Social decision making in terms of euroscience

Dr Anahita Khorrami .MD-PhD of cognitive neuroscience

Education an Research manager of Brain and Cognition Clinic

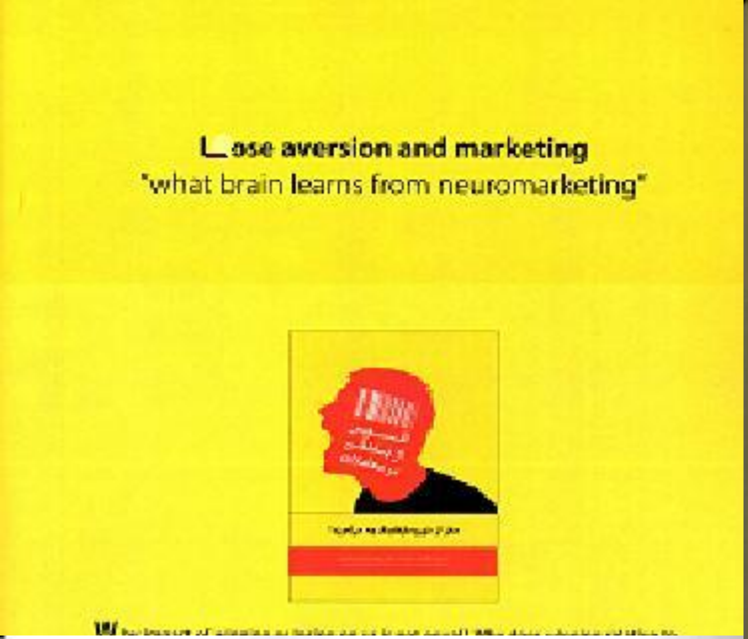
Mordad 1399

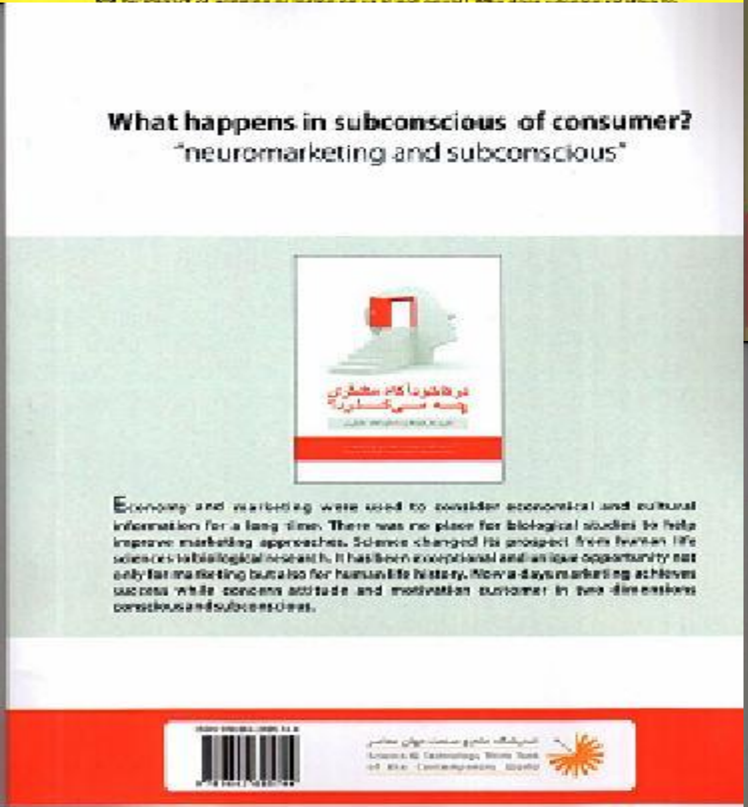
khorramianahita@yahoo.com

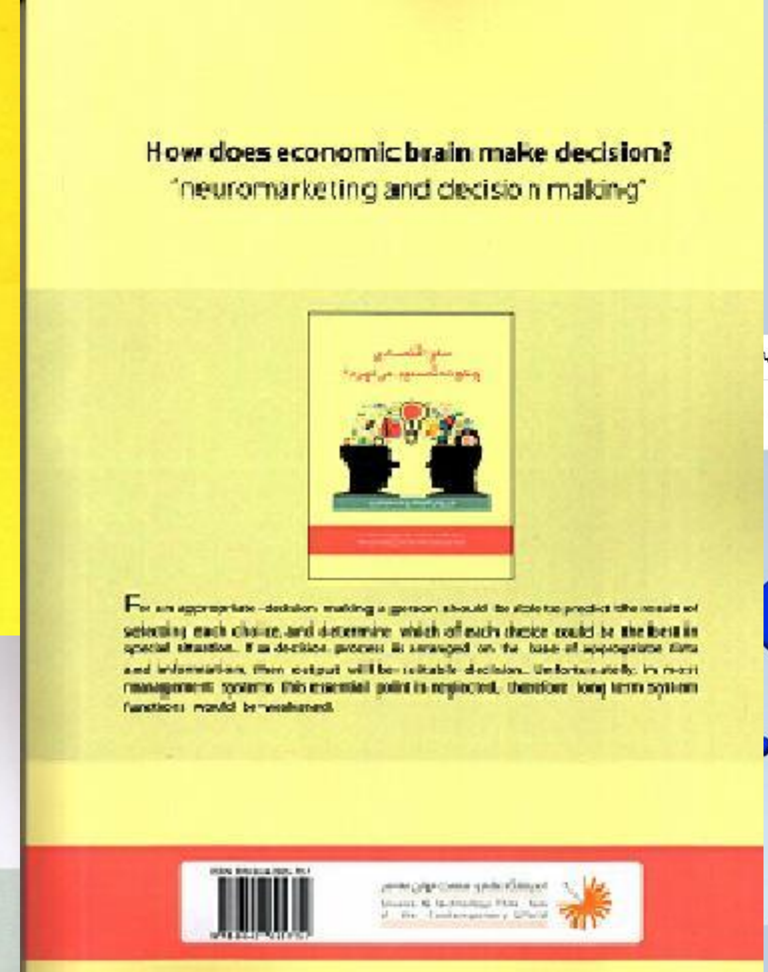
- بررسی تاثیرات تبلیغات خود همخوانی و ناخود همخوانی بر رفتار و مغز مشتری : روش بازاریابی عصب پایه(امیر احمدی)
- اثر نمایشی از دریچه علوم اعصاب: رابطه اثر و مخاطب بر اساس یافته های آزمایشگاهی (سارا عندلیب)
- ارزیابی احساسات در افراد تکانشی و برون گرا در مواجهه با تصاویر IAPSبر اساس ویژگی های سیگنال های مغزی(روح انگیز علیمرادی)
- تحلیل خوشه ای مشتریان در خرید علی بر اساس نوع محصول انتخابی(مصطفی فلاح)
- بازاریابی علی؛ توسعه رفتار خیرخواهانه در زندگی مشتریان(مصطفی فلاح)
- Gender Differences in Sensorimotor Empathy for Pain: A Single-Pulse TMS Study (هاشم صادقی)
- Theory of mind in light of neurocognitive studiesنظریه ذهن در پرتو مطالعات عصب شناختی(آذر مجمد زاده)
- بازاریابی علی؛ تفاوتها چگونه شکل میگیرد (مصطفی فلاح)
- Evaluation of Self- and Other-reference Effect on Processing of Positive and Negative

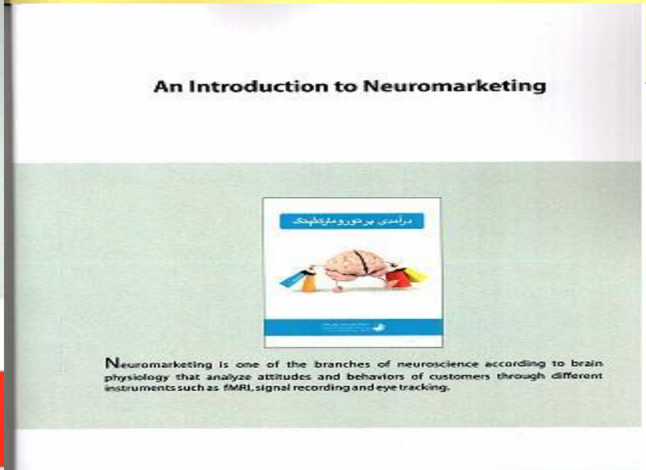
(نسرین عروجی)

- اثر تجربه کاربری گوشی هوشمند بر تصمیمگیری دو انتخابی سریع(مهدیه نوروزیان)


Lose aversion and marketing
"what brain learns from neuromarketing"


What happens in subconscious of consumer?
"neuromarketing and subconscious"


How does economic brain make decision?
"neuromarketing and decision making"


An Introduction to Neuromarketing
Neuromarketing is one of the branches of neuroscience according to brain physiology that analyze attitudes and behaviors of customers through different instruments such as fMRI, signal recording and eye tracking.


تبلیغات مبتنی بر شناخت مغز
دکتر آناهیتا خرمی بنارکی
نگار کریمی
Brain Based Advertisement.2020 تبلیغات مبتنی بر شناخت مغز، دکتر آناهیتا خرمی بنارکی، نگار کریمی، بها
Stats
Comments
Citations
References
Related research (10+)
Share
بهار ۱۳۹۹

Topics in Social-Cognitive Neuroscience

Social Level

Behavioral Level

Cognitive Level

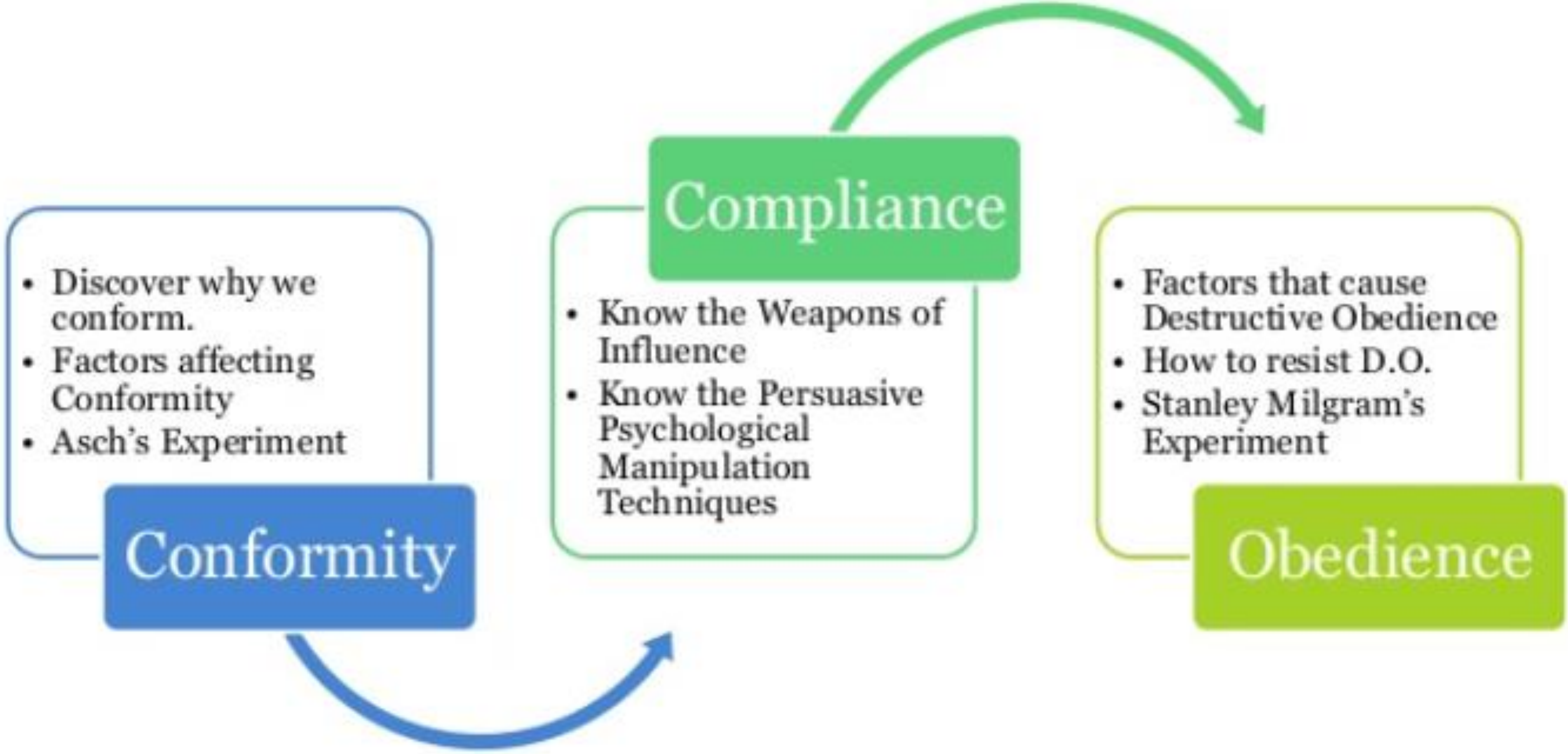
Neural Level

- How do we process and represent other people's minds and how do they influence us?

SOCIAL IN FLUENCE

BEING IN GROUP

- Perception and memory of socially salient features (i.e. **facial attractiveness**, trustworthiness, **emotional expressions**)
- Action observation (**Imitation**, mirror neurons)
- Theory of Mind (TOM) & Mentalizing
- Empathy
- Moral emotions and moral and social reasoning
- **Self Concept, Distinction between Self and Others**


Discover why we conform.
Factors affecting Conformity
Asch's Experiment
Conformity
Compliance
Know the Weapons of Influence
Know the Persuasive Psychological Manipulation Techniques
Factors that cause Destructive Obedience
How to resist D.O.
Stanley Milgram's Experiment
Obedience

Economic and Machine Learning and Neuroscience

- Theoretical frameworks in economics and machine learning and their applications in recent behavioral and neurobiological studies are summarized

- Examples of such applications in clinical domains are also discussed for **substance abuse**, Parkinson's disease, **attention-deficit/hyperactivity** disorder,schizophrenia, **mood disorders**, and autism(Lesion study)

- Decision making is an abstract term referring to the process of **selecting a particular option among a set of alternatives** expected **to produce different outcomes.**

- it can be used to describe an extremely broad range of behaviors, ranging from various taxes of **unicellular organisms** to complex political behaviors in **human society.**

Two different approaches have dominated the studies of decision making

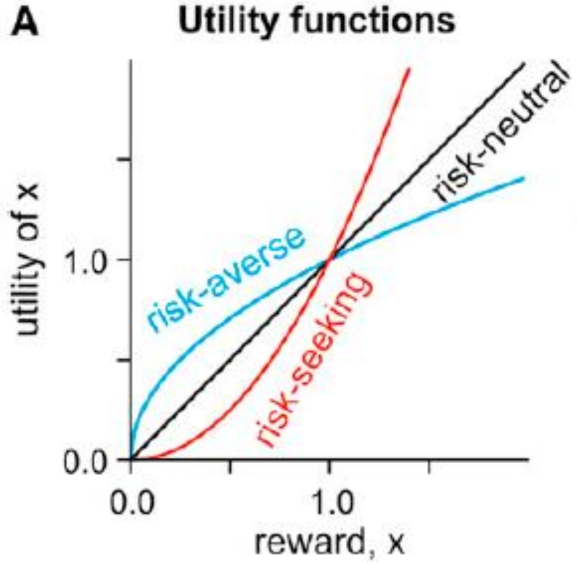
- 1-a normative or prescriptive approach addresses the question of what is the best or optimal choice for a given type of decision-making problem.: EX: the principle of utility maximization in economics and the concept of **equilibrium in the game theory** describe how self-interested rational agents should behave individually or in a group, respectively (von Neumann and Morgenstern, 1944)
- 2-Real behaviors of humans and animals **seldom match** the predictions of such normative theories. Thus, empirical studies seek to identify a set of principles that can parsimoniously account for
- the actual choices of humans and animals: EX:Similarly, empirical studies have demonstrated that humans often choose their behaviors **altruistically** and thus **deviate from the predictions from the classical game theory** (Camerer, 2003)

- Recently, these two traditional approaches of decision making research have merged with two additional disciplines
- **1-First**, it is now increasingly appreciated that ***learning*** plays an important role in decision making, although this has been ignored in most economic theories. In particular, *reinforcement learning theory*, originally rooted in psychological theories of learning in animals (Mackintosh, 1974) and *optimal control theory* (Bellman, 1957), provides a ***valuable framework to model how decision-making strategies are tuned by experience*** (Sutton and Barto, 1998).
- **2-Second**, and more importantly for the purpose researchers have begun to elucidate a number of ***important core mechanisms in the brain*** responsible for various **computational steps of decision making** and **reinforcement learning** (Wang, 2008; Kable and Glimcher, 2009; Lee et al., 2012)

economic and reinforcement learning and decision making"neuroscience"

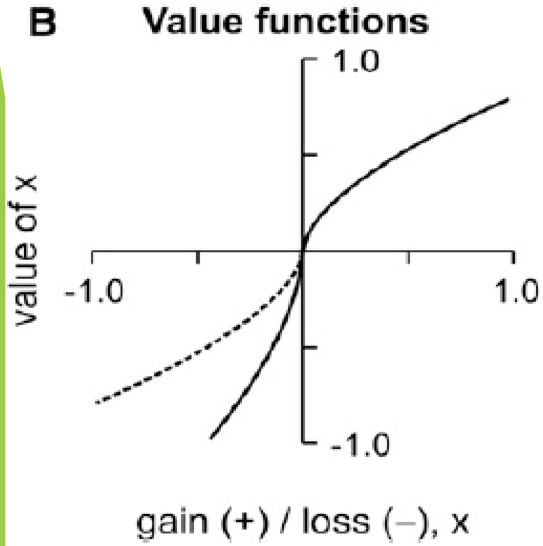
- Actions are chosen through coordination among multiple brain systems, each implementing a distinct set of **computational algorithms** (Dayan et al., 2006; Rangel et al., 2008; Lee et al., 2012; van der Meer et al., 2012; Delgado and Dickerson, 2012).

