Decision making and the brain: Imprecision handling reflected in the light of neuroeconomics

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1 Introduction

Neuroeconomics is a multidisciplinary research field, that applies brain imaging technology to explaining economical theories in human behavior. Particularly decision making and game theory have been under study. The focus is on describing and verifying the decision making mechanisms underlying choices with measured brain stimulus. The research involves mathematicians and economists furthermore psychological and behavioral theorists. The measurements are often carried out in contact with medical neuroscientists. The results of neuroeconomical studies are widespread. The results involve human cognition and planning abilities, that are in close contact with social sciences (cognitive psychology), language processing, learning skills and even with juridical discussion through criminal behavior.

Decision making theories, among other behavioral studies, can be approached from two different angles: from a descriptive paradigm or from a prescriptive paradigm.
The former is concerned with empirical observation of actual behavior in choosing tasks, whereas the latter assumes a rational decision maker who follows principles in an ideal manner. The true understanding of decision making behavior, following contemporary thinking, is found by interconnecting the two paradigms finding a model that combines the rational intentions with an emotional filter to an actual outcome. The field of neuroeconomics strives for finding economical and mathematical theories correlation in brain function with modern brain activity measurement devices such as fMRI, EEG, MEG and PET.

First the central imaging techniques applied in brain research are introduced. Then neuroeconomics is approached from a prescriptive angle and research topics that support the viewpoint are demonstrated. The third column is devoted to descriptive studies on neuroeconomics. Then in the fourth column the PAIRS model is introduced and finally the suggestions for neuroeconomical application to PAIRS are defined.

2 Imaging Techniques in brain research

Several imaging techniques have been used to explore the structural and functional properties of the brain. Here is briefly explained their function and use in brain imaging.

- **fMRI** functional Magnetic Resonance Imaging. Magnetic resonance imaging (MRI) technique provides very precise anatomical images of brain sections. They are acquired by setting the tissue under a strong, uniform magnetic field. In medical applications the field strength ranges from 0.3 to 3 Teslas, in laboratory use the equipment reaches 20 Tesla fields. The magnetic field forces the atomic nuclei with non-zero spin number to align either parallel or antiparallel to the magnetic field lines. A brief electromagnetic pulse is exposed to the tissue which causes some hydrogen atoms to relax from the aligned position. This creates an echo respective to material’s hydrogen density that can be detected. Thus, bones due to low hydrogen content are pictured with lesser accuracy, whereas fat and water containing tissues are depicted in fine details. Functional MRI measures the change in blood flow. The oxygenated hemoglobin is dimagnetic, but as the active tissue consumes the oxygen, the hemoglobin turns paramagnetic with the level of deoxygenation. The magnetic resonance signal is therefore different, which can be detected with a sequence of RF pulses to form the Blood Oxygenation Level Dependent BOLD contrast. The fMRI is accurate in spatial resolution, but in temporal resolution it is not as creditable due to the dependence on blood flow but not the electrical dynamics of the neurons. Here are shown many examples of fMRI scans a.a in picture13.

- **EEG** Electroencephalography. Electroencephalogram presents the electrical activity of the current brain functioning. Activity is measured from the altering potential between the electrodes placed on the scalp. EEG can not show each action potential or whether the potential is excitatory or
Figure 1: Examples of different wave types acquired with EEG.

inhibitory in nature, but it represents an overall synchronized response. The wave types are known for normal behavior such as relaxed alert state (α, 7 – 13 Hz), anxious concentration (β, 13 – 25 Hz), problem solving (γ, 25 – 80 Hz), light sleep (θ, 3.5 – 7 Hz). From EEG scans can be detected also the less normal activity patches characterizing states typical for epilepsy, abnormally low activity (δ, 0.5 – 3.5 Hz) and drug confused activity (WAIS). The spatial resolution of EEG is poor, even when using EEG topography to triangulate the source the technique cannot compete with fMRI. However, EEG has a very high (< msec) time resolution and it is the only alternative to measure direct brain activation avoiding the disturbance of metabolism in the results. The limitations in spatial resolution can be improved with simultaneous PET or fMRI scans.

