. E., HUNT, L. T., WOOLRICH, M. W. & RUSHWORTH, M. F. 2008. Associative learning of social value. Nature, 456, 245-9.

BIELE, G., RIESKAMP, J., KRUGEL, L. K. & HEEKEREN, H. R. 2011. The neural basis of following advice. PLoS Biol, 9, e1001089.

BURKE, C. J., TOBLER, P. N., BADDELEY, M. & SCHULTZ, W. 2010. Neural mechanisms of observational learning. Proc Natl Acad Sci U S A, 107, 14431-6.

BUSH, G., LUU, P. & POSNER, M. I. 2000. Cognitive and emotional influences in anterior cingulate cortex. Trends in Cognitive Sciences, 4, 215-222.

CAMPBELL-MEIKLEJOHN, D. K., BACH, D. R., ROEPSTORFF, A., DOLAN, R. J. & FRITH, C. D. 2010. How the opinion of others affects our valuation of objects. Curr Biol, 20, 1165-70.

CAMPBELL-MEIKLEJOHN, D. K., KANAI, R., BAHRAMI, B., BACH, D. R., DOLAN, R. J., ROEPSTORFF, A. & FRITH, C. D. 2012. Structure of orbitofrontal cortex predicts social influence. Current biology : CB, 22, R123-R124.

CHANG, S., WINECOFF, A. & PLATT, M. 2011. Vicarious Reinforcement in Rhesus Macaques (Macaca Mulatta). Frontiers in Neuroscience, 5.

CHRISTODOULOU, C., BANFIELD, G. & CLEANTHOUS, A. 2010. Self-control with spiking and non-spiking neural networks playing games. J Physiol Paris, 104, 108-17.

CLARK, I. & DUMAS, G. 2015. Toward a neural basis for peer-interaction: what makes peer-learning tick? Front Psychol, 6, 28.

COHEN, J. Y., HAESLER, S., VONG, L., LOWELL, B. B. & UCHIDA, N. 2012. Neuron-type-specific signals for reward and punishment in the ventral tegmental area. Nature, 482, 85-8.

COLLINS, A. G. E., CIULLO, B. & FRANK, M. J. 2017. Working Memory Load Strengthens Reward Prediction Errors. 37, 4332-4342.

DAMASIO, A. R. 1996. The somatic marker hypothesis and the possible functions of the prefrontal cortex. Philos Trans R Soc Lond B Biol Sci, 351, 1413-20.

DE WIT, S. & DICKINSON, A. 2009. Associative theories of goal-directed behavior: a case for animal-human translational models. Psychological research, 73, 463-476.

DIXON, M. L. & CHRISTOFF, K. 2014. The lateral prefrontal cortex and complex value-based learning and decision making. Neurosci Biobehav Rev, 45, 9-18.

DOYA, K. 2007. Bayesian Brain: Probabilistic Approaches to Neural Coding, MIT Press.

DOYA, K. 2008. Modulators of decision making. Nat Neurosci, 11, 410-6.

EVANS, J. S. 2008. Dual-processing accounts of reasoning, judgment, and social cognition. Annu Rev Psychol, 59, 255-78.

EVANS, J. S. & STANOVICH, K. E. 2013. Dual-Process Theories of Higher Cognition: Advancing the Debate. Perspect Psychol Sci, 8, 223-41.

FREEMAN, W.J., 2000. Neurodynamics - An Exploration in Mesoscopic Brain Dynamics. London: Springer.

FREEMAN, W. 1979. Nonlinear gain mediating cortical stimulus-response relations Biological Cybernetics 33(4):237-47

FIGNER, B., KNOCH, D., JOHNSON, E. J., KROSCH, A. R., LISANBY, S. H., FEHR, E. & WEBER, E. U. 2010. Lateral prefrontal cortex and self-control in intertemporal choice. Nat Neurosci, 13, 538-9.

GALLESE, V., KEYSERS, C. & RIZZOLATTI, G. 2004. A unifying view of the basis of social cognition. Trends Cogn Sci, 8, 396-403.

GARIEPY, J. F., WATSON, K. K., DU, E., XIE, D. L., ERB, J., AMASINO, D. & PLATT, M. L. 2014. Social learning in humans and other animals. Front Neurosci, 8, 58.