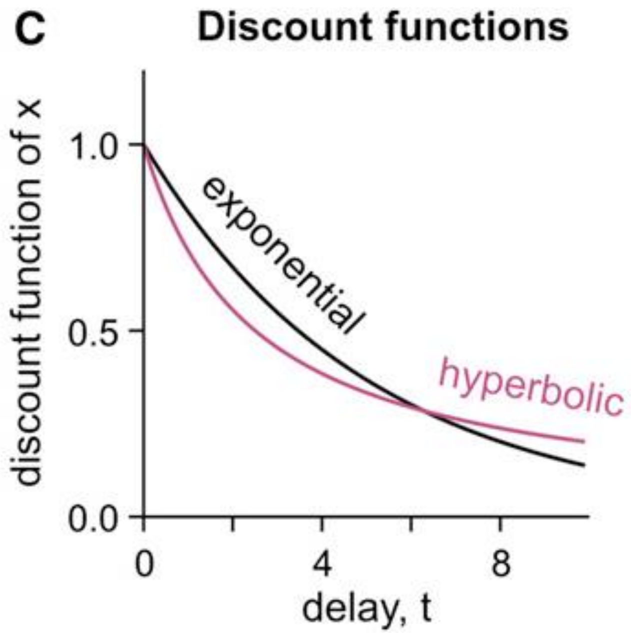
Models of Decision Making



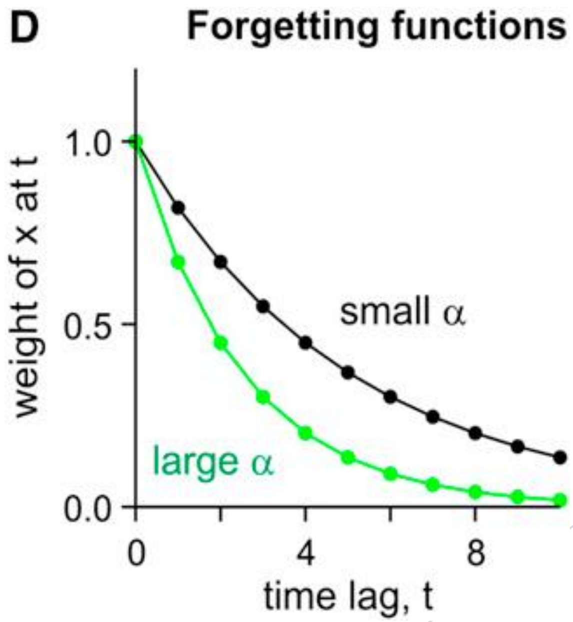
- **Utility functions** with different types of risk preference

- **Value functions** in prospect theory. Solid (dotted) line shows the value function with (without) loss aversion



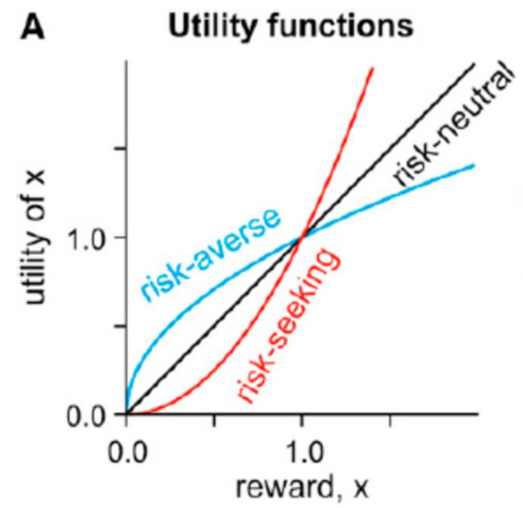


- Exponential versus hyperbolic temporal discount functions.



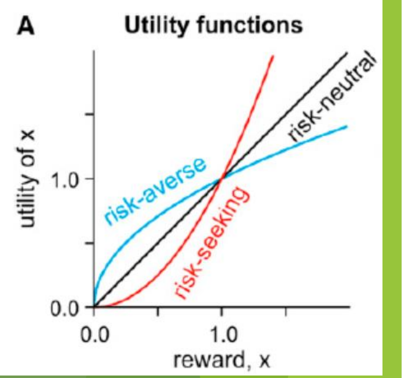
- **Weights assigned to the previous outcomes at different time lags according to two different learning rates (a) in a model-free reinforcement learning algorithm**

Economic Decision Making
Decision Making under Risk



- Economy :Utility: the strength of a decision maker's preference for a particular option. When the preference of a decision maker between different outcomes satisfies a certain **set of properties**, such as **transitivity**, the utility of a given option can be expressed as a real number.
- When the outcomes of a **choice are uncertain**, its **utility** can be computed as **the average of the utilities of different outcomes weighted by their probabilities**, and is referred to as **expected utility** (von Neumann and Morgenstern, 1944).
- In this:the **shape of the utility function** determines the decision maker's **attitude** toward ***uncertainty or risk.***

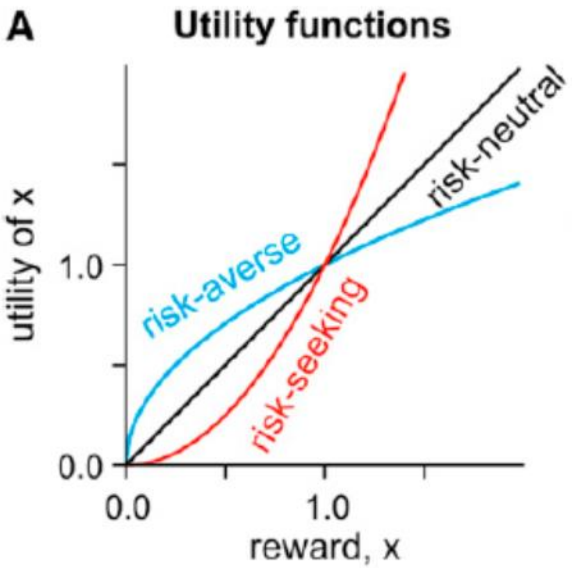
UT Exam



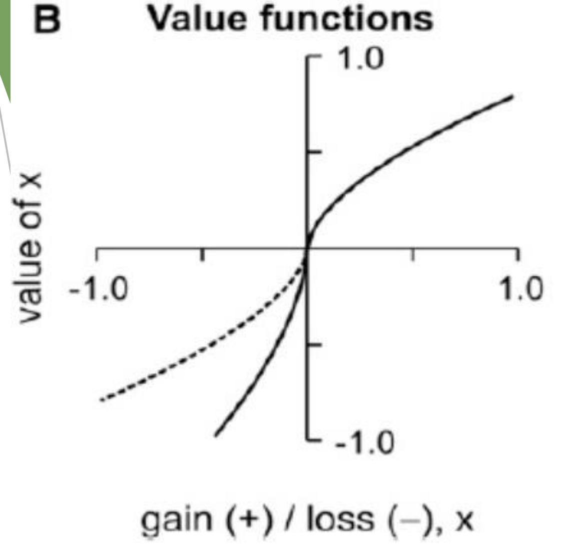
- When the **utility function increases linearly** with the quantity of a particular good, such as money, the ***decision maker would be indifferent*** between the **certainty of receiving** x and ***the chance of doubling*** x or **getting nothing** with **equal probabilities**= ***risk-neutral DM***
- When the utility function is **concave** and has a **negative second derivative**, this implies that the **utility of getting** x **is less than twice the utility of getting x/2**=avoid the same gamble= ***risk averse DM***
- A decision maker whose choices are consistent with the principle of maximizing expected utilities = ***rational DM***, regardless of his or her **attitude toward risk.**
- Rational decision makers, *only the probabilities and utilities* of different outcomes should influence their choices

choices of human decision makers are influenced by other contextual factors

- Status quo,
- Different outcomes are weighted by quantities
- Only loosely related to probabilities



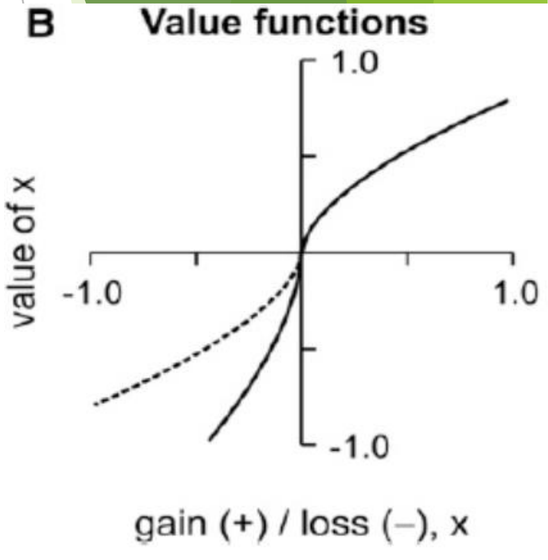
In prospect theory (Kahneman and Tversky, 1979),



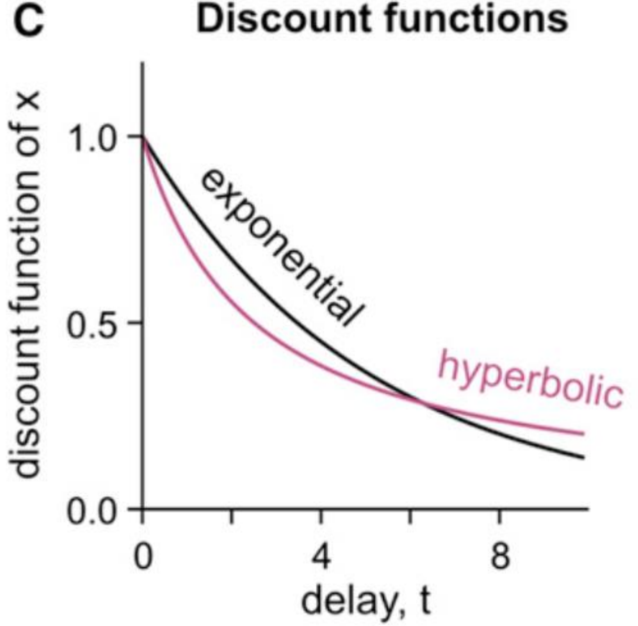
- the **desirability** of a decision outcome is determined by its ***deviation from a reference point***.
- The precise location of the reference point can change **depending on the description of alternative options**, and gains and losses from this reference point are evaluated differently by the so-called ***value function***.
- the term "**value**" is used somewhat more **loosely** even when **preference does not satisfy** the **formal definition of utility**. In prospect theory, the value function is concave for gains and convex for losses, accounting for the empirical findings that **humans are risk-averse and risk-seeking for gains and losses**, respectively.

Loss Aversion
Value function:EX

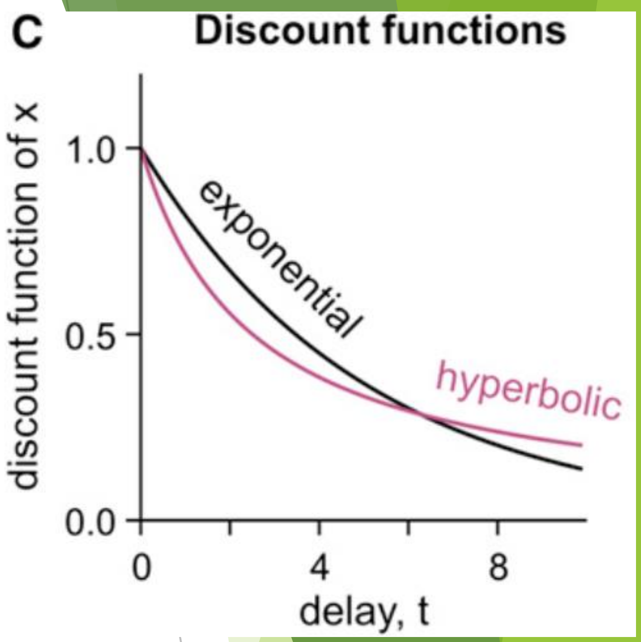
- most people would prefer **a sure gain of $1,000** to a **50% chance of gaining $2,000**, while preferring a **50% chance of losing $2,000** to a **sure loss of $1,000**.
- the slope of the value function near the **reference point** is **approximately twice as large for losses** than for gains.
- **1**-This accounts for the fact that humans are often more sensitive to a loss than a gain of the same magnitude, which is referred to as **loss aversion** (Tversky and Kahneman, 1992).
- **2-Deficiency in expected utility theory:** in real life, the exact probabilities of different outcomes from a particular choice are often unknown. This type of ***uncertainty is referred to as ambiguity.***
- The term ambiguity aversion is often used to describe the **tendency to avoid** an option for which the *exact probabilities of different outcomes are not known* (Camerer and Weber, 1992).



Intertemporal Choice



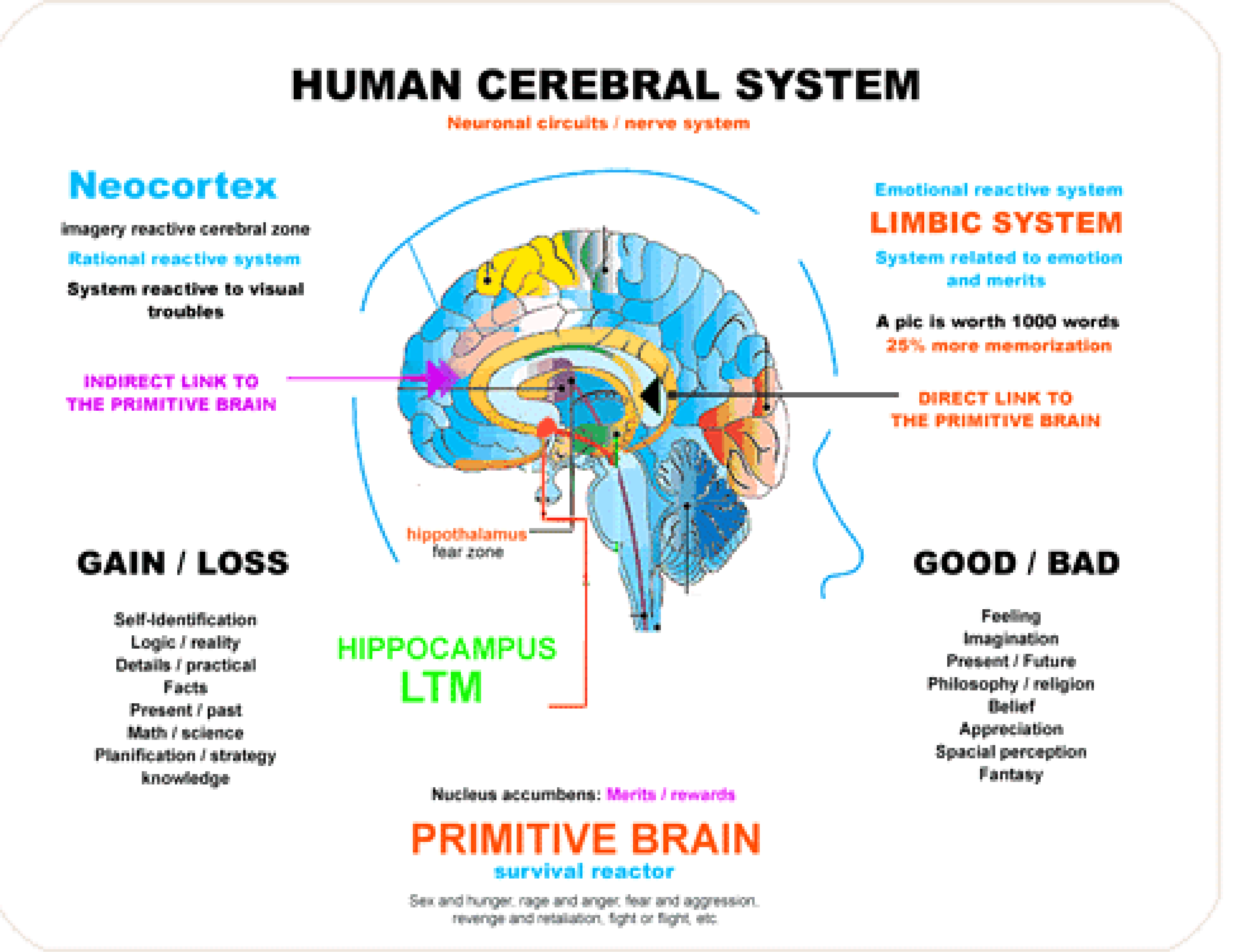
- For practically all decisions made in real life, reward from chosen action become available after substantial delays.
- Faced with a choice between a small but immediate reward and a larger but **more** delayed **reward**, humans and animals tend to prefer
- the Smaller reward if the difference in the reward magnitude is sufficiently small or if the **delay for the larger reward is too long**. This implies that the utility for a delayed reward decreases with the duration of its delay.
- Formally, a ***discount function*** is defined as the **fraction of the** utility for delayed reward relative to **that of the same reward** without any delay.



- A **discount function** that **decays steeply with reward delay** corresponds to **an impatient impulsive decision maker** who **assigns a large weight to an immediate reward.** A variety mathematical functions have been proposed for discount functions, including an **exponent function** (Samuelson, 1937)
- An important property of an **exponential discount function** is that the rate of discounting ***per unit length of time is constant***.=*__discount functions are time consistent.__*
- EX: a decision maker prefers **one of the two rewards expected after unequal delays**, the mere passage of time does not alter this preference.
- Majority of empirical studies in humans and animals **found that discount rate decreases for long delays**(Mazur, 2000). This can be ***__modeled more accurately by hyperbolic or quasihyperbolic discount functions__*** (Green and Myerson,2004; Phelps and Pollak, 1968; Laibson, 1997; Hwang et al.,2009;). Compared to the exponential discount function,
- **hyperbolic discount functions** imply that decision makers are particularly attracted **to the immediate reward with no delay** , although the same person might prefer a **larger and more delayed reward** if **some additional delays are added to both options equally.** This is referred to ***__as preference reversal__*** (Strotz,1955–1956).