MEG

Magnetoecephalography. Magnetoecephalography measures also the direct activation of the neurons. The electric currents of neurons are the size of one picotesla (10^{−15} T), which create weak magnetic fields. These fields are measured with ultra sensitive SQUID-sensors and disturbances, a.o. the Earth’s magnetic field, are prevented with a shielded laboratory and noise cancellation algorithms. The electric current originates from the
net electric current in the dendrites. Currents deriving from action potentials elicit magnetic fields, that cancel out due to opposite flow directions. To reach the measurable strength of field approximately 50,000 active parallel oriented neurons are needed, therefore MEG measures often the pyramidal cell layer activation of cortex. The difficulty with MEG imaging is related to the proof of Helmholtz in 1850 known as the inverse problem, which states that even if the electrical and magnetic fields were known exactly around the source, the primary currents cannot be uniquely defined. The best result is therefore under keen discussion and the most common techniques for finding it are using a conductance model of the head and an iterative localization algorithm or using blind source separation method of independent component analysis ICA or using source localization techniques e.g. SAM (Synthetic Aperture Magnetometry). MEG has very good temporal and spatial resolutions.

PET  Positron Emission Tomography. PET is a nuclear medicine imaging device. It is based on radiotracer imaging technique, where positron emitting labels are attached to the subject of the study and their decay at the active location is detected producing a three dimensional map of functional processes in the body in vivo. A radiotracer (e.g. FESP or FDG is commonly used with dopaminergic processes) travels a few millimetres in tissue before annihilating with an electron. The annihilation produces two 511 keV photons traveling in opposite directions. The technique relies on simultaneous detection of the pair of photons: photons which do not arrive in pairs (i.e. within nanoseconds) are ignored due to their probable origin from different sources. The photons are detected with scintillator material bismuth germanate BGO. The scintillator converts their wavelength to light of a wavelength which can be detected by photomultiplier tubes.
Figure 3: Example of a PET image where human dopamine system is presented in healthy subject and in Parkinson’s decease case.

(PMTs). PMT detectors multiply the signal produced by incident light as much as $10^8$ times stronger signal for further processing required in image reconstruction. PET is a functional imaging device. The anatomical information is usually acquired from a CT or MRI scans.

3 Prescriptive approach to neuroeconomics

3.1 Expected Utility: Utility theory

Expected utility theory describes an individual preference order of selected goods. Expected utility was first developed by Daniel Bernoulli [1] describing a theory for goods with a known utility value. The theory was further proceeded by John von Neumann and Oskar Morgenstern [3] adding the uncertainty of the outcome into definition. The developed theory describes the decision maker’s belief in acquiring the desired outcome as well as an individual value for the magnitude of desire in each case. Expected utility is defined in its simplest form by utility function $u : C \rightarrow \mathbb{R}$ for which

$$x \succ y \Leftrightarrow \sum_C x(c)u(c) > \sum_C y(c)u(c)$$

(1)

for all $x, y \in X$

where $X$ is a set of finite support probability distributions (lotteries) and $C$ is a set of mutually exclusive outcomes of decision (consequences). $\succ$ denotes a preference
relation. It is also assumed that $X$ is closed under every binary operation $\otimes_\lambda$ in a set of operations for

$$\lambda \in [0, 1]$$

with

$$x \otimes_\lambda y = \lambda x + (1 - \lambda)y$$

Bernoulli was convinced that people generally are risk averse. His model is logarithmic, strictly concave and thus the expected utility value for a given good is always less than it’s calculated objective value. Von Neumann and Morgenstern developed the model for utility value further. They introduced risk neutral and risk seeking models, where desire for a good is the same as or even exceeding the objective value respectively.

**Neuroeconomic approach to expected utility**

Knutson et al [2] present a descriptive standpoint in their research on desire, utility and preferences. Their results imply that anticipation of risky decision making task activates thalamus, dorsal striatum and specifically for gain outcome, ventral striatum region of nucleus accumbens, NAcc. They find that the intensity of NAcc stimulation is proportional to anticipated gain magnitude. Positive gain outcome causes increased activation in medial prefrontal cortex, MPFC, whereas loss outcome deactivates the MPFC region. Additionally the anticipative activation is more likely to increase excitement towards the upcoming gain. The activation in MPFC influences the steering of the NAcc driven excitement and arousal by learning from experience through discrimination of a wanted anticipated outcome and an experienced loss. The anticipated loss generated brain stimulation in the thalamus and medial caudate in dorsal striatum as for anticipated gain only lacking NAcc activation.