GOLD, J. I. & SHADLEN, M. N. 2007. The neural basis of decision making. Annu Rev Neurosci, 30, 535-74.

GRAY, J. R., BRAVER, T. S. & RAICHLE, M. E. 2002. Integration of emotion and cognition in the lateral prefrontal cortex. Proc Natl Acad Sci U S A, 99, 4115-20.

GREDEBÄCK, G. & MELINDER, A. 2010. Infants' understanding of everyday social interactions: A dual process account. Cognition, 114, 197-206.

GUPTA, R., KOSCIK, T. R., BECHARA, A. & TRANEL, D. 2011. The amygdala and decision-making. Neuropsychologia, 49, 760-6.

HAUSER, T. U., IANNACCONE, R., WALITZA, S., BRANDEIS, D. & BREM, S. 2015. Cognitive flexibility in adolescence: neural and behavioral mechanisms of reward prediction error processing in adaptive decision making during development. Neuroimage, 104, 347-54.

HEYES, C. 2001. Causes and consequences of imitation. Trends Cogn Sci, 5.

HEYES, C. 2012. What's social about social learning? J Comp Psychol, 126, 193-202.

HUGHES, B. L. & BEER, J. S. 2012. Orbitofrontal cortex and anterior cingulate cortex are modulated by motivated social cognition. Cereb Cortex, 22, 1372-81.

IACOBONI, M., WOODS, R. P., BRASS, M., BEKKERING, H., MAZZIOTTA, J. C. & RIZZOLATTI, G. 1999. Cortical mechanisms of human imitation. Science, 286.

JENISON, R. L. 2014. Directional influence between the human amygdala and orbitofrontal cortex at the time of decision-making. PLoS One, 9, e109689.

JOHN, Y. J., BULLOCK, D., ZIKOPOULOS, B. & BARBAS, H. 2013. Anatomy and computational modeling of networks underlying cognitive-emotional interaction. Front Hum Neurosci, 7, 101.

JONES, R. M., SOMERVILLE, L. H., LI, J., RUBERRY, E. J., LIBBY, V., GLOVER, G., VOSS, H. U., BALLON, D. J. & CASEY, B. J. 2011. Behavioral and neural properties of social reinforcement learning. J Neurosci, 31, 13039-45.

KABLE, J. W. & GLIMCHER, P. W. 2009. The neurobiology of decision: consensus and controversy. Neuron, 63, 733-45.

KAHNEMAN, D. 2011. Thinking, fast and slow, First edition. New York : Farrar, Straus and Giroux, 2011.

KAHNEMAN, D. & TVERSKY, A. 1979. Prospect Theory: An Analysis of Decision under Risk. Econometrica, 47, 263-91.

KNILL, D. C. & POUGET, A. 2004. The Bayesian brain: the role of uncertainty in neural coding and computation. Trends in Neurosciences, 27, 712-719.

KOECHLIN, E. & SUMMERFIELD, C. 2007. An information theoretical approach to prefrontal executive function. Trends Cogn Sci, 11, 229-35.

LAK, A., STAUFFER, W. R. & SCHULTZ, W. 2014. Dopamine prediction error responses integrate subjective value from different reward dimensions. Proc Natl Acad Sci U S A, 111, 2343-8.

LALAND, K. N., ODLING-SMEE, J. & MYLES, S. 2010. How culture shaped the human genome: bringing genetics and the human sciences together. Nat Rev Genet, 11, 137-48.

LAVIN, C., MELIS, C., MIKULAN, E., GELORMINI, C., HUEPE, D. & IBANEZ, A. 2013. The anterior cingulate cortex: an integrative hub for human socially-driven interactions. Frontiers in Neuroscience, 7.

LEE, D., SEO, H. & JUNG, M. W. 2012. Neural basis of reinforcement learning and decision making. Annu Rev Neurosci, 35, 287-308.

LEE, V. K. & HARRIS, L. T. 2013. How social cognition can inform social decision making. Front Neurosci, 7, 259.

LEVINE, D. S. 2009. Brain pathways for cognitive-emotional decision making in the human animal. Neural Netw, 22, 286-93.