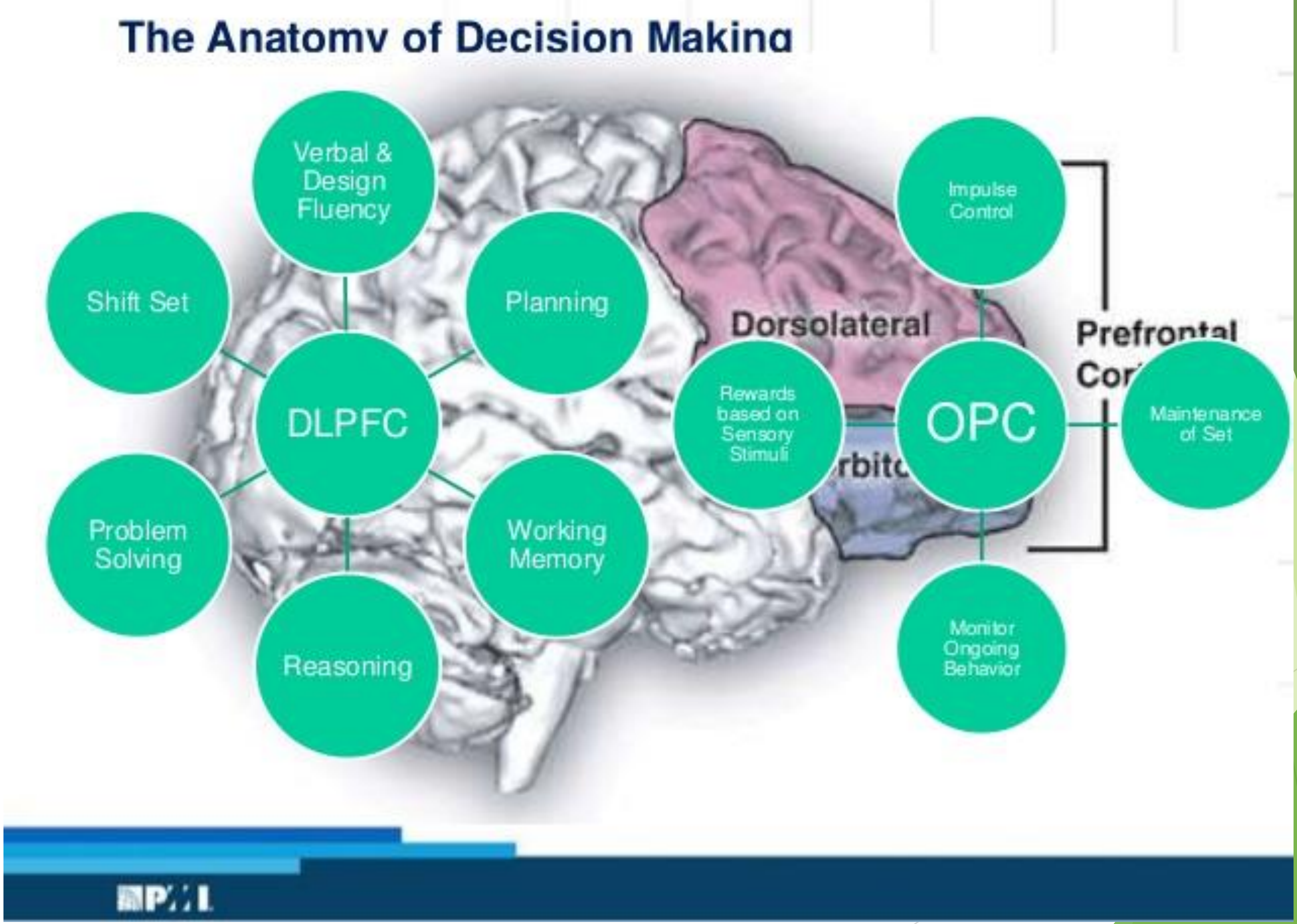
Some limitations

- **1-First**, there are cases in which humans display **negative time preference**, namely, *the value of an outcome increases when it is delayed* (Loewenstein, 1987)EX:some people prefer to **obtain a kiss from their favorite movie stars after a delay** than immediately, suggesting that they might derive some satisfaction from the **anticipation of pleasurable** future outcomes. Similarly, some people **prefer to experience painful** events sooner rather than later (Berns et al., 2006).
- **2-Second**, when people choose between two **different sequences of outcomes**, the **overall utility** of a particular outcome sequence **may not correspond to the sum of the discounted utilities** of individual outcomes. Instead, human decision makers ***tend to prefer a sequence of outcomes that improve over time*** (Loewenstein and Prelec, 1993).


HUMAN CEREBRAL SYSTEM
Neuronal circuits / nerve system
Neocortex
imagery reactive cerebral zone
Rational reactive system
System reactive to visual troubles
INDIRECT LINK TO THE PRIMITIVE BRAIN
Emotional reactive system
LIMBIC SYSTEM
System related to emotion and merits
A pic is worth 1000 words
25% more memorization
DIRECT LINK TO THE PRIMITIVE BRAIN
hippothalamus
fear zone
GAIN / LOSS
Self-identification
Logic / reality
Details / practical
Facts
Present / past
Math / science
Planification / strategy
knowledge
HIPPOCAMPUS
LTM
GOOD / BAD
Feeling
Imagination
Present / Future
Philosophy / religion
Belief
Appreciation
Spacial perception
Fantasy
Nucleus accumbens: Merits / rewards
PRIMITIVE BRAIN
survival reactor
Sex and hunger, rage and anger, fear and aggression, revenge and retaliation, fight or flight, etc.

Neural Encoding of Utilities and Values

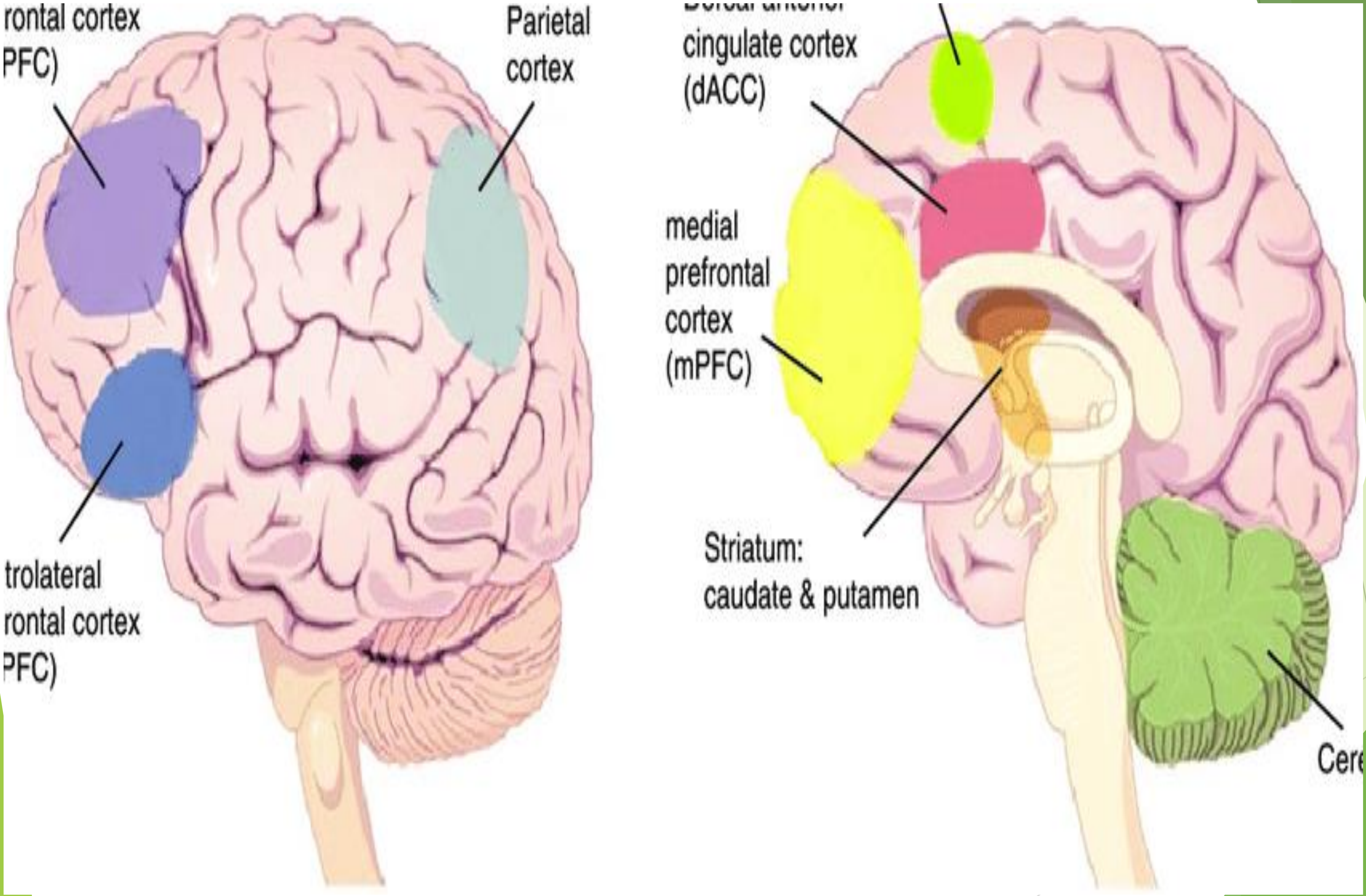
- Multiple brain regions during decision making involving ***uncertain outcomes.***
- neurons modulating their activity ***according to the expected value*** of reward available from a ***particular target location*** are found in the **basal ganglia** (Samejima et al., 2005), **posterior parietal cortex** (Platt and Glimcher, 1999; Dorris and Glimcher, 2004; Sugrue et al., 2004; Seo et al., 2009; Louie et al., 2011), **premotor cortex** (Pastor-Bernier and Cisek, 2011), and **medial prefrontal cortex** (Sohn and Lee, 2007; Seo and Lee, 2009; So and Stuphorn, 2010)
- Many of these brain areas might in fact encode the **signals related to utilities of reward expected from specific actions**, ***even when the probabilities and timing of reward vary***. For example, ***temporally discounted values*** are encoded by neurons in the **prefrontal cortex** (Kim et al., 2008), **posterior parietal cortex** (Louie and Glimcher, 2010), and **the striatum** (Cai et al., 2011).
- **FMRI** signals: related **to *utilities*** in multiple brain areas, including the **(VMPFC**) and **ventral striatum** (Kuhnen and Knutson, 2005; Knutson et al., 2005; Knutson et al., 2007; Luhmann et al., 2008; Chib et al., 2009; Levy et al., 2011). Consistent with the results from **single-neuron** recording studies (Sohn and Lee, 2007), signals related to **values of reward expected** from **specific motor actions** have been identified in the human **supplementary motor area** (Wunderlich et al., 2009). Activity in the **VMPFC and ventral striatum** display additional characteristics of **value signals used for decision making.** activity in each of these areas is ***influenced oppositely by expected gains and losses.***
- activity in these areas is **more enhanced for expected losses** than for expected gains, and **this difference** is related to the **level of loss aversion across individuals** (Tom et al., 2007).


The Anatomy of Decision Making
Verbal & Design Fluency
Shift Set
Planning
DLPFC
Problem Solving
Working Memory
Reasoning
Dorsolateral
Impulse Control
Rewards based on Sensory Stimuli
OPC
Maintenance of Set
Monitor Ongoing Behavior

- The **VMPFC** and **ventral striatum** also reflects **temporally discounted values** for **delayed reward during inter-temporal choice** (Kable and Glimcher,2007; Pine et al., 2009).
- FMRI and lesion studies : the **amygdala** might play a role in **estimating value functions** according **to potential <u>losses</u>**.
- EX, the **amygdala** changes according to whether **a particular outcome is framed as a gain or a loss** (De Martino et al., 2006), and **loss aversion is abolished in patients with *<u>focal lesions</u>* in the amygdala** (De Martino et al., 2010).

DLPFC

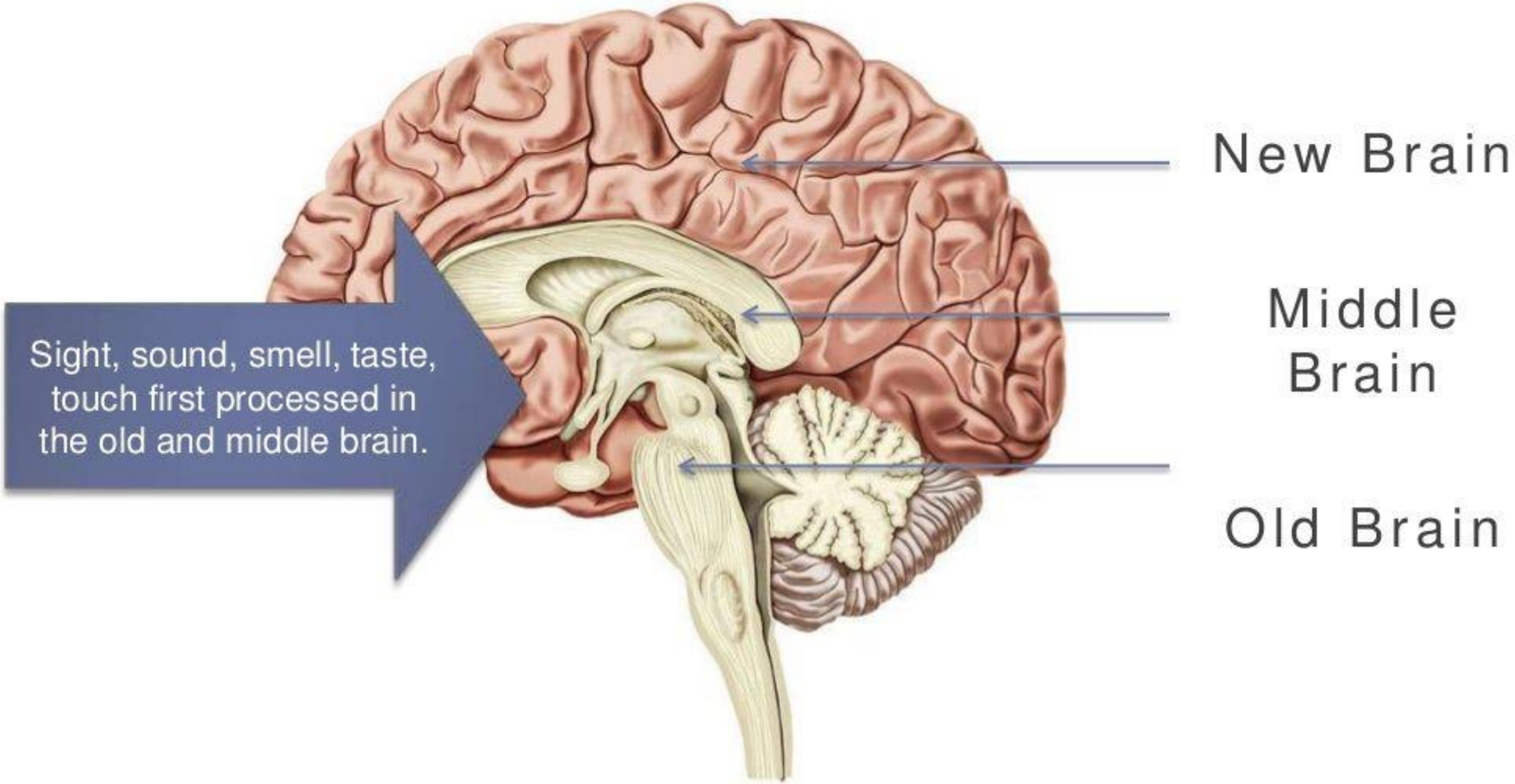
- Decisions are based **on values computed for specific** goods or their locations, and which brain areas encode the value signals actually used for **action selection**, **might vary depending** on the nature of choices to be made (Lee et al., 2012).
- DLPFC: **flexible switching between different** types of **value signals** used for decision making. This is possible, since the DLPFC is connected with many other brain areas that encode **different types of value signals** (Petrides and Pandya, 1984; Carmichael and Price, 1996; Miller and Cohen, 2001).
- In addition, **individual neurons in the DLPFC** can modulate their activity according ***to value signals associated with specific objects as well as their locations*** (Kim et al., 2012b).
- In contrast, **neurons in the *primate orbitofrontal*** cortex tend to encode the signals related to **utilities assigned to specific goods independent of their locations** (Padoa-Schioppa and Assad, 2006).


rontal cortex
PFC)
Parietal
cortex
trolateral
rontal cortex
PFC)
cingulate cortex
(dACC)
medial
prefrontal
cortex
(mPFC)
Striatum:
caudate & putamen
Cere

In addition to the desirability of expected outcomes

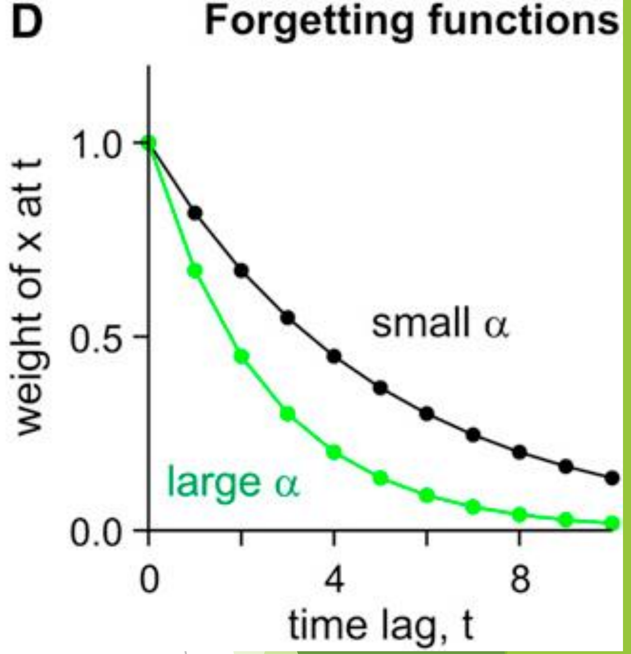
- the likelihood of choosing a particular action is also influenced by the **cost of performing that action**. Although the activity of neurons in the ***orbitofrontal cortex*** and ***striatum*** is often modulated by multiple **parameters of reward**,
- the signals related to the cost or efforts **associated with a particular action** might be processed preferentially in the ***anterior cingulate cortex***. This possibility is consistent with the results **from lesion studies** (Walton et al., 2003; Rudebeck et al., 2006), as well as **single-neuron recording** and **neuroimaging studies** (Croxson et al., 2009; Kennerley et al.,2009; Pre´ vost et al., 2010; Hillman and Bilkey, 2010)

The 3 Brains of Decision-Making



Reinforcement Learning Multiple Systems for Reinforcement Learning

- most economic decision-making experiments: subjects select from a small number of options with relatively **well-characterized outcomes**
- Real life: are more complex, and it is often necessary to make appropriate changes in our decision-making strategies **through experience**
- 1-First, the **likelihood that a particular action** would be chosen would change depending on whether its **previous outcome was reinforcing or punishing** (Thorndike, 1911)
- 2- Second, new information about the regularities in our environment can be used to **improve the outcomes** of our choices, even when it **is not directly related to reward or penalties** (Tolman, 1948).