### 3.2 Decision Making under Uncertainty: Prospect Theory

Prospect theory was first developed by D. Kahneman and A. Tversky [4] in 1979 and it still is the most common model of behavioral utility under risk. The DM’s subjective value is presented by a function that is concave for gains, convex for losses and steeper for losses than gains (4). The value function

$$V(x, p) = v(x)w(p)$$

is a probability distribution of all possible outcomes. It is divided in two components where $v(x)$ is a measure for subjective value of consequence $x$ and $w(p)$ denotes the impact of probability $p$ to the attractiveness of the lottery. Uncertainty is presented with the weighting function $w(p)$ that overweights low probabilities and underweights high probabilities. This is parameterized with value function

$$v(x) = \begin{cases} \lambda^\alpha x \geq 0 \\ -\lambda(-x)^\beta x < 0 \end{cases}$$

(2)
where $\alpha, \beta > 0$ denote measures respectively for gains and losses. $\lambda$ is a coefficient for loss aversion. Loss aversion grows in importance as $\lambda$ increases. Weighting function for probabilities is defined as

$$w(p) = \frac{\delta p^\gamma}{\delta p^\gamma + (1-p)^\gamma}$$

where $\gamma > 0$ measures the degree of curvature and $\delta > 0$ stands for elevation of weighting function. Weighting function ranges from impossibility to certainty, $w(p) = 0$ to $w(p) = 1$. Three principal differences in respect to utility theory are

- Utility function represents the individual value for wealth whereas prospect theory value represents the individual value for gains and losses in respect to a reference point $v(0) = 0$.
- The value function is not relative to outcome probability but to a decision weight, $w(p)$, that defines the value of the probability to the decision maker rather than the probability itself.
- Prospect theory allows framing and editing the decision. Decision maker tends to alter the decision based on the same prospect due to changes in values over time and different representations of the values.

**Neuroeconomical approach to prospect theory**

Here are presented the findings of Trepel et al.[5] concerning neural basis for prospect theory. In order to follow the description two terms must be introduced. Firstly, decision utility is related to weight of an outcome which affects decision making. Secondly, experience utility is of a hedonic value of utility.

The main focus of prospect theory is naturally in decision utility. However, the weight is often strongly influenced by the experienced utility value that the outcome
pursues. The distinction between the different types of utility is important in understanding human processing of reward and punishment. There is experienced reward and punishment that corresponds to experienced utility whereas anticipated reward and punishment reflect decision utility.

In the following the brain structures are described that in the light of recent studies are believed to give rise to decision making procedures corresponding to prospect theory.

**Dopamine system**

Dopamine (DA) is a neurotransmitter that is produced in midbrain, in the areas of substantia nigra pars compacta and the ventral tegmental area presented in figure (5). Dopamine pathways are responsible for motivated behavior and decision making (mesocortical pathway), reward, addictions and pleasure (mesolimbic pathway) as well as motor control (nigrostriatal pathway). The dopaminergic system is the primary substrate for the representation of decision utility because dopamine neurons increase their firing in the presence of unexpected rewards but decrease firing as the reward is assumed. However, DA is not solely responsible for pleasurable reward and thus lack of DA does not prevent a hedonic sensation, but transforms i.e. “wanting” into less inspiring “liking”. It is also believed that dopaminergic systems may code the degree of risk associated with decision.

![Figure 5: Schematic representation on dopamine system. Olfactory bulb and mesolimbic system are routes used in motivated behavior due to reward.](image_url)
Ventral striatum (caudate nucleus and putamen)

Ventral striatum integrates signals between the prefrontal cortex shown in figure(??), amygdala and hippocampus. Recent studies indicate that it is critical for experiencing anticipated reward and specially it increases firing as an anticipated reward rises in magnitude during a risky investment turning to winning business or at a certain gain.

![Figure 6: Location of striatum (putamen)](image)

Prefrontal cortex

The prefrontal cortex shown in figure (??) is a large area responsible for planning, learning, cognitive and social behavior and expression of personality. In decision making different areas of prefrontal cortex take part in different tasks.

- Dorsolateral prefrontal cortex (DLPFC) is maintaining and manipulating cognitive representations of working memory. It also takes part in planning future actions that rise from those representations. Patients with lesions in DLPFC have difficulties in understanding strategies or rules and particularly applying them in their behavior.