LEWICKI, R. J., MCALLISTER, D. J. & BIES, R. J. 1998. Trust and distrust: New relationships and realities. The Academy of Management Review, 23, 438-458.

LIEBERMAN, M. D. 2007. Social cognitive neuroscience: a review of core processes. Annu Rev Psychol, 58, 259-89.

LIEBERMAN, M. D. 2013. Social: Why Our Brains are Wired to Connect, OUP Oxford.

LILJENSTRÖM, H. & SVEDIN, U. (Eds.) 2016. Towards a Fossil-Free Society – In the Stockholm-Mälar Region. COMPLEX WP4 Final Scientific Report, Human Nature Series. Sigtuna: Sigtunastiftelsen, ISBN 978-91-976048-4-0. doi: 10.13140/RG.2.2.36656.97284.

LILJENSTRÖM H. 1995 Autonomous Learning with Complex Dynamics. International Journal of Inteligent Systems 10:119–153.

LILJENSTRÖM, H. 1991. MODELING THE DYNAMICS OF OLFACTORY CORTEX USING SIMPLIFIED NETWORK UNITS AND REALISTIC ARCHITECTURE. International Journal of Neural Systems, 02, 1-15.

LILJENSTROM, H. & WU, X. B. 1995. Noise-enhanced performance in a cortical associative memory model. Int J Neural Syst, 6, 19-29.

MEDALLA, M. & BARBAS, H. 2012. The Anterior Cingulate Cortex May Enhance Inhibition of Lateral Prefrontal Cortex Via m2 Cholinergic Receptors at Dual Synaptic Sites. The Journal of Neuroscience, 32, 15611-15625.

MONFARDINI, E., BOUSSAOUD, D., BROVELLI, A., WICKER, B., KEYSERS, C. & GAZZOLA, V. 2013. Vicarious Neural Processing of Outcomes during Observational Learning. Figshare.

MUKHERJEE, K. 2010. A dual system model of preferences under risk. Psychol Rev, 117, 243-55.

PALOMERO-GALLAGHER, N., MOHLBERG, H., ZILLES, K. & VOGT, B. 2008. Cytology and receptor architecture of human anterior cingulate cortex. J Comp Neurol, 508, 906-26.

PETRIDES, M. 2005. Lateral prefrontal cortex: architectonic and functional organization. Philos Trans R Soc Lond B Biol Sci, 360, 781-95.

PRIBRAM, K. H. 1987. The subdivisions of the frontal cortex revisited. The frontal lobes revisited. New York, NY, US: The IRBN Press.

REMPEL-CLOWER, N. L. 2007. Role of orbitofrontal cortex connections in emotion. Ann N Y Acad Sci, 1121, 72-86.

RICH, D., CAZETTES, F., WANG, Y., PEÑA, J. L. & FISCHER, B. J. 2015. Neural representation of probabilities for Bayesian inference. Journal of Computational Neuroscience, 38, 315-323.

RICH, E. L. & WALLIS, J. D. 2013. Prefrontal-amygdala interactions underlying value coding. Neuron, 80, 1344-6.

RIZZOLATTI, G., FOGASSI, L. & GALLESE, V. 2001. Neurophysiological mechanisms underlying the understanding and imitation of action. Nat Rev Neurosci, 2.

ROMPF, S. A. 2015. Trust and Rationality: An Integrative Framework for Trust Research, Wiesbaden, Springer Fachmedien Wiesbaden, Wiesbaden.

ROTTER, J. B. 1971. Generalized Expectancies for Interpersonal Trust. American Psychologist, 26.

SCHULTZ, W. 1998. Predictive reward signal of dopamine neurons. J Neurophysiol, 80, 1-27.

SCHULTZ, W. & DICKINSON, A. 2000. Neuronal coding of prediction errors. Annu Rev Neurosci, 23, 473-500.

SOKOL-HESSNER, P., HUTCHERSON, C., HARE, T. & RANGEL, A. 2012. Decision value computation in DLPFC and VMPFC adjusts to the available decision time. Eur J Neurosci, 35, 1065-74.

STALLEN, M., SMIDTS, A. & SANFEY, A. G. 2013. Peer influence: neural mechanisms underlying in-group conformity. Front Hum Neurosci, 7, 50.