Reinforcement learning theory

- : a powerful framework to formalize how these **two different kinds of information can modify** the values associated with **alternative actions** (Sutton and Barto, 1998).
- In this framework, it is assumed that the decision maker is fully **knowledgeable about the current state** of his or her environment, which determines **the outcome of each action** as well as the **probability distribution of its future states**. This property is referred to **as Markovian**.
- **reinforcement learning theory**, a **value function** corresponds to the **decision maker's subjective estimate for the long-term benefits expected from being in a particular state or taking a particular action in a particular state**. These **two different types of value functions** are referred **to as state and action value** functions, respectively. **Action value functions** in **reinforcement learning theory play a role similar to that of utilities in economics**,but there are two main **differences.**
- 1-First, **value functions are only** estimates, since they are **continually adjusted according to the decision maker's** experience.
- 2-Second, **value functions are related to choices only probabilistically**. This can be beneficial,since such apparently **suboptimal behaviors** can eventually **increase the accuracy of value functions**, thereby providing ***a potential solution to the exploration-exploitation dilemma***(Sutton and Barto, 1998).

Reinforcement learning theory

- ***Value functions***, can be **estimated** according **to several different algorithms**, which might be implemented by different **anatomical substrates** in the brain (Daw et al., 2005; Dayan et al., 2006; van der Meer et al., 2012).
- These ***different algorithms*** are captured **by animal learning theories**.
- 1-First, a sensory stimulus (conditioned stimulus, CS) **reliably predicting appetitive or aversive outcome** (unconditioned stimulus, US) eventually acquires **the ability to evoke a predetermined behavioral response** (conditioned response, CR) similar **to the responses originally triggered by the predicted stimulus** (unconditioned response, UR; Mackintosh, 1974). The strength of this association can be referred to as the **Pavlovian value of the CS** (Dayanet al., 2006).
- **2- Second**, during ***instrumental model-free reinforcement learning***, or ***simply habit learning***, value function correspond to the **value of appetitive** or ***aversive outcome expected from an arbitrary action*** or ***its antecedent cues***. Computationally, ***these two types of learning can be described similarly*** using **a simple temporal difference (TD) learning algorithm**, analogous to the ***Rescorla-Wagner rule*** (Rescorla and Wagner, 1972).

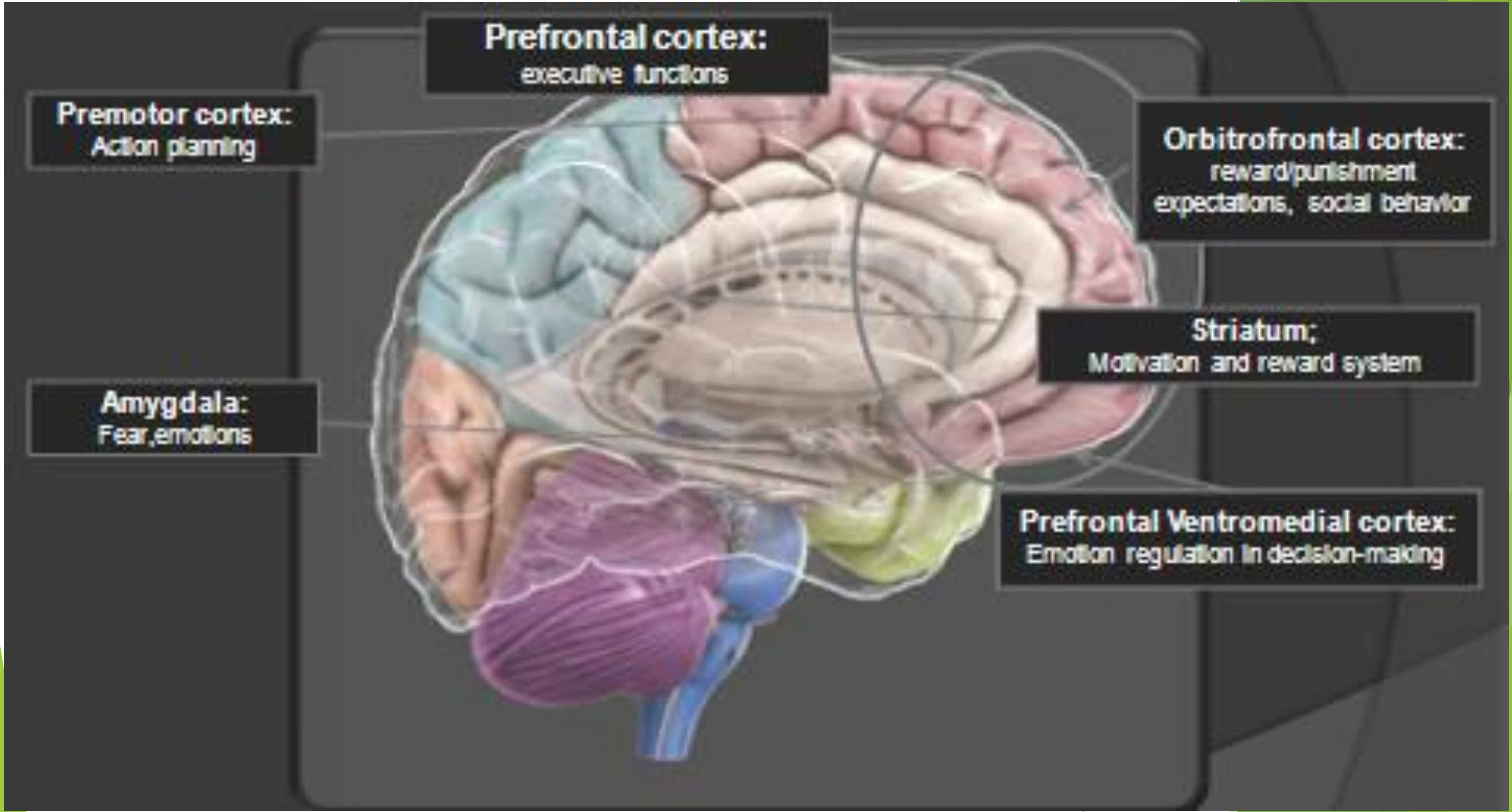
- In ***both cases***, **value functions are adjusted according to the difference between** the **actual outcome and the outcome expected from the current value functions**. This **difference is referred** to as the **reward prediction error**. In the **case of Pavlovian learning**, the **value function** is **updated for the action predetermined by the US,** ***whereas*** for ***habit learning***, the **value function is updated for any** arbitrary action **chosen by the decision maker** (Dayan et al., 2006).
- **The rate in** which the ***reward prediction error*** is **incorporated into the value function** is ***controlled by a learning rate***.
- ***A small learning rate*** allows the decision maker ***to integrate the outcomes from previous actions over a large time scale*** .
- ***Learning rates can be adjusted according to the stability of the decision-making environment***t (Behrens et al.,2007; Bernacchia et al., 2011).

- Finally, when humans and animals acquire new information about the properties of their environment, this knowledge can be utilized to update the value functions for some actions and improve decision-making strategies, without experiencing the actual outcomes of their actions (Tolman, 1948).
- This is **referred to as model-based reinforcement learning**, since the **value functions** are **updated by simulating the outcomes expected from various actions** using the decision maker's **internal or mental model of the environment** (Sutton and Barto, 1998; Doll et al., 2012).
- Formally, **the knowledge or model of the decision maker's environment** can be captured by transition probabilities for the environment **to switch between two different states** (Sutton and Barto, 1998).
- Therefore, when **the estimates of these transition probabilities are revised**, the **likelihood of different outcomes expected from various actions can be recalculated**, even **if the outcomes from all the states remain unchanged** (Packard and McGaugh, 1996).
- Similarly, if the **subjective values of specific outcomes** change as a result of **selective feeding** or **taste aversion**, the **value functions for actions leading to those outcomes** can **be revised without directly experiencing them** (Holland and Straub, 1979; Dickinson, 1985).
- Therefore, **the choices predicted by model-free** and **model-based reinforcement learning** algorithms, as well as their corresponding neural mechanisms, might be different.

Neural Substrates of Model-free Reinforcement Learning

- As described above, **errors in predicting affective outcomes**, namely, reward prediction errors, are postulated to **drive model-free reinforcement learning**, including both Pavlovian conditioning and habit learning.
- An important clue for the neural mechanism of **reinforcement learning** was therefore provided by the observation that **the phasic activity of midbrain dopamine neurons encodes the reward prediction error** (Schultz, 1998).
- Dopamine neurons **innervate many different targets** in the brain, including the **cerebral cortex** (Lewis et al., 2001), **striatum** (Bolam et al., 2000; Nicola et al., 2000), and **amygdala** (Sadikot and Parent, 1990).
- In particular, **the amygdala might be involved** in both **fear conditioning** (LeDoux, 2000) and **appetitive Pavlovian conditioning** (Hatfield et al., 1996; Parkinson et al., 2000; Paton et al., 2006).
- **Induction of synaptic plasticity in the amygdala** that **underlies Pavlovian conditioning** might depend on the **activation of dopamine receptors** (Guarraci et al., 1999; Bissie ` re et al., 2003).
- In addition, the **ventral striatum** also contributes **to several different forms of appetitive Pavlovian conditioning**,such ***as auto-shaping***, ***conditioned place preference***, and ***second-order conditioning*** (Cardinal et al., 2002).

- Given the **increased range of actions controlled by habit learning**, the anatomical substrates for habit learning might be more extensive compared to the areas related to Pavlovian conditioning, and are likely to span both cortical and subcortical areas.
- Nevertheless, the ***striatum*** has received much attention due to its **dense innervation by dopamine neurons** (Houk et al., 1995).
- The striatum ***integrates inputs from almost all cortical areas***, and ***influences the activity of neurons in the motor structures***, such as the **superior colliculus** and pedunculopontine nucleus, largely through **disinhibitory mechanisms** (Chevalier and Deniau, 1990; Mink, 1996).
- In addition, **striatal neurons** in **the direct and indirect pathways** express **D1 and D2 dopamine receptors** respectively, and might influence the outputs of the basal ganglia antagonistically (Kravitz et al., 2010; Tai et al., 2012; but see Cui et al., 2013).


Prefrontal cortex:
executive functions
Premotor cortex:
Action planning
Orbitrofrontal cortex:
reward/punishment
expectations, social behavior
Striatum;
Motivation and reward system
Amygdala:
Fear,emotions
Prefrontal Ventromedial cortex:
Emotion regulation in decision-making

- **Dopamine-dependent, bidirectional modulation of corticostriatal synapses might provide** the biophysical substrates for integrating the reward prediction error signals *into value functions in the striatum* (Shen et al., 2008; Pawlak and Kerr, 2008; Wickens, 2009).
- Indeed, neurons in **the striatum** often ***encode the value functions for specific actions*** (Samejima et al., 2005; Lau and Glimcher, 2008; Cai et al., 2011; Kim et al., 2009, 2013).
- In addition, **signals necessary for updating the value functions**, including the value of the chosen action and reward prediction errors, are also found in **the striatum** (Kim et al., 2009; Oyama et al., 2010; Asaad and Eskandar, 2011).
- Moreover, the **dorsolateral striatum**, or **the putamen**, might be particularly involved in controlling habitual motor actions (Hikosaka et al., 1999; Tricomi et al., 2009).
- Although the **striatum** is most commonly associated with **model-free reinforcement learning**, **additional brain areas** are likely to be involved in **the process of updating action value functions**, **depending on the specific type of value functions in question**.
- Indeed, **signals related to value functions** and reward prediction errors are found in **many different areas** (Lee et al., 2012).
- Similarly, ***using a multivariate decoding analysis***, signals **related to rewarding** and ***punishing outcomes*** can **be decoded from the majority of cortical and subcortical areas** (Figure 2; Vickery et al.,2011).

Neural Substrates for Model-Based ReinforcementLearning

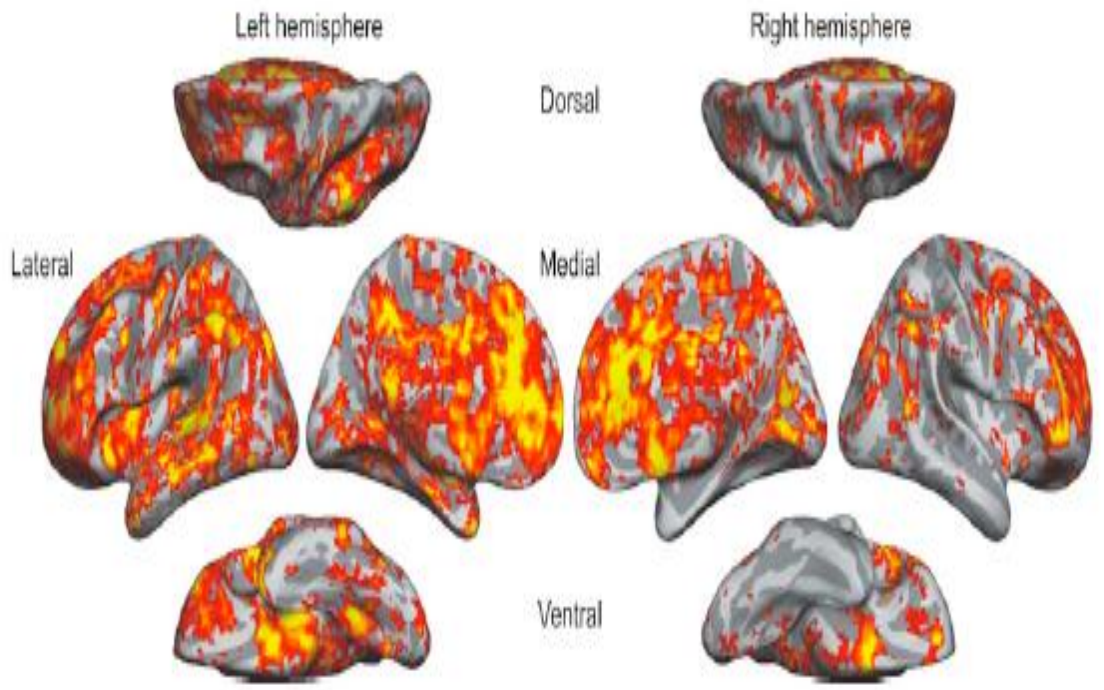
- The neural substrates for model-based reinforcement learning are much **less well understood compared to those for Pavlovian conditioning and habit learning** (Doll et al., 2012).
- nature **of computations** for **simulating the possible outcomes** and **their neural implementations** might vary widely across various decision-making problems.
- EX, **separate regions of the frontal cortex** and **striatum in the rodent** brain might underlie model-based reinforcement learning (***place learning***) and ***habit learning*** (***response learning***; Tolman et al., 1946).
- In particular, lesions in the **dorsolateral striatum** and **infralimbic cortex** impair **habit learning**,
- lesions in the **dorsomedial striatum** and **prelimbic cortex** impair (Balleine and Dickinson, 1998; Killcross and Coutureau, 2003; Yin and Knowlton, 2**model based reinforcement learning**006).
- In addition, **lesions or inactivation** of the **hippocampus** ***suppresses the strategies based*** on model-based reinforcement learning (Packard et al., 1989; Packard and McGaugh, 1996).
- **To update the value functions** in model based reinforcement learning, the ***new information from the decision maker's environment needs to be combined with the previous knowledge appropriately***. **Encoding** and **updating** the information about the **decision maker's environment** might **rely on the prefrontal cortex** and **posterior parietal cortex** (Pan et al., 2008; Gla¨ scher et al., 2010; Jones et al., 2012).