- Ventromdial prefrontal cortex (VMPFC) appears to imply responses of anticipated losses. Patients with lesions in VMPFC have normal reactions to experienced losses but do not develop normal responses in risky choices. Areas in VMPFC are stimulated also as experiencing reward but not when anticipating reward.

Amygdala

Amygdala, which is shown in figure (7), plays an important part in learning and in emotions. It is quite a complex structure that is essential in fear responses and also
learning from stimuli that arise these fear responses (e.g. perception fearful face responses). Amygdala is stronger associated with negative responses than positive but not exclusively.

Amygdala is responsible for representing experience utility for losses as well as in decision utility when outcomes are negative. Patients with amygdala lesions have difficulties in learning to choose a less risky alternative in decision making tasks. It is suggested that amygdala is also involved in anticipatory fear for loss and thus with lesion patients this fear is unrecognized.

Figure 7: Location of amygdala

**Neural representation of prospect theory**

These findings are merely suggestions how the neuroscientific evidence could be related to prospect theory since any firm proof is yet unfound.

1. Shape of value function is similar for both gains and losses which implies that a common structure explains this behavior. Striatum appears to fire for both gain and loss related information. However, Yeung and Sanfey[16] have found also conflicting material, where losses and gains arise stimulation in different structures.

2. Loss and risk aversion. The value function is usually 2-3 times steeper for losses than for gains of equal amount and for mixed prospects loss aversion accounts for risk aversion. The ventral striatum is connecting the positive and negative value signals from all the structures of decision-making and thus has access for coding both types of prospects. Moreover, amygdala and VMPFC are involved in learning due to reward association and also risk aversion. Decreased learning abilities connect to decreased risk aversion. Also noradrenaline and serotonin
driven systems are believed to have effect on amount/steepness of loss aversion but not as strongly to the curvature of value function.

3. The S-shape of weighting function is believed to characterize psychophysics of diminishing sensitivity. Another suggestion is that the behavior of overweighting low-probability losses and underweighting high-probability gains reflects fear that could involve amygdala. Similarly behavior of overweighting low-probability gains and underweighting high-probability losses reflects hope, that involves ventral striatum. The neural basis for these suggestions still lack proof.

4. The elevation of weighting function is assumed to follow impulsivity, given that an impulsive participation in gambles would elevate weighting function, parameter $\delta$. This suggests that DA- and serotonin systems are involved as they are involved in impulsive behavior as well.

5. Passive framing, valuation, operations are due to spontaneous processing taking place in limbic and basal ganglia regions. On the contrary, active framing and editing operations are governed by rule-based, cognitive processing taking place in lateral and dorsomedial cortices.

There is a growing interest in finding neural basis of decision making procedures which still remain in a suggestive level. Future work will be needed to find neural proof for cognitive and behavioral strategies now presented in theoretical form.

Neuroeconomics and prospect theory were combined by C Trepel, C Fox and R Poldrak [5], who found the neural mechanisms that underlie the dynamics of prospect theory. Their results comprise a detailed description of activation in brain regions involved in risky decision making and means for further edition of previous outcome.

For value function $v(x)$ (2) anticipated gain causes increasing dopamine release driven activation in ventral striatum as well as in ACC anterior cingulate cortex. Anticipated losses activate amygdala. Additionally, experienced gains activate both dorsal and ventral striatum. Dorsal striatum is found to process experienced reward magnitude and valence, whereas ventral striatum is responds to anticipated and experienced rewards. Moreover, ventromedial prefrontal cortex, VMPFC, is activated by experienced gains and it is responsible for evaluation of rewards and preferences. Amygdala reacts for loss aversion through noradrenaline mediated activation.

For weighting function $w(p)$ (3) overweighting with a low $p$ causes ventral striatum activation and underweighting with a high value of $p$ activates amygdala.

Trepel et al. found that alteration of decision making task require complex processing. Lateral and dorsomedial prefrontal cortex areas process the controlled cognitive, rule-based evaluation tasks, whereas spontaneous, affective estimation processing takes place in limbic and in basal ganglia areas.