WAGER, T. D., DAVIDSON, M. L., HUGHES, B. L., LINDQUIST, M. A. & OCHSNER, K. N. 2008. Prefrontal-subcortical pathways mediating successful emotion regulation. Neuron, 59, 1037-50.

WISE, R. A. 2004. Dopamine, learning and motivation. Nat Rev Neurosci, 5, 483-94.

ZHANG, W., SCHNEIDER, D. M., BELOVA, M. A., MORRISON, S. E., PATON, J. J. & SALZMAN, C. D. 2013. Functional circuits and anatomical distribution of response properties in the primate amygdala. J Neurosci, 33, 722-33.

ZILLI, E. A. & HASSELMO, M. E. 2008. Modeling the role of working memory and episodic memory in behavioral tasks. Hippocampus, 18, 193-209.

Popular science summary

Every day, we are bombarded with various types of information received from our surroundings. This information forms our mind-sets and attitudes as a guiding light for our decisions. We should not forget that we are a social creature and a part of the information that we receive comes from our society. It plays an undeniable role in forming our perspective on life. Social advice and social attachments are inseparable variables influencing the opinions and life styles of individuals. The outcomes of our decisions, primarily actions, make an impact on the environment. This perpetual interaction is a major concern in today's world. Decision making is one of the examples that underlies this interaction and climate change is its inevitable consequence. We deal with socially embedded decisions concerning various forms of consumption patterns, in particular the choice of transport between home and work. Making decisions about travel options is one of the most influential variables on the climate.

To tackle the issue of climate change, we need to investigate if and how people can change their decisions, and hence their behaviors, based on changed attitudes, beliefs and social information. In this regard, we have to address some questions, for example: How are individual decisions influenced by others and by various environmental conditions? How is it possible to enhance rational decisions in our daily life? How would emotion and cognition contribute to making decisions? Which kind of information processing affects our long and short term decisions?

In order to answer these questions, in this thesis, I've focused on the decision making process (DM) in the light of neuropsychology and cognitive neuroscience, taking the case example of every day travel decisions. The main goal is to explore the relationship between the micro (neuron), meso (brain structures), and macro (cognition/behavior) scales in the DM in the experiential and social context. I am using neural network modeling as the main tool in realizing my goals. The developed neural network model maneuvers on two different approaches of individual and social aspects of decision making. Mainly, I focus on the neural structures of brain areas involved in DM.

The modelling of orbitofrontal cortex, lateral prefrontal cortex, and amygdala and their interactions, satisfy the first aim of this thesis at the individual level of DM. Adaptive decision making process is realized under the interactions of individuals, where trust as a social capital is a crucial aspect of social cognition. Social learning, perception, and decision making are strongly linked to the concept of trust. In the second part of this thesis, I've studied the impact of social variables, i.e. trust, on the individual decision making process. Considering the transport case example, I've developed further the original model by adding the anterior cingulate cortex to scrutinize the individual decisions, i.e. ways of traveling to work, influenced by social variables.

Understanding DM is helpful, not only for individuals, but also for organizations, authorities or other policy makers and businesses, who wish to influence the behavior of people. Given the proposed models and assumptions, and based on the computer simulations, we can still make some preliminary conclusions. However, it is important to consider that changes in climate based on the alternative strategies emerge after a long period of time. Therefore, by modifying our behaviors that align our lifestyles with the interests of the environment, we can bequeath a healthy environment to the next generation.

Populärvetenskaplig sammanfattning

Varje dag bombarderas vi med olika typer av information som tas emot från vår omgivning. Denna information påverkar våra tankesätt och attityder som är grunden för våra beslut. Vi får inte glömma att vi är sociala varelser och en stor del av den information vi får kommer från vårt samhälle, vilket spelar en viktig roll för våra perspektiv på livet. Sociala råd och sociala band påverkar våra åsikter och livsstilar och resultatet av våra beslut och handlingar har en inverkan på miljön. Denna ständiga interaktion mellan människa och miljö skapar ofta problem i dagens värld, inte minst klimatförändring. Människors beslut i vardagssituationer, t.ex. vad gäller konsumtions- och resvanor, har stora konsekvenser för miljö och klimat.