- In addition, **persistent activity** =the **computations** related to ***reinforcement learning*** and **decision making** in addition to working memory (Kim et al., 2008; Curtis and Lee, 2010).
- Given that ***persistent activity*** in **the prefrontal cortex** is strongly **influenced by dopamine** and **norepinephrine** (Arnsten et al., 2012),
- The **neural mechanisms of mental simulations** necessary for **estimating the hypothetical outcomes predicted** from **this new knowledge** are also poorly understood, but **might include the hippocampus**.
- EX:, the animal is **at a choice point during a maze learning task**, activity of neurons in the **hippocampus** briefly **represents the potential goal locations**, which has been interpreted as a ***neural correlate of mental simulation*** (Tolman, 1948; Johnson and Redish, 2007).
- In addition, the **orbitofrontal cortex** might play an important role **in selecting actions** according **to the value functions estimated** by **model based reinforcement** learning algorithms, when the ***subjective values of expected outcomes change*** (Izquierdo et al., 2004; Valentin et al., 2007).

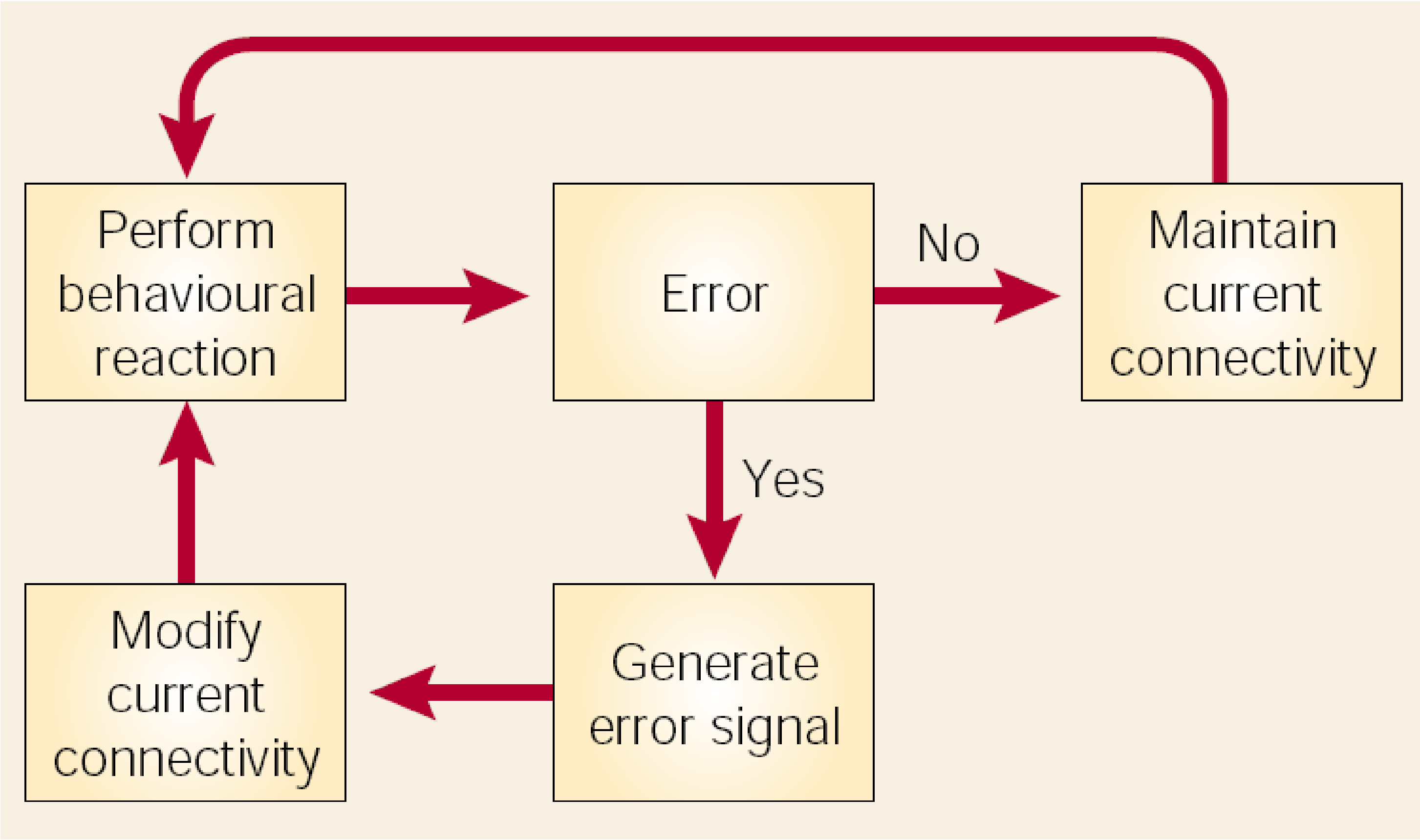
- the neural substrates involved in **updating value functions** according **to different reinforcement learning algorithms** might **overlap substantially**.
- EX:, ***reward prediction error signals*** encoded in the ventral striatum reflect the **estimates** derived from both ***model-free and modelbased reinforcement learning algorithms*** (Lohrenz et al., 2007; Daw et al., 2011; Wimmer et al., 2012).

- Figure 2. Ubiquitous Reward Signals in theBrain

Brain areas encoding reward signals during a matching pennies task that was identified with a multivoxel pattern analysis (Vickery et al., 2011).



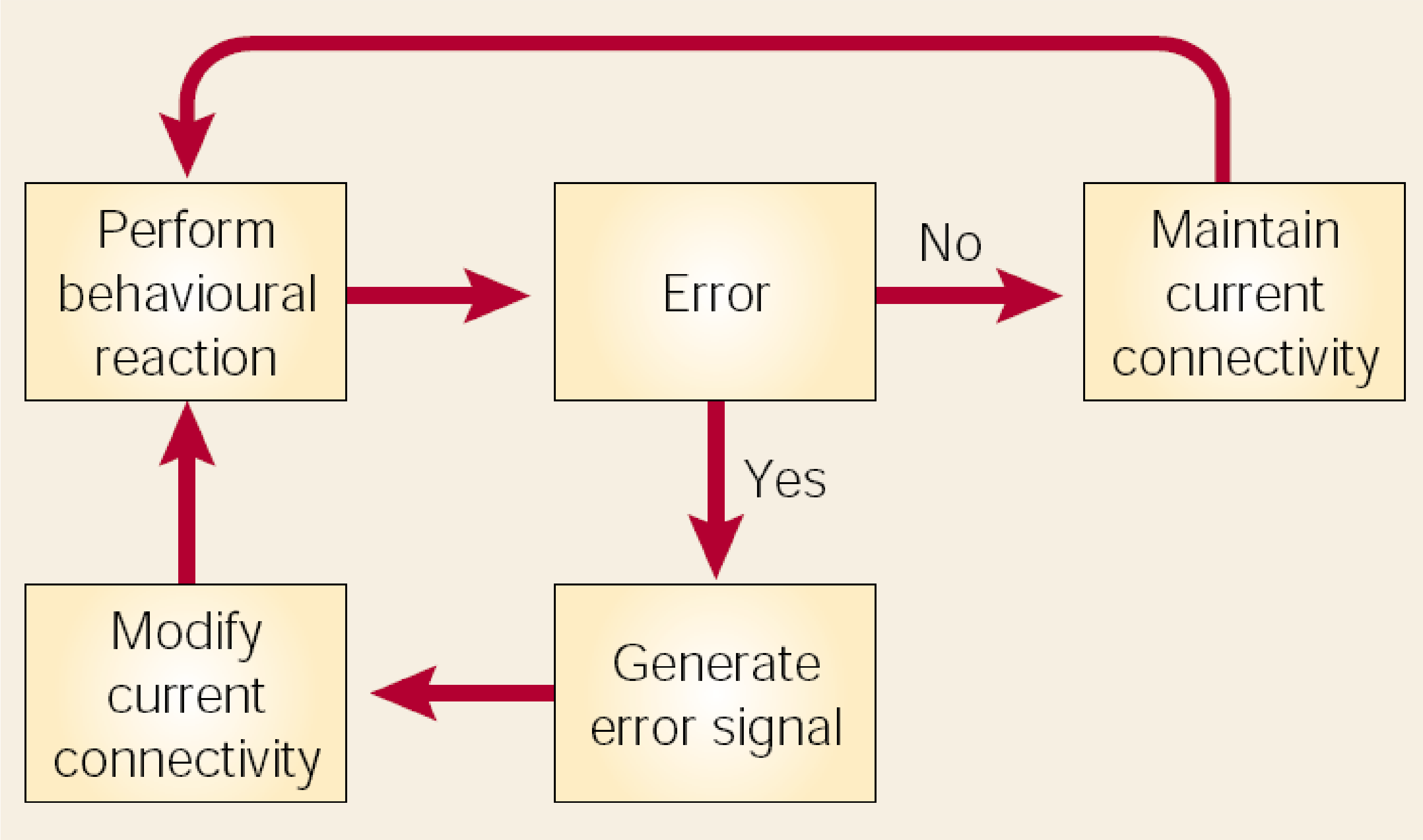
Learning Theory



NATURE REVIEWS | NEUROSCIENCE
VOLUME 1 | DECEMBER 2000

Prediction error – the discrepancy between an actually received reward and its prediction.
Learning is proportional to the prediction error.

Dopamine response = Reward occurred – Reward predicted



NATURE REVIEWS | NEUROSCIENCE
VOLUME 1 | DECEMBER 2000

Mental Simulation and Default Network

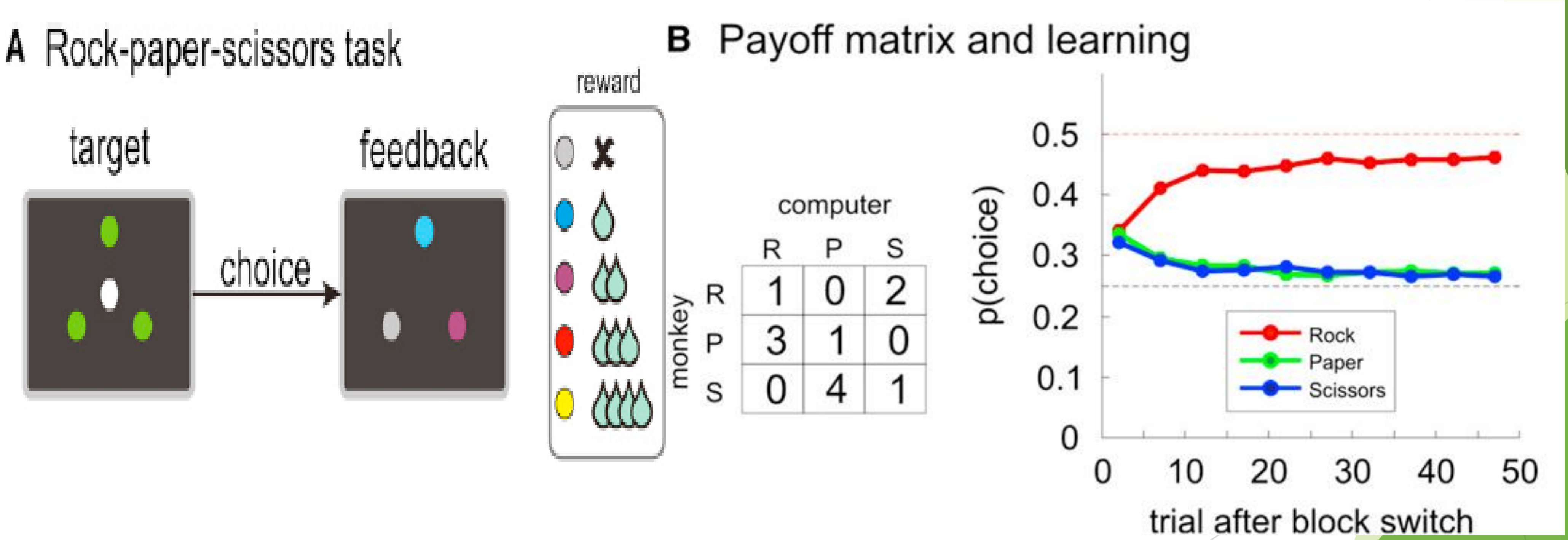
- **Several cognitive processes closely related** to episodic memory, such as ***self-projection***, ***episodic future thinking***, ***mental time travel***, and ***scene construction*** (Atance and O'Neill, 2001; Tulving, 2002; Hassabis and Maguire, 2007; Corballis, 2013),
- might be **involved in** simulating the **outcomes of hypothetical actions.**
- **Common to all** of these processes is the activation of the memory traces relevant for **predicting the likely outcomes of potential actions in the present context. In addition**, even ***when possible outcomes are explicitly specified for each option***,
- the process of ***evaluating the subjective values*** of each option **might still rely on mental simulation**. This might be particularly **true during intertemporal choice**. In fact, **imagining a future planned event** during **intertemporal choice reduces the rate of temporal discounting** (Boyer, 2008; Peters and Bu¨ chel, 2010).

- It has been proposed that the computations involved in episodic future thinking and **mental time travel** might be **implemented in the default network** (Buckner and Carroll, 2007).
- The default network (DMN) refers to a set of **brain areas** that increase their activity when the subjects are **not engaged in a specific cognitive task**, such as **during intertrial intervals**, presumably **reflecting the activity related to more spontaneous cognitive processes**.
- This network **includes** the ***medial prefrontal cortex***, ***posterior cingulate cortex***, and ***medial temporal lobe*** (Buckner et al., 2008).
- Mental **simulation of hypothetical outcomes** might be ***an important component of such spontaneous cognition***.
- EX:, **during intertemporal choice**, the activity of the ***posterior cingulate cortex*** reflects the ***subjective values of delayed reward*** (Kable and Glimcher, 2007).
- Moreover, activity in the ***posterior cingulate cortex*** **and** ***hippocampus*** is higher during *intertemporal choice* **than** **uncertain outcomes** ***without any delays*** (Luhmann et al., 2008; Ballard and Knutson, 2009).
- The functional coupling between ***the hippocampus and the anterior cingulate cortex*** is also correlated with how ***much episodic future thinking*** affects the ***preference for delayed reward*** (Peters and Bu¨ chel, 2010).

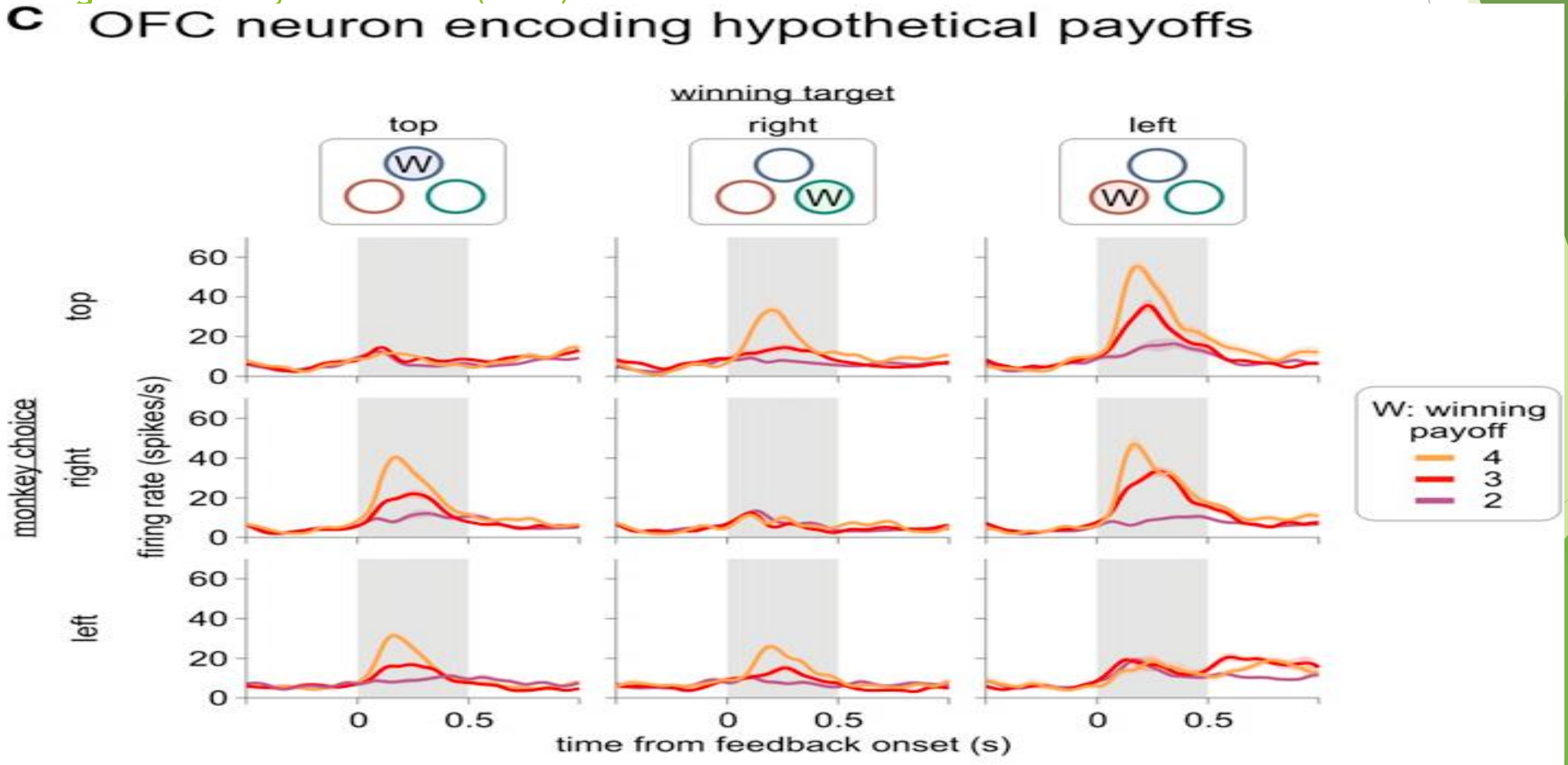
Hypothetical Outcome Signals in the Orbitofrontal Cortex

(A) Visual stimuli displayed during the choice and feedback epochs of a rock-paper-scissors task used in Abe and Lee (2011). Different colors for feedback stimuli were associated with different amounts of juice reward.