4 Descriptive approach

Descriptive approach to cognitive brain research initiates with task creation. The outcomes of the task set a basis for hypothesis and the theory is developed from the starting point of explaining the actual results.
4.1 Predicting error likelihood stimulation in anterior cingulate cortex

Predicting error likelihood in the Anterior Cingulate Cortex

In this report Brown and Braver [6] develop a computational model to detect how Anterior Cingulate Cortex, ACC, that is known to take part in goal-directed behavior, represents a likelihood of conflict between actual and intended events. The focus is in dynamic behavior, because ACC does not only fire in situation of detected error, but also the intensity of response is proportional to the perceived likelihood of an error in each situation. Thus ACC is a center for estimating risk of an intended event in near future. ACC is located in deep midbrain area in frontal cortex as seen in figure (8).

![Figure 8: Location of Anterior Cingulate Cortex, ACC](image)

In this paper Brown and Braver develop a computational model of how ACC may represent a prediction of error likelihood, especially how it develops through experience. Also the implications of the model are in focus. In the error-likelihood hypotheses a training signal is also found that gives rise to ACC stimulus specific behavior. Phasic midbrain dopamine neuron activity is critical in reinforcement learning and the phasic suppression of dopamine apparently gives rise to error-related negativity. This training signal may be dopaminergic as phasic dopamine suppression taking place in error situations may give rise to ACC activation that is stronger when stimulus is more frequent.

Hypothesis testing

The hypotheses has been tested with two computer models and their correlation to ACC activation with fMRI. The first model is a variant of the well-known stop-signal paradigm for inhibitory control. From previous work concerning human testing presents that stop-signal trials are connected with increased ACC activity. The task consisted
Figure 9: Subjects were shown a series of blue or white cues and asked to push a certain button or another depending on a direction of an arrow. From brain imaging data could be found that since blue cues contained higher probability for errors ACC reacted finally to just blue colour with stimulation providing an early warning signal for learned risk.
of conditions with high and low error rates and with a presence or absence of conflicting response, schematic representation is showed in figure (9). Assessment of error-likelihood model were acquired with comparing correct trials without response conflict through high and low error-rate conditions when controlling response conflict and errors.

In the computational model simulated ACC neuron units received stimuli. As error occurrences were tested ACC received an error signal representing phasic suppression of affarent dopaminergic signals. ACC firing was recorded adaptive as the stimulus-specific input signal increased the firing and the error was present. Also as weights increased in activated stimulus inputs the firing decreased in inactive stimulus units. The model was directly compared with a competing model of ACC function where coactivation of incompatible response representations cause the measured response conflict by ACC. In this model input synaptic weights were fixed, not adaptive as in stimulus-specific model, and their origin was in the response rather than in stimulus.

In both models, activity from ACC excited a control signal that sent continuous, nonspecific inhibition to the response layer. This control signal is found to account for the adjustments of repetitious trials in behavioral performance caused by ACC activity fluctuations.

**Results**

Both error-likelihood and conflict models represented an equivalent behavioral performance which had a good fit to human behavioral data but lacked neuroimaging data support. The current results also provide evidence for an error-likelihood account of ACC function. The magnitude of ACC activity is used to train ACC to signal when predicting a likelihood of an error occurring in response to a given task. The error-likelihood model predicts that the ACC activity arises in proportion to negative reinforcement. This system is highly adaptive forming an early warning function for required cognitive control. In addition, the results support the hypothesis of dopamine driven training signal in ACC accounts for reinforcement learning as well as recruitment of cognitive control.

Conflict and error detection ACC effects are regarded as special cases of the error-likelihood model. Because errors generally occur more often in conflicting situations, response conflict effects in ACC may represent a higher error likelihood rather than an explicit computation of conflict per se. An additional connection from frontal medial activity response to ACC layers in the model could provide ACC a selective response to particular combinations of stimuli and internal representations of incorrect response execution, which are highly predictive of undesired consequences.

The error-likelihood model and the theoretical framework have proved to provide a tool for understanding how error, conflict and error-likelihood prediction effects can be acquired by ACC via continuous exposure to task environments. Moreover, the results illustrate the benefits of integrating neuroimaging data and computational modeling for hypothesis generation and theory testing in the neural mechanisms of cognition.
4.2 Decision making abilities of lesion patients

Brain lesion study is the classical technique for examining brain function, dysfunction and their impact on cognition. The first lesion studies were performed already three centuries ago. Despite the new imaging techniques that have revolutionized the information available in the field of brain research, some of their problems are solved with lesion studies. For example the depth of magnetically applied cognitive impairment, 'transient lesion', is limited to quite superficial brain areas. Lesion studies also provide a significant support for other research results.