För att ta itu med klimatfrågan måste vi undersöka om och hur människor kan ändra sina beslut, och därmed deras beteende, baserat på förändrade attityder, övertygelser och social information. I det avseendet måste vi ta upp några frågor, till exempel: Hur påverkas enskilda beslut av andra och av olika miljöförhållanden? Hur är det möjligt att ta mer rationella beslut i vårt dagliga liv? Hur skulle känslor och kognition kunna bidra till att fatta klimat- och miljövänliga beslut? Hur behandlar vi (våra hjärnor) inre och yttre information, och hur påverkar denna informationsbehandling våra kort- och långsiktiga beslut?

För att kunna svara på dessa frågor har jag i denna avhandling fokuserat på den individuella beslutsprocessen (DM) i ljuset av neuropsykologi och kognitiv neurovetenskap, och tar som exempel vardagliga resebeslut. Huvudmålet är att undersöka förhållandet mellan mikro- (neuronala), meso- (hjärnstrukturer) och makro- (kognition/beteende)-nivåer i DM, för såväl individuella som sociala sammanhang. Jag använder neuronnätsmodellering som huvudverktyg för detta ändamål. Den neuronnätsmodell som jag utvecklat tar hänsyn till både individuella och sociala aspekter av beslutsfattandet. I huvudsak fokuserar jag på neurala strukturer i de hjärnområden som anses vara involverade i DM.

Modelleringen av orbitofrontala barken, laterala prefrontala barken, samt amygdala och deras interaktioner uppfyller det första syftet med denna avhandling på den individuella nivån av DM. En adaptiv beslutsprocess uppnås genom individens sociala interaktioner, där förtroende (tillit) är en viktig aspekt av den sociala kognitionen. Social inlärning, uppfattning och beslutsfattande är starkt kopplade till begreppet förtroende. I den andra delen av denna avhandling har jag studerat konsekvenserna av sådana sociala variabler, dvs förtroende, på den enskilda beslutsprocessen. Med tanke på exemplet med resevanor har jag vidareutvecklat originalmodellen genom att lägga till den främre cingulära barken för att studera hur de enskilda besluten, dvs hur vi väljer att resa från hemmet till arbetet, påverkas av den sociala interaktionen.

Att förstå hur vi fattar beslut är till stor hjälp, inte bara för individer, utan även för organisationer, myndigheter eller andra beslutsfattare och företag som vill påverka människors beteende. Även om det för närvarande saknas relevanta data för att testa våra modeller, kan dessa ändå ge vissa insikter i hur våra beslut påverkas av såväl individuella som sociala faktorer, och några preliminära slutsatser kan göras. Bland annat visar de på att attityd- och beteendeförändringar normalt tar lång tid, och kräver att såväl det rationella som det emotionella tänkandet får påverka våra beslut. Det gäller då att vi ändrar vår livsstil och tänker mer långsiktigt och mindre själviskt för att kommande generationer ska kunna leva i en hälsosam miljö och i ett drägligt klimat.

Acknowledgements

The first part of this Licentiate thesis has been part of a European research program, “COMPLEX”, with the aim of developing new methods for building up a more complete picture of climate change and its underlying factors.

First of all, I would like to thank and express the deepest appreciation to my supervisor, Professor Hans Liljenström for his guidance and critical review of the research output at various stages. I am very grateful for his persistent advice and support in various ways from the very beginning. His follow up on the writing phase and careful review of the final manuscript are also highly appreciated.

I would like thank Professor Åsa Mackenzie and Professor Dietrich von Rosen for providing valuable guidance and support throughout this study.

I would like to thank Dr. Andreas Olsson for providing a unique opportunity for me to be part of his group at the Emotion Lab at Karolinska Institutet. His guidance and advice have been great help for me to develop the second part of this thesis.

I would like to thank my beloved husband for his strong support during this period. Undoubtedly, he has played a great role in this success. His understanding, patience, love and encouragement when it was mostly required helped me to overcome the tough moments in these years.

I would like to thank my parents and my brother for their unconditional love, support, and constant encouragement and guidance throughout my entire life. I do believe that it has been an absolute privilege for me to be raised by them.

Finally, I would like to thank my friends and colleagues who directly or indirectly helped me during my Licentiate studies.

Appended Papers