B) Payoff matrix (left) and changes in choice probabilities (right) during the same task (R, rock; P, paper; S, scissors). Dotted lines correspond to **the Nash-equilibrium strategy** (0.5 for rock and 0.25 for paper and scissors, respectively).



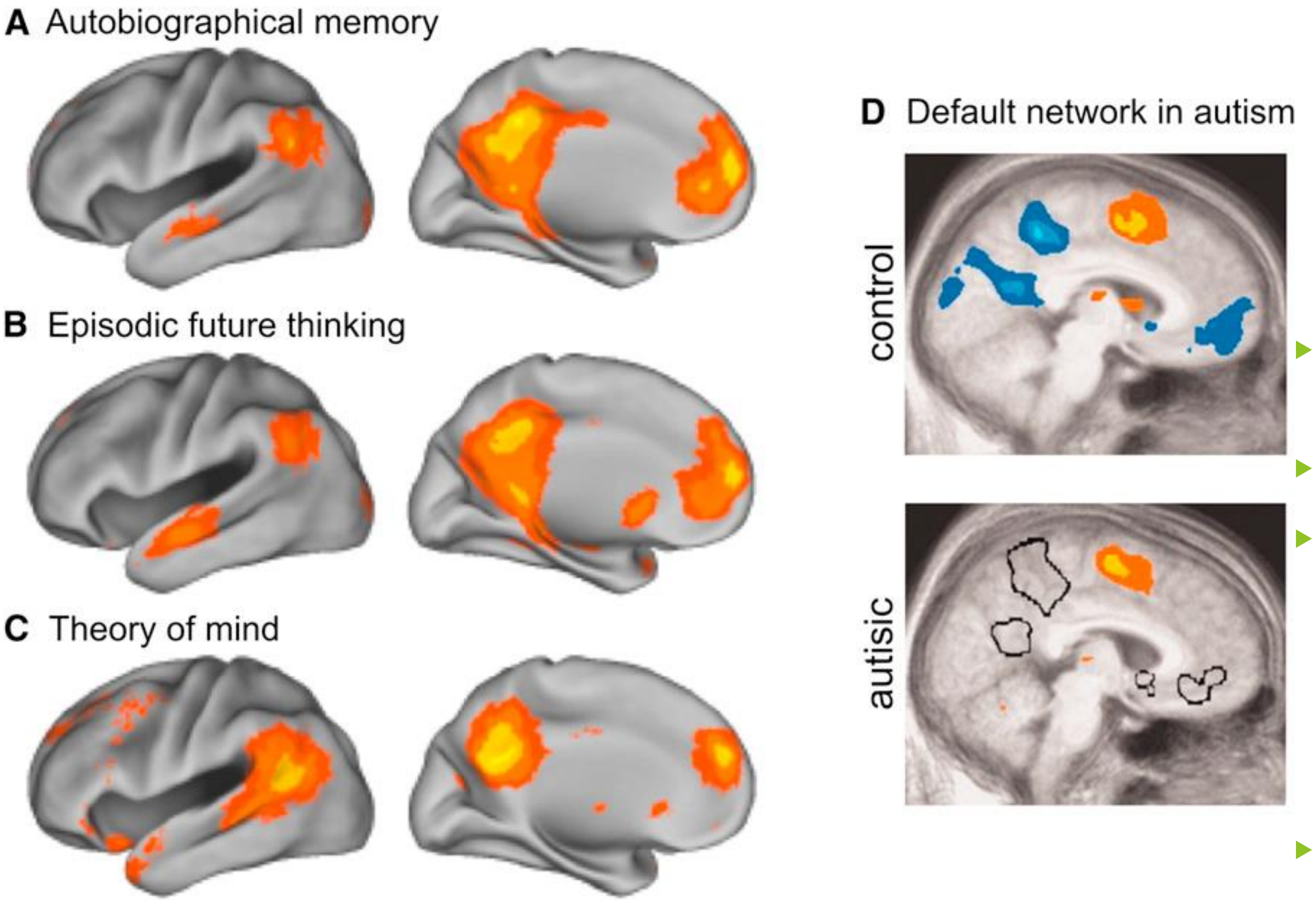
(C) Activity of a neuron in the **orbitofrontal** cortex that encoded the hypothetical outcomes **from unchosen actions**. Spike density functions are plotted separately according to the position (columns) and payoffs (line colors) of the **winning target** and **the position of the target** chosen by the animal (rows).



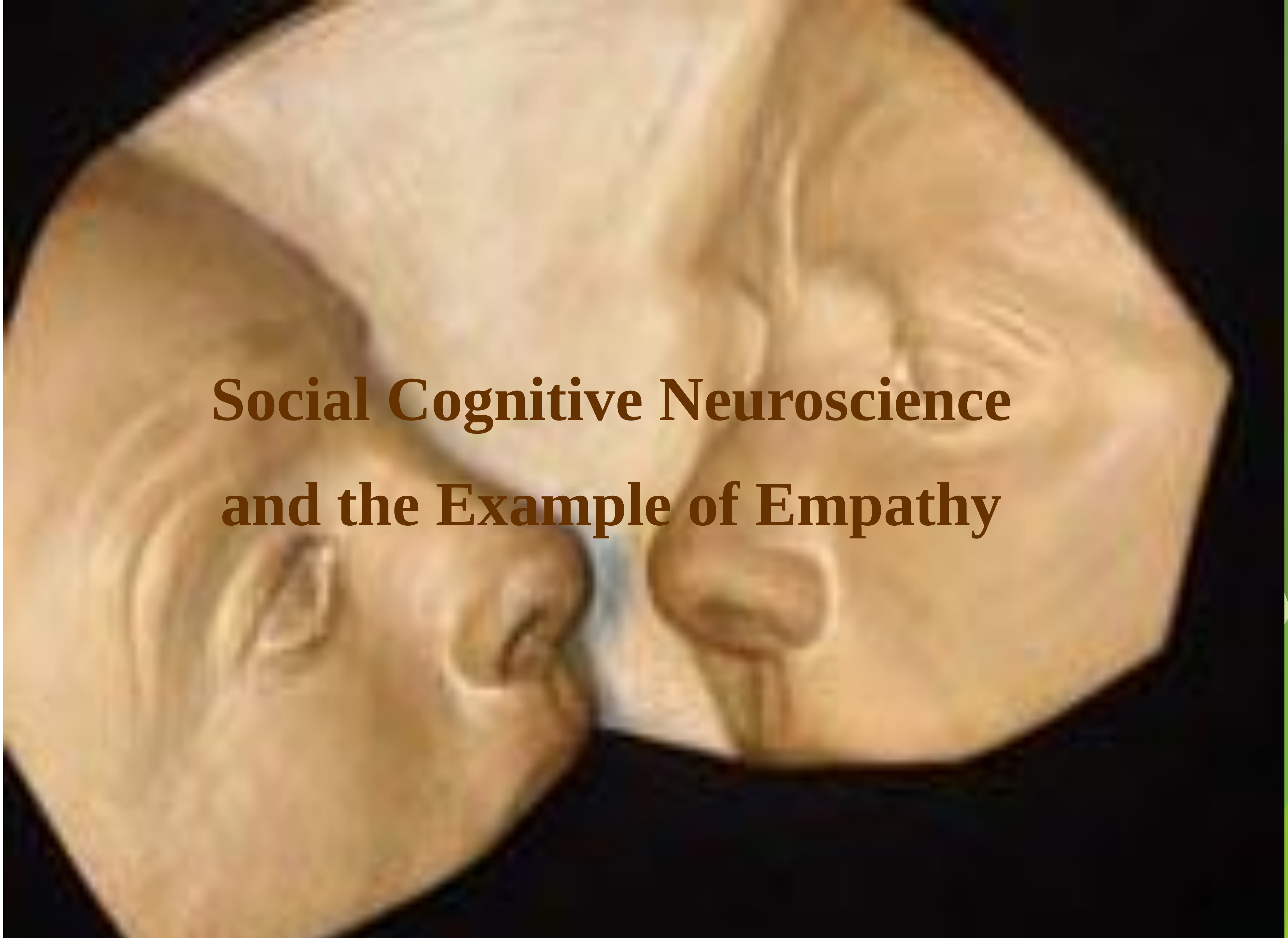
Social brain

- The most complex and challenging forms of decision making take place in a social context (Behrens et al., 2009; Seo and Lee, 2012). During social interactions, outcomes are jointly determined by the actions of multiple decision makers (or players).
- In **game theory** (von Neumann and Morgenstern, 1944), a set of strategies chosen by all players is referred to as a **Nash equilibrium**, if **none of the players can benefit** from changing their strategies unilaterally (Nash, 1950). In such classical game theoretic analyses, it is assumed that **players pursue only their self-interests** and are **not limited in their cognitive** abilities. **In practice, these assumptions are often violated**, and choices made by humans tend to deviate from Nash equilibriums (Camerer, 2003). Nevertheless, when the same ***games are played repeatedly***, strategies of decision makers **tend to approach the equilibriums.**

- Different tasks: The results from these studies have demonstrated that both humans and animals apply **a combination of *model-free and model-based* reinforcement learning** algorithms (Camerer and Ho, 1999; Camerer, 2003; Lee, 2008; Abe et al., 2011; Zhu et al., 2012). *Dependent to*: The **ability to make inferences** about the ***knowledge and beliefs of other*** decision-making agents is referred to as the **theory of mind** (Premack and Woodruff, 1978; Gallagher and Frith, 2003).
- Models of other players: theory of mind, such as the **dorsomedial prefrontal cortex** and **superior temporal** sulcus (Hampton et al., 2008; Behrens et al., 2008).
- ***Most cortical areas*** included in **the default network** are activated similarly during the tasks related to **episodic or autobiographical** memory, prospection, and **theory of mind** (Gusnard et al., 2001; Spreng et al., 2009, Spreng and Grady, 2010;)



- Figure 4. Functions and Dysfunctions of the
- Default Network
- (A–C) Cortical areas activated by the recall of autobiographical memory (A), episodic future thinking (B), and mental **simulation of other people's perspective** (C). Reproduced from Buckner et al. (2008).
- (D) **Deactivation in the default network** (blue, top) is absent in the brains of autistic individuals (black outlines, bottom; Kennedy et al., 2006).



Social Cognitive Neuroscience and the Example of Empathy

Topics in Social-Cognitive Neuroscience

- How do we process and represent other people’s minds and how do they influence us?

Social Level
Behavioral Level
Cognitive Level
Neural Level

- Perception and memory of socially salient features (i.e. **facial attractiveness**, trustworthiness, **emotional expressions**)
- Action observation (**Imitation**, mirror neurons)
- Theory of Mind (TOM) & Mentalizing
- Empathy
- Moral emotions and moral and social reasoning
- **Self Concept, Distinction between Self and Others**

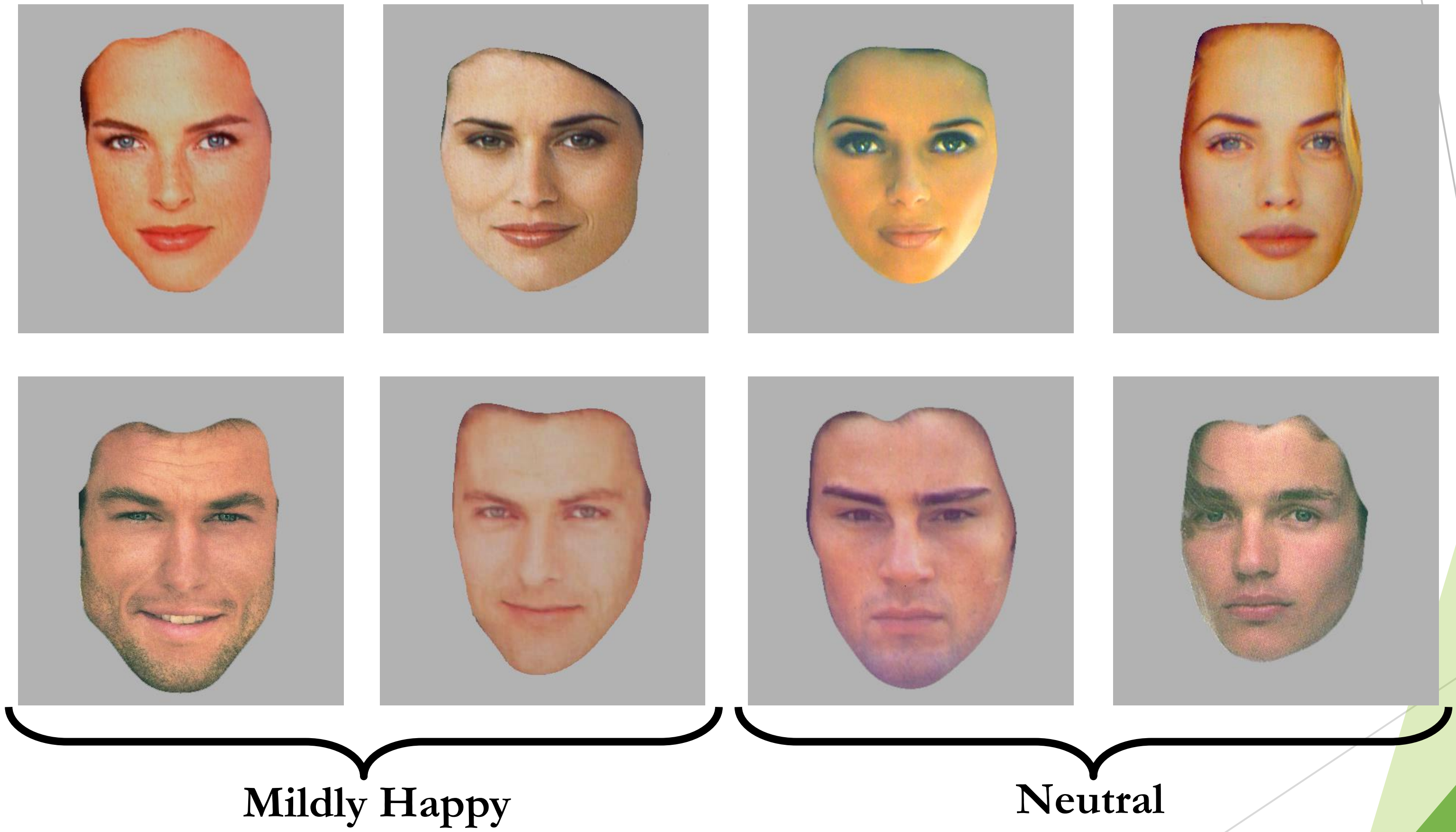
Perception of Socially Salient Features

Emotional Facial Expressions

Familiar and Famous Faces

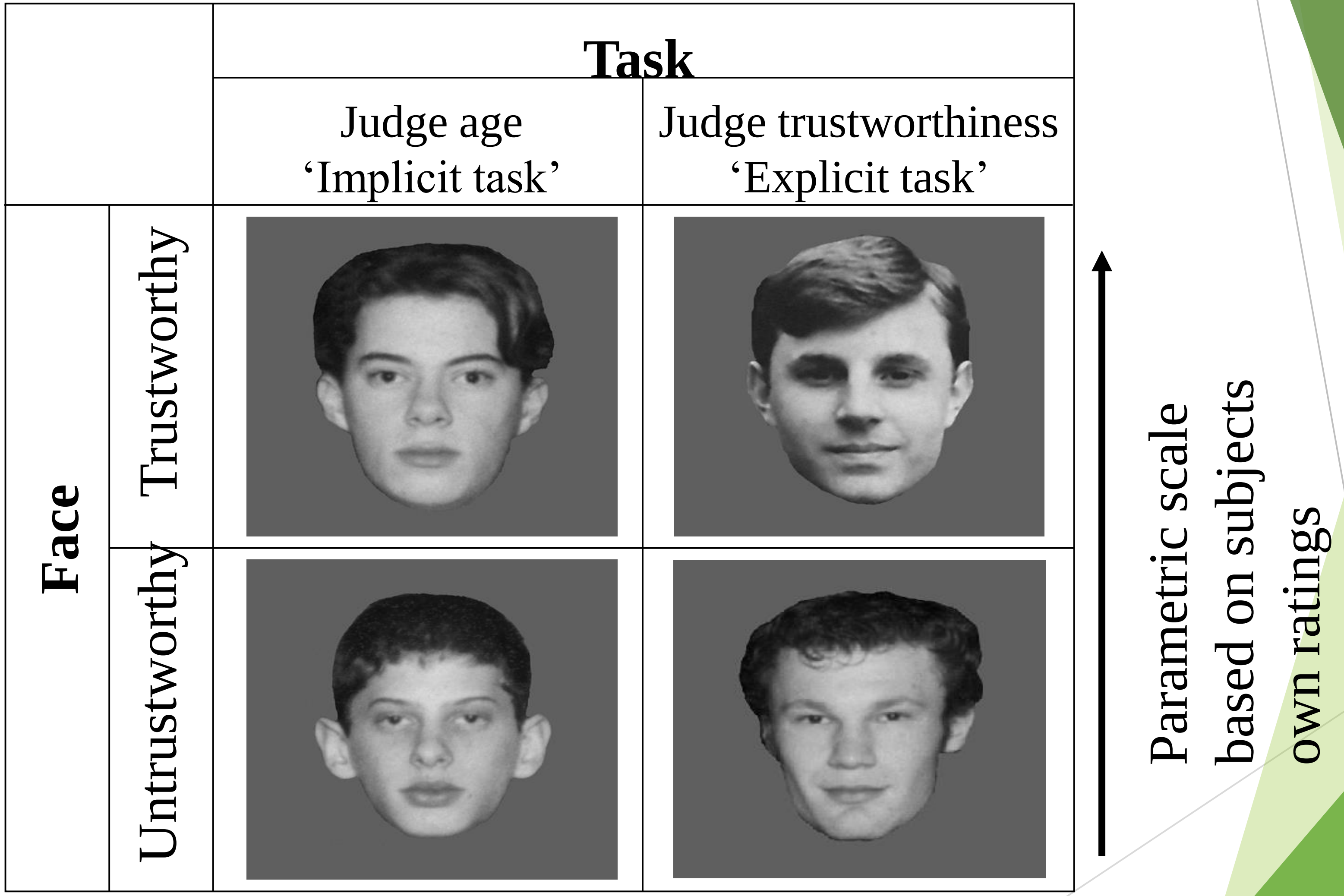
Morris et al. (1986). *Nature*; Phillips et al., (1997). *Nature*.