An interesting lesion study directly concerning decision-making is carried out by Manes, Sahakian et al. [8]. In this study the focus is in finding the association between human prefrontal cortex and practical decision-making tasks. The patients are divided into four groups according to their lesion type (OBF - orbitofrontal group, DL - dorsolateral group, DM - dorsomedial group and Large - large frontal lesions' group) and they are also compared with a healthy control group (CTRL). Groups are tested with three tasks to examine their cognitive performances and six neuropsychological tests to describe differences in recognition memory, working memory, planning ability and attentional set-shifting skills of different groups. Decision making tests are here more interesting. They include: The Iowa Gambling task, that is developed by Bechara et al. [9], the Gamble task and the Risk task, both developed by Rogers et al. in [10] and [11]. The Iowa Gambling task tests how eagerly the subject is to increase risk taking in order to reach a higher reward versus a safer outcome alternative with low risk but also lower outcome. The Gamble task separates the risk-taking behavior from probabilistic nature of decision making by first giving an opportunity to bet for an outcome and thereafter set a confidence estimate (from 5% to 95%) for their bet. The Risk task follows the procedure of the Gamble task with the difference, that this time the confidence for the choice is preset and fixed. Now with each choice the subject wins or loses the given outcome when the choice is made right or wrong respectively.

The results concerning the neuropsychological differences form a distinctive trend where the orbitofrontal group performed best of the lesion groups and the Large group managed worst in comparison with the healthy Control group. The common deficiency in all lesion groups was the lengthened deliberation times independent of the decision quality.

The results in decision-making tasks prove, that the group of unilateral lesion in orbitofrontal cortex patients perform outstandingly well. The only true difference to control group found, was again the long deliberation time, as was also in other lesion groups, but the decision making quality was promising. The dorsomedial, dorsolateral and large lesion groups chose rather a less likely but a higher risk containing alternatives than controls. Among these the large group was most often the most divergent of the others.

The results emphasize that in cognitive processes the size of the lesion and additionally damage to both dorsal and ventral prefrontal cortex areas are crucial features to impaired decision making.

As an application to further decision making stimulation studies even with perfectly healthy subjects this lesion study can be used to focus the attention to lateral stimulation in decision making and also into dorsomedial and dorsolateral prefrontal cortices as
they here account most for the impaired performance in decision-making tasks.

4.3 The formation of motivation in brain

Above are presented the central dynamic models of decision making. I would like to emphasize with a paragraph an important component of decision making process: motivation and action selection. Action selection concentrates on mechanisms of choosing the best action to perform next. In other words action selection forms preference hierarchies over alternatives available. Reinforcement learning has similar features when focused on the mechanism, since it is also based on the choice of continuing the action that causes pleasure or wanted outcome. The pleasure that purely arouses from the action or from the acquired outcome is experienced primarily due to activity in dopamine driven circuits in fore and mid brain. The dopamine circuits in mid brain take place in basal ganglia, which comprises a control device for sensorimotor action, but is recently considered to play a significant part in cognitive choices, learning and decision making.

A very detailed explanation of the loop architecture of basal ganglia is found in McHaffie et al. paper [15], that primarily concentrates on sensorimotor paths but assumes that the same procedure applies also to emotional and cognitive tasks as the basal ganglia input and output nuclei include limbic and cortical structures.

Dopamine is the most interesting neurotransmitter in basal ganglia involved with cognitive processing. Dopamine functions in several ways and it is found in four circuits: mesocortical, mesolimbic, nigrostriatal and tuberoinfundibular pathway:

- The mesocortical pathway connects the ventral tegmentum to the frontal lobes. It is essential to the normal cognitive function of the dorsolateral prefrontal cortex and is believed to be involved in motivation and emotional response.

- The mesolimbic pathway links the ventral tegmentum area to the nucleus accumbens. In nucleus accumbens dopamine transmitted connections are processed into feelings of pleasure, reward, desire and the neuropsychological state of addiction.