Social Rewards: Attractive Faces



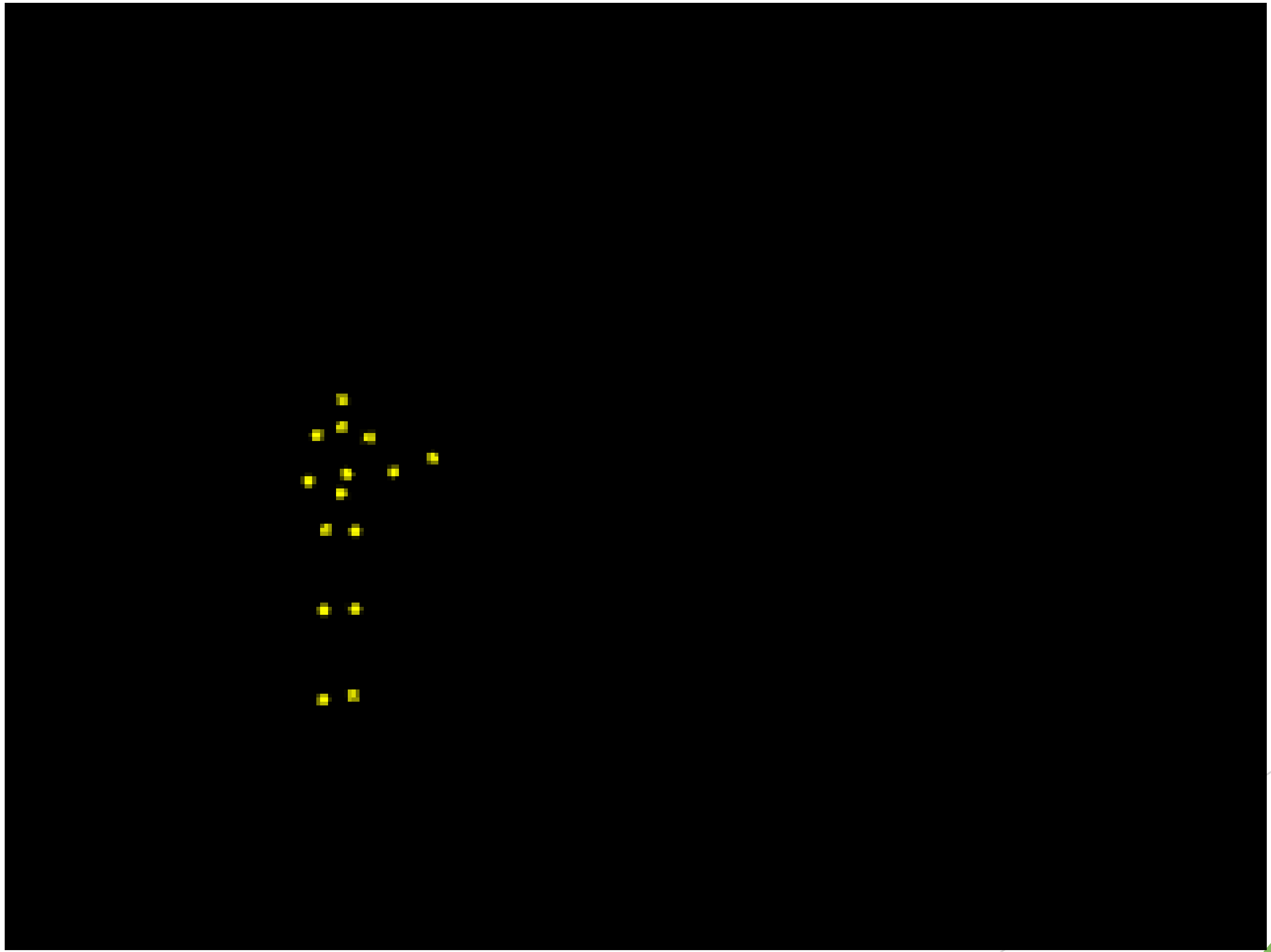
O'Doherty et al. (2003). *Neuropsychologia*

Social Judgement: Trustworthiness of Faces

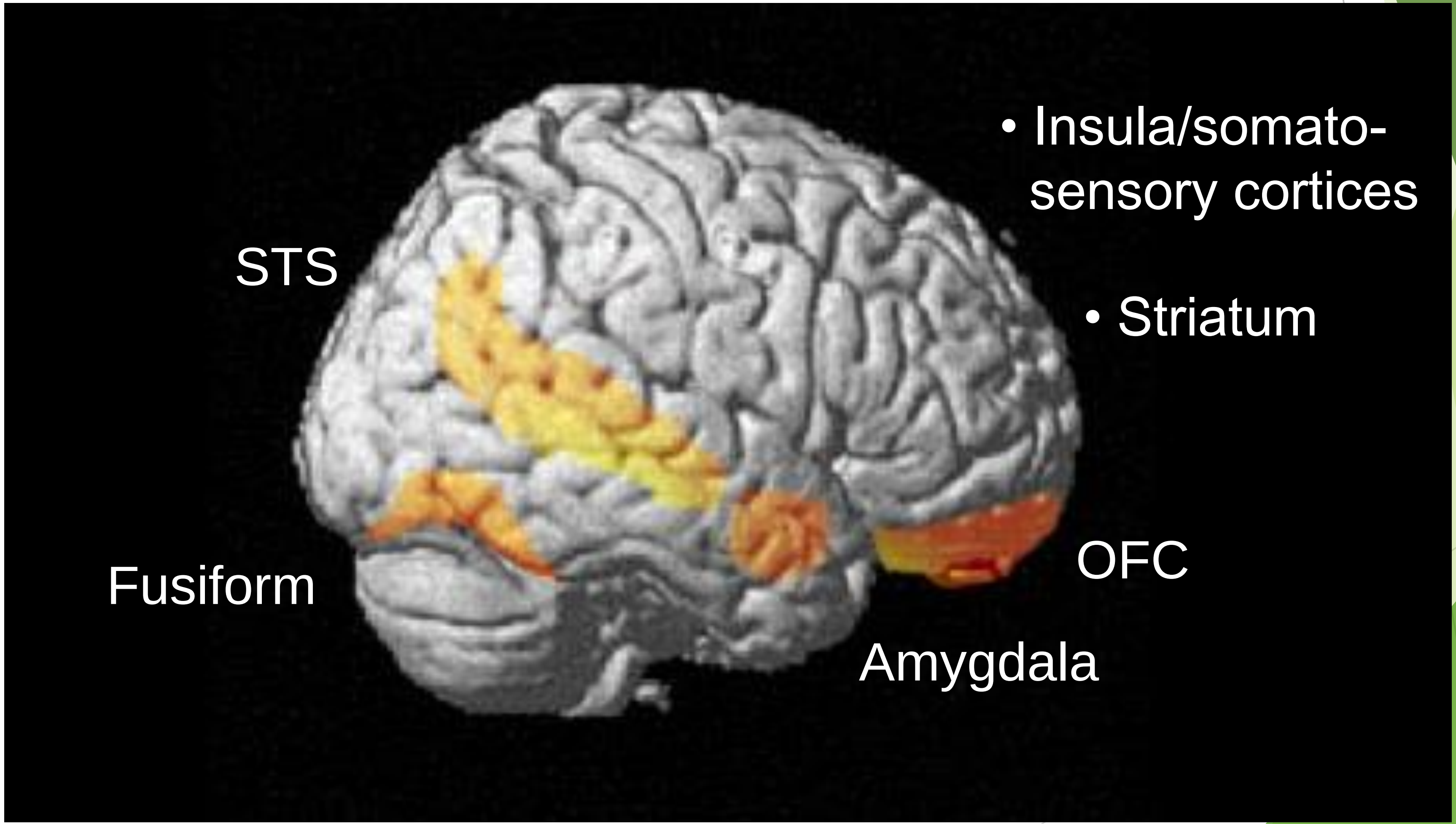


Winston et al. (2002). *Nature Neuroscience*

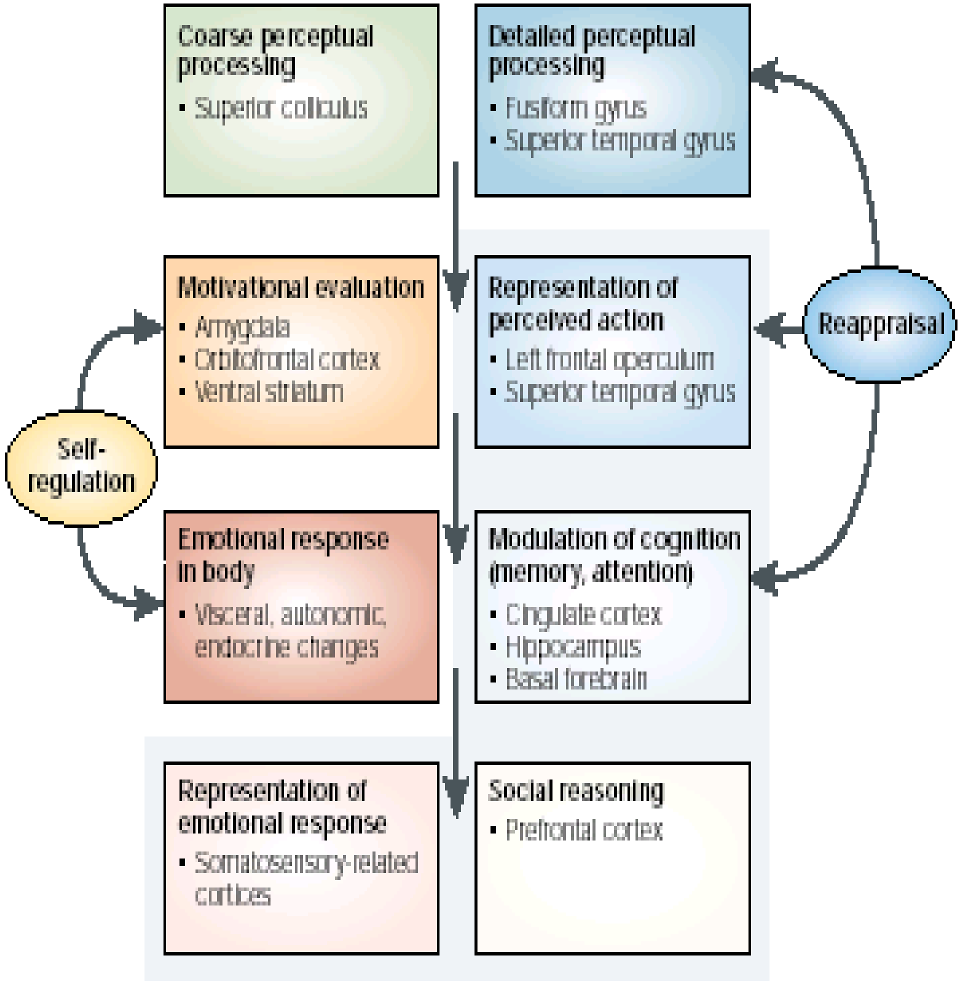
Socially Salient Cues of the Body: Biological Motion



General Findings
Brothers' Extended Model of Social Cognition



Adolphs Model of Social Cognition (2003)



Motivational Evaluation

- Amygdala
- Orbito-frontal cortex
- Ventral striatum

Detailed perceptual processing

- Fusiform gyrus
- Superior temporal gyrus

Emotional Response in body

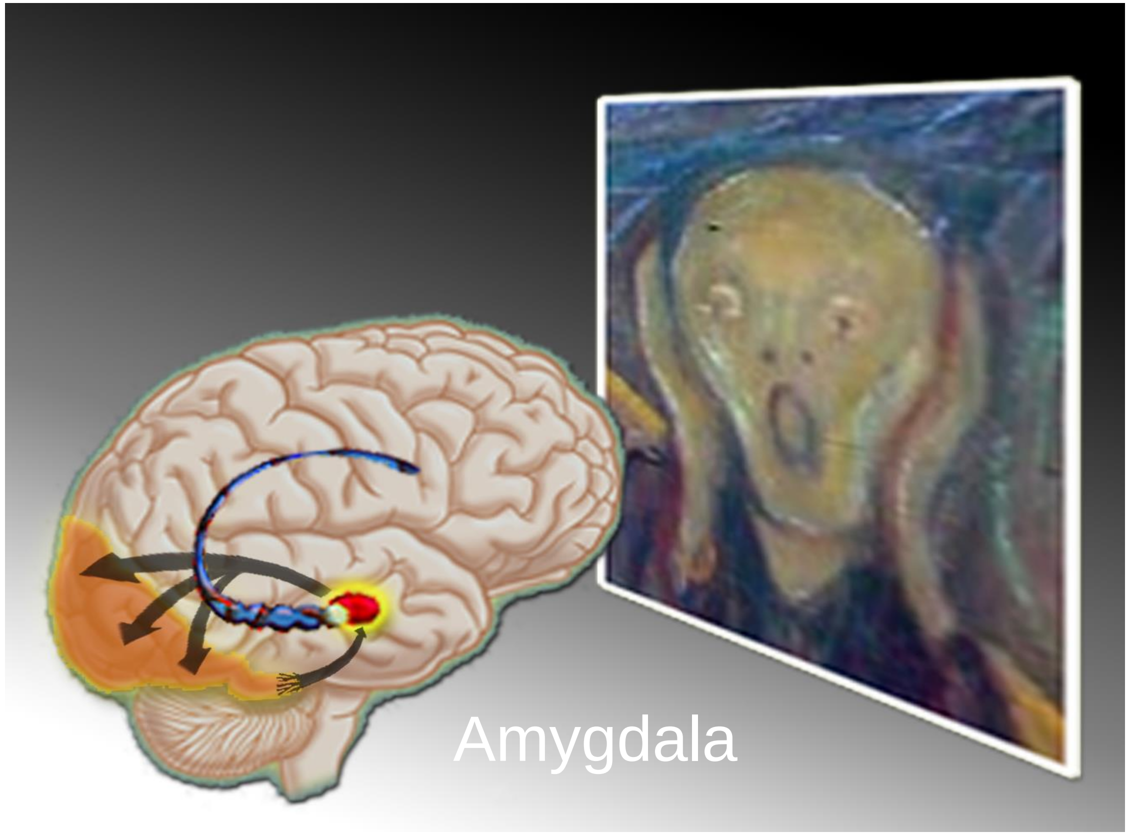
- autonomic, visceral endocrine change

Representation of emotion response

- Insula-somatosensory cortices

Adolphs, R. (2003). Cognitive Neuroscience of Human Social Behavior. *Nature Neuroscience Reviews*

The Amygdala and its Modulatory Role



Social-Cognitive Neuroscience

Social Neuroscience provides insights into people's ability to understand the mental states and share the feelings of others.

Three Streams of Research in Social Neuroscience

- Theory of Mind (TOM) & Mentalizing
- Action Observation, Imitation (Mirror Neurons)
- Empathy

Modern Social Neuroscience:
How do we Understand the Other ?

- Theory of Mind (TOM) & Mentalizing

  refers to our ability to understand mental states such as **intentions, desires and believes of** others.

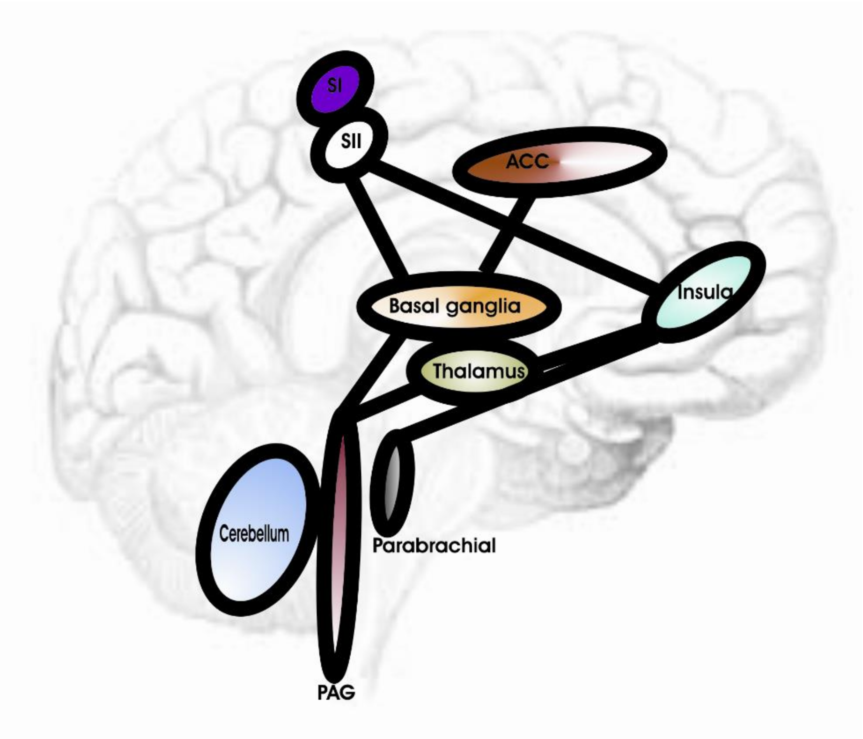
- Empathy

  refers to our ability to share the feelings of others, be it a particular emotion or sensory state of the other.

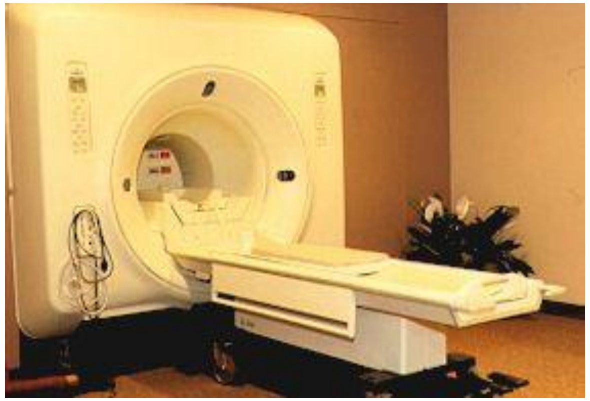



A Paradigm to Measure Empathy ‚In Vivo' Using the Example of Pain

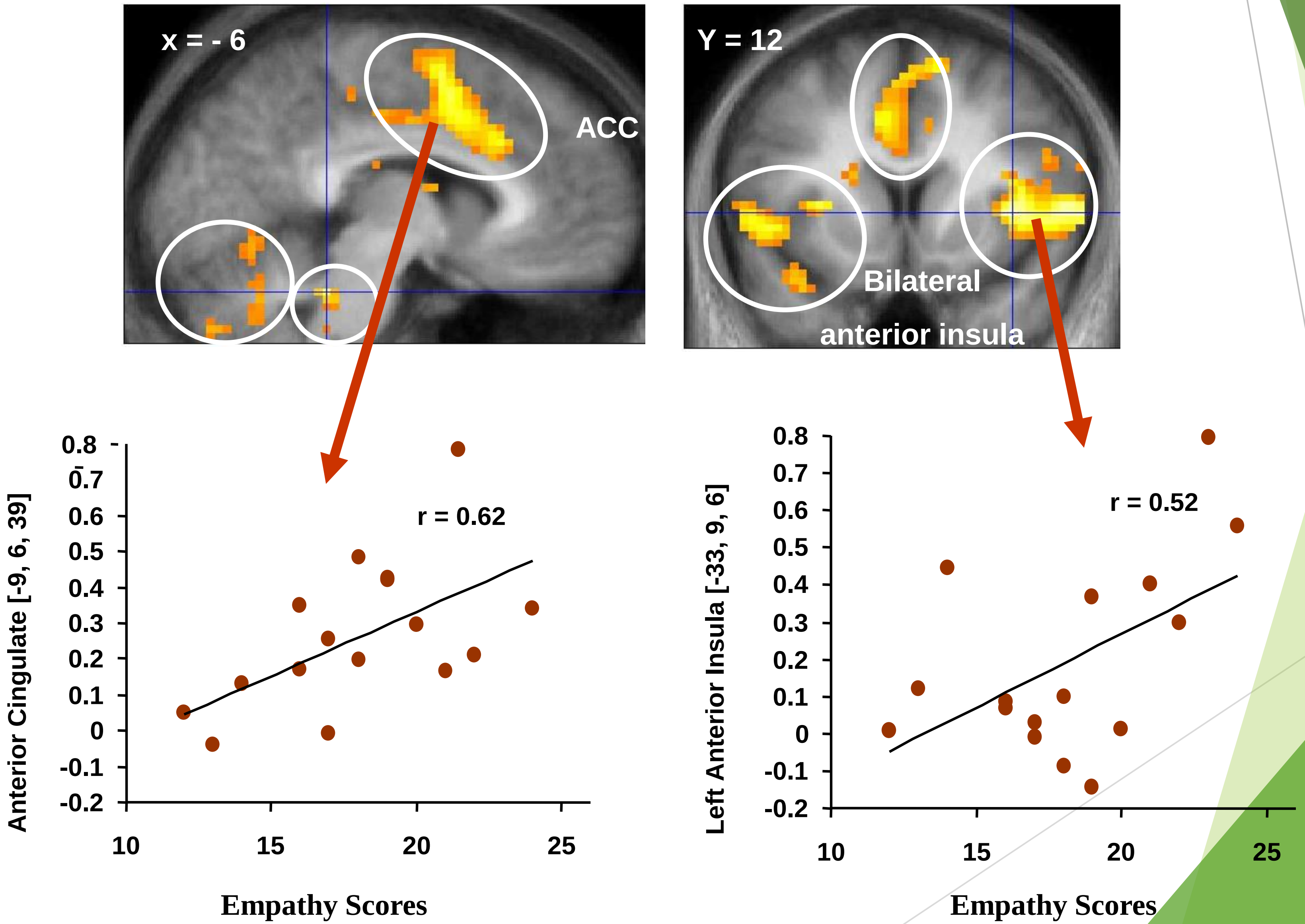
The 'Pain Matrix' in the Brain



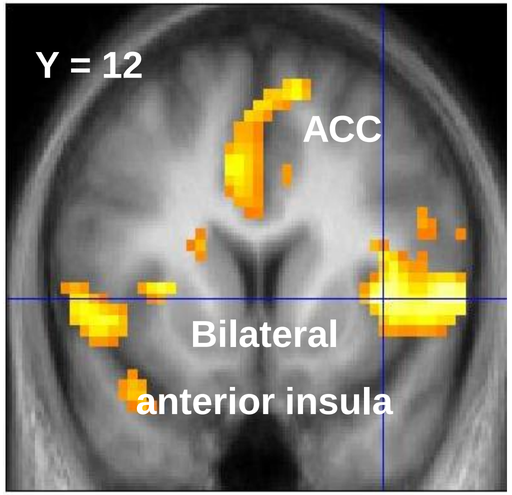
Singer et al. (2004). Science



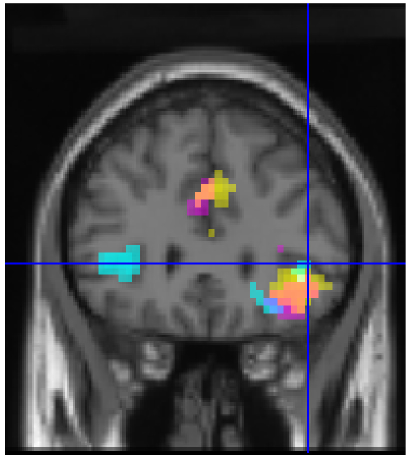
Shared Networks for Pain in Self and Others



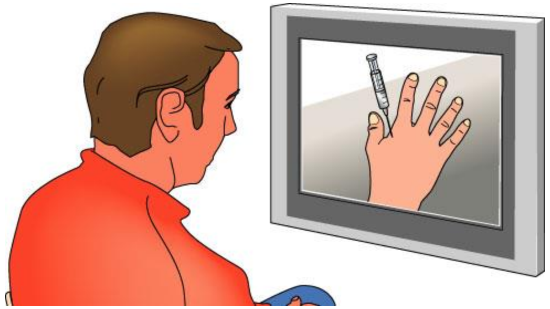
Recent fMRI Studies on Empathy for Pain



Singer et al. (2004).

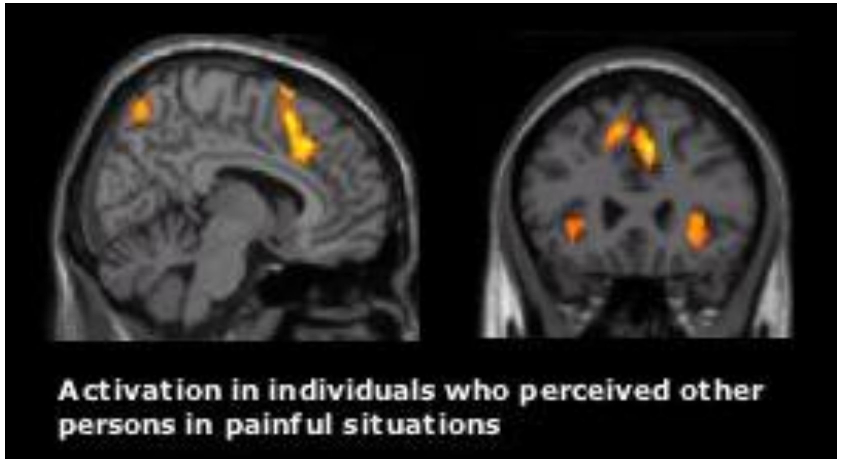


Singer et al. (2006). Nature



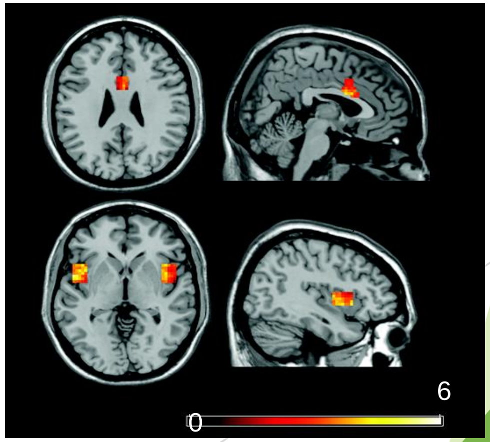
Morrison et al. (in 2004).

Seeing pictures of body parts in painful situations



Jackson, Metzoff & Decety (2004). *NeuroImage*.

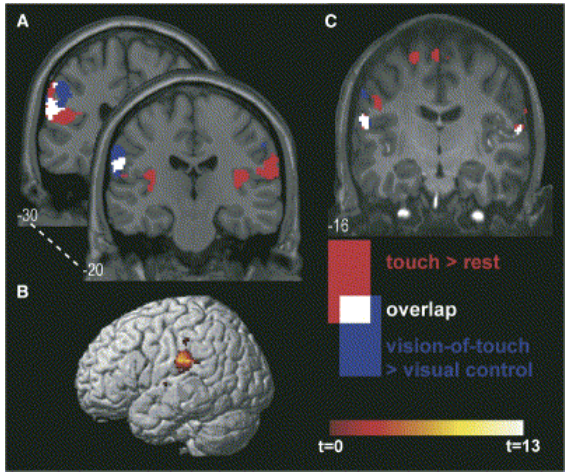
Seeing facial expressions of Pain

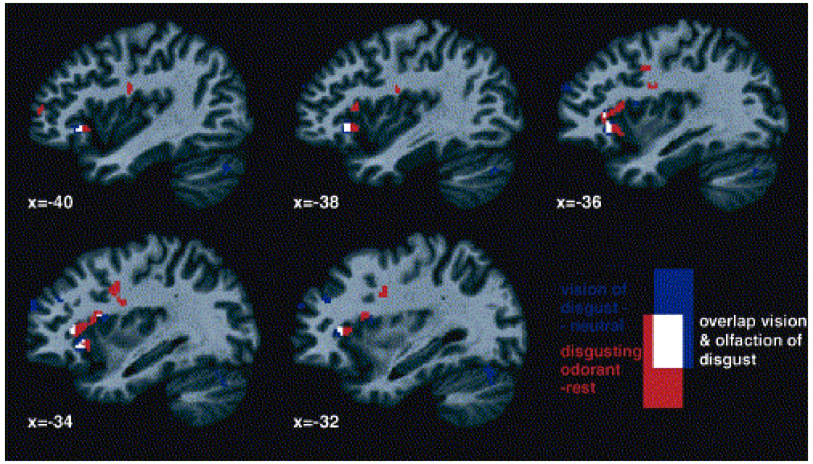


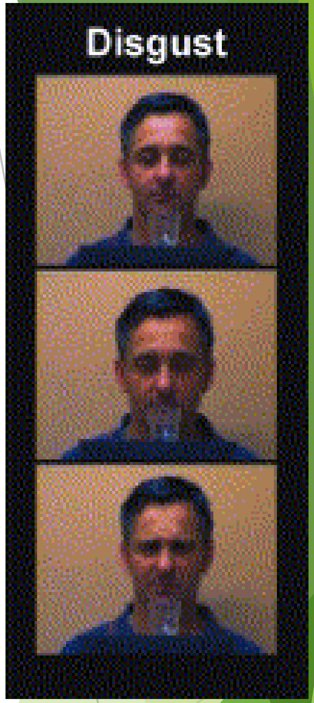
Botvinick et al. (in press).

fMRI Studies on Emotional Contagion

- Wicker et al., 2003. Both **the observation of disgusted faces** and **smelling disgusting odours** activated the same **restricted** group of brain structures, including **the insula and ACC**.







- Keysers et al., 2004. Secondary but not the primary **somatosensory** cortex is activated when the participants were **touched** and when they observed someone or something else getting touched by objects.
- but see Blakemore et al., 2005

Conclusion

When empathizing with others' affective states

we activate **representations reflecting the same**

bodily states in ourselves. These shared affective

representations allow us to know how **it feels like for**

someone else to be for example in pain even in the

absence of any stimulation to our own body

Modulation of Empathic Responses

- **Theories** of **social preferences** predict that empathy should be modulated by the perceived fairness of other individuals, and that individual agents punish violations of social norms.
- Thus, empathy should be reduced or abolished towards agents whose behaviour deemed socially unfair and thus whom we dislike.

- Instead we might expect to observe evidence of ‘Schadenfreude’ – the feeling of satisfaction experienced when **social violators experienc** **punishment** –as predicted by studies of **altruistic punishment**

The Experimental Paradigm

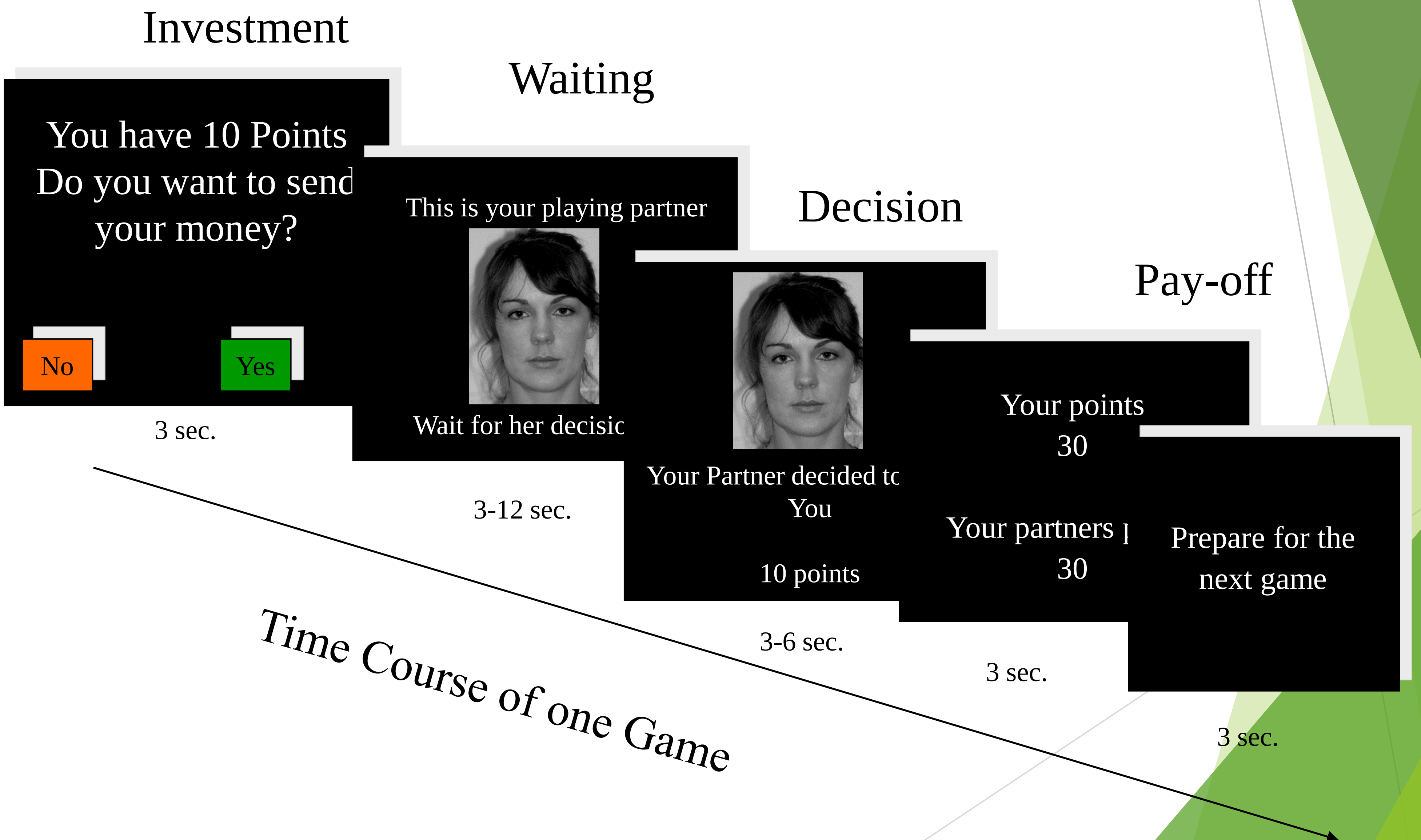
- **Stage 1: Social learning**
  - Subjects play repeated prisoners dilemma with 2 opponents – one fair, the other unfair

Singer et al. (2004). Neuron

- **Stage 2: Empathy for Pain Paradigm**
  - Subjects observe both players in an in-vivo empathy for pain study

Singer et al. (2006). *Nature*

One Game of the Social Learning Phase



Conclusions

- Perceived fairness learned in social interactions strongly modulate empathic responses – seen in both behaviour and neural activity
  - Loss of empathic activity seen in AI / ACC is accompanied by activity in accumbens correlates with the expressed desired for revenge to unfair individuals (in men)
- The data suggest gender difference which have to be pursued.
- This may be part of proposed proximate mechanisms behind altruistic punishment

  (e.g., social preference models,

  models of strong reciprocity;

  Boyd, Camerer, Gintis, Fehr, Gaechter, Rabin).


THE END
Thanks YOU