- The nigrostriatal pathway connects the substantia nigra with the striatum. It is part the basal ganglia motor loop and is primarily involved in production of movement.

- The tuberoinfundibular pathway runs between the hypothalamus and the pituitary gland and it is involved in hormonal regulation, maternal behaviour, pregnancy and sensory processes.

These circuits take place or begin in basal ganglia, that is a set of nuclei consisting of striatum, external and internal segments of globus pallidus, subthalamic nucleus and substantia nigra(11) or in close contact to it such as VTA ventral tegmental area. In the globus pallidus can be found two cortical zones that are heavily involved in cognitive processes: First the peri-principalis region of the prefrontal cortex appears to mediate the encoding of spatial working memory. Secondly the area TE of the inferotemporal
Figure 10: Dopamine pathways.

Dopamine is involved in visual working memory. Thus, in addition to projections to motor cortical areas, basal ganglia output influences cortical regions that are involved in working memory and perception.

Dopamine conveys feelings of desire, enjoyment and addiction. In addition, it makes our attention absorb into subjects considered important. These subjects may also elicit fear or caution, not solemnly pleasing feelings or rewarding outcomes. Thus, dopamine creates a preference order for attention. In addition, the lack of dopamine causes severe disease in humans such as ADHD, Tourette’s chorea, and Parkinson’s disease (picture (3)), that cause deficits in attentional set shifting, working memory, planning and problem solving.

5 Decision making model of preference assessment by imprecise ratio statements

Often a traditional decision-making model assumes an exact and complete model, which is monotonous and time consuming to calculate. Additionally it is quite inapplicable in modeling human decision-making processes, that is based on approximation and heuristics described closer by Cairns et al. in [13], and sometimes also on a wild guess. Preference Assessment by Imprecise Ratio Statements, PAIRS, model of Salo and Hämäläinen [12] is an efficient tool for decision making under imprecise infor-
Figure 11: Coronal slices of human brain showing the basal ganglia, globus pallidus: external segment (GPe), globus pallidus: internal segment (GPi), and more caudally subthalamic nucleus (STN), substantia nigra (SN).

mation. The model converts the approximations into value intervals and dominance relations with linear programming. Also an interesting feature from neuroscientist’s point of view is the flexibility of the model in the possibility to revise the interval judgment during the procedure. It also enhances the achieving of the outcome by finding the most preferred alternative(s) before all the judgments are executed. This is very distinctively following a normative paradigm as studies in paragraph 2 (??)

Intervals are defined as follows: Interval model assumes linear preference order such that the interval judgments can be written

\[ I_{ij} = [l_{ij}, u_{ij}] \]  

where \( u \) is an upper bound and \( l \) is a lower bound for defining relative preference of \( i \)th to \( j \)th attribute. In the mutual, crossing area constrained by intervals, a feasible region can be found, that satisfies all requirements set with attributes for the alternatives. In figure (12) feasible region is found for interval judgment of \( I_{12} = [1, 2] \) and \( I_{13} = [1, 3] \). When the value function is imprecise there is a range of values available for each alternative. For any fixed set of local weights the value of alternative \( x \) is

\[ v(x) = \sum_{a_i \in \tau} w_i v_i(x_i) \]  

Due to the functional independence of the outcome of \( x \) on attribute \( a_j \) can have any value in the range of \([v_j^{-}(x), v_j^{+}(x)]\) regardless of other values on other attributes. Thus, the lower \( v(x) \) and the upper \( v(x) \) bound of an imprecise function is defined as

\[ v(x) = \min \sum_{a_i \in \tau} w_i v_i(x) \]  

\[ v(x) = \max \sum_{a_i \in \tau} w_i v_i(x) \]  

respectively to compute the maximum (or minimum) value for alternative \( x \).
Pairwise dominance plays an important part in finding the feasible region. Pairwise dominance is defined as

\[ \min_{a_i \in T} \sum_{a_i} w_i [v_i(x) - v_i(y)] > 0 \]

i.e. alternative \( x \) dominates alternative \( y \) if for any fixed set of feasible local weights the value of the worst outcome in \( x \) is greater than the value of best outcome in \( y \). Thus regardless of further narrowing \( x \), the relation of \( x \) and \( y \) remains unchanged and is always more preferred of the two.

Even though PAIRS does not force the DM to find the value intervals in a specified order, it is helpful to begin with too wide intervals that can be defined along the procedure to prevent inconsistent or redundant judgments. Inconsistent judgments leave the feasible region empty whereas redundant judgment adds on evaluating work but does not have an effect on result. For all attributes \( a \) in the feasible region, we assume that the exists a local weight at \( a_k \) that gives \( a_i \) a strictly positive value to \( a_i \), i.e. for all

\[ \tilde{v}(x) = \max_{a_i \in T} \sum_{a_i} w_i \tilde{v}_i(x) \] (8)

Because quite clearly \( a_i \) would not have relevance for \( a_k \) if the upper statement does not hold. Consistency bounds define the effect earlier judgments have in relation of attributes \( a_i, a_j \in (a_k) \) where

\[ I_{ij} = [\hat{l}_{ij}, \hat{u}_{ij}] \]
when

\[ \hat{u}_{ij} = \max_{s \in S_{ik}} \frac{s_i}{s_j} \]  

(9)

\[ \hat{l}_{ij} = \frac{l}{\hat{u}_{ij}} \]  

(10)

\( u_{ij} \) gets value \( \infty \) when \( s_i > 0, s_j = 0 \) and value 0 when \( s_i = s_j = 0 \). As defined above (8) \( s_i > 0 \) for some \( s \in S_k \) to allow \( \hat{u}_{ij} > 0 \) and \( \hat{l}_{ij} \) be well defined. When applying the consistency intervals to judgment we find that a refined or a new judgment \( x'_{ij} \) to an older version \( x_{ij} \) gives us a feasible region \( S'_{ij} \) to replace \( S_{ij} \). We find that \( [S'_{ij} \neq \emptyset] \subset S_{ij} \) and \( S_{ij} \) satisfies (8) only when the refined interval \( S'_{ij} \) overlaps with consistency interval. However, its is possible for DM to find judgments that lie outside of the consistency interval, but the earlier restricting judgments must be then relaxed.

**PAIRS applied to neuroeconomics**

A neuroeconomic application of interval model explains the dynamics of the brain activation with the interval model. The first requirement of course is to gather information that suites the formulation of PAIRS. One test setting to find brain behavior suitable for interval model is to divide the task in two parts, as Manes et al. in [8]. In their Gamble task subjects set a quality and trust estimation for their own evaluation of a probable outcome. Thus, the corresponding stimulations are found for weighting function and value function. The value of an attribute is to be judged separately and the quality or the probability of the judgment as weight afterwards. The possible brain areas assumed to be accounting for decision making under risk also with the interval model dynamics are based to research results reviewed previously. They include prefrontal cortex areas: the dorsomedial and dorsolateral prefrontal cortices (4.2) activate during cognitive processing and positive arousal experience stimulates MPFC (3.1) and ventral MPFC in (3.2). Also nucleus accumbens, NAcc (3.1) is likely to be involved in forming motivation and forming weighting data of the alternatives. Additionally amygdala (3.2) and anterior cingulate cortex, ACC (3.2), activation take part in experiencing risk in uncertain and imprecise evaluations. Also dopamine activation offers a possibility to find the brain stimulus corresponding to an optimal solution or preferred set of alternatives during the evaluation. Dopamine (4.3) levels can be measured with PET scanning devices presented in Volkow et al work[14].

Benefits of using interval model in neuroeconomic problems are found in a flexible and exact formulation for a data set that consists of differently evaluated attributes and their relative importance. When applying a data set a density function based formulation, all the evaluated attributes must be presented within a common function and further refinement of judgment typical to PAIRS is not allowed. Neuroeconomical evaluations of different value estimates and experienced risk are not the most suitable data to fit into a prefixed density function expression. Interval model’s re-evaluation of attributes during the procedure suits well quality evaluation in comparison to quantitative data.
Figure 13: Sagittal fMRI scan of brain areas, that are assumed to be involved in decision making process. Dopaminergic areas are better viewed in coronal section (11) and thus here omitted.
An interesting comparison is determining the subject’s experience of feasible region solution. Would the subject’s natural satisfaction agree with the mathematical optimum? Does an individual experience moving towards the feasible region as learning or finding a preferred outcome? Does that learning/moving towards optimum involve dopamine elicited activity as expected?

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