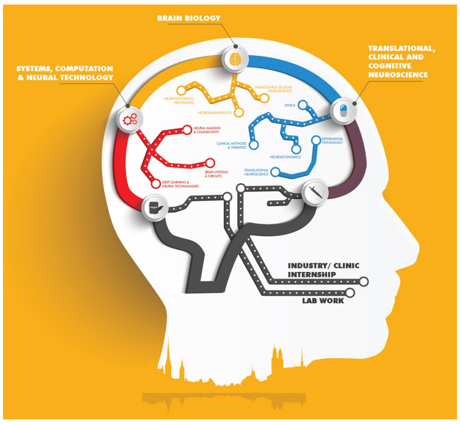

Interdisciplinary Brain Sciences MSc

Principles of Neuroeconomics

Elective Core

Lesson Notes

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1 Lecture 1

Adding neuroscience to explanations make explanations sound better to non-neuroscience novices. Interestingly, the "seductive allure" study could not be replicated.

2 Lecture 2: Reward Learning Part I

2.1 Outline

- Classical Conditioning
- Instrumental conditioning
- Models explaining conditioning effects:
  - Rescorla-Wagner
  - Temporal Difference

2.2 Why Reward Learning

- A basic tenet of economics and other decision sciences is that preferences drive choices.
- Therefore, the formation of preferences is important to understanding decision making.
- We are not born knowing everything, so we have to learn our preferences.

2.3 How do we learn about rewards and form preferences

- Often, when we talk about learning colloquially, we are referring to memorizing facts or procedures.
- Similar memory processes can be involved in reward learning.
- This lecture, however, will be based on implicit learning processes

2.4 How do we learn about rewards and form preferences?

- The brain has evolved to learn about rewards and form preferences by pairing stimuli with those outcomes:
  - The shape and smell of apples can be paired with sweet taste and nutrients
- Once a pairing has been formed, an organism can respond to that stimuli.

2.5 Stimulus associations

- Unconditioned stimulus leads way to unconditioned response.
- For example: A rat seeing a cat is an unconditioned stimulus. The rat freezing is the unconditioned response.

2.6 Classical Conditioning

- Uses a conditioned stimulus to unconditioned stimulus pairing to study learning.
- The process of classical conditioning pairs new stimuli that have no automatic response with an unconditioned stimulus that has an automatic response.
- Aka Pavlovian conditioning.

2.7 Pavlov's Experiments

- Pavlov was studying the digestive system.
- They were measuring the saliva output in dogs. And they realized that dogs salivated right before food giving because footsteps towards the enclosure was paired with incoming food.
- Pavlov then ran this study by replacing footsteps with the sound of a bell, which is a very neutral sound.
- Dogs salivated with bells, as they paired the sound of the bell with incoming food, which was the reward.

2.8 Terminology

- US:= Unconditioned stimulus
- UR:= Unconditioned response
- CS:= Conditioned stimulus
- CR:= Conditioned response

2.9 Contingency not just contiguity

It is not enough to have a CS and US occur with temporal contiguity, there must be a contingency between the CS and US such that $P(US \mid CS) > P(US \mid no\ CS)$

- Contiguity definition: the sequential occurrence or proximity of stimulus and response, causing their association in the mind.
- Contingency definition: Contingency theory proposes that for learning to take place, a stimulus must provide the subject information about the likelihood that certain events will occur.

2.10 Types of classical conditioning

- Excitatory conditioning. Conditioned stimulus implies unconditioned stimulus, which results in conditioned response. Example: Pavlov
- Inhibitory conditioning: Conditioned stimulus implies the absence of unconditioned stimulus. Conditioned stimulus implies no conditioned response after training. For example, when you shine light and not show food, organism knows that light implies the absence of food. No salivation at all.
- Appetitive conditioning: US appetitive
  - pair tone with food
- Aversive conditioning: US aversive
  - pair tone with an electric shock

2.11 Examples of excitatory conditioning

2.11.1 Simple motor responses: eye-blink conditioning

- Rabbit learns that a tone predicts a puff of air in the face and begins to blink when the tone is heard in the absence of air puffs.
- Note: Classical conditioning effects are tested in the absence of the unconditioned stimulus.
  - This way we can be sure that it is the CS that produces the response and not the US.

2.11.2 Bodily functions can also be conditioned

- In rats, a US = electric shock triggers an UR = endorphin release, which induces analgesia.
- Experiment: CS = tone, US = shock.
- Result: licking of wounded paw decreases in presence of tone (CS), meaning that the tone reduced the pain
- How?
  - Lester and Fanselow show that the CS elicits the UR, endorphin release
  - Their data show that the effect is reduced when rats injected with naltrexone, an opioid antagonist blocks the action of endorphins.

2.11.3 More complex motor responses in blue gourami (fish)

- CS signals rival male → Bites and tail fighting increases
- CS signals presence of female → More courtship and appeasement behaviors

2.11.4 Learning about hedonic utility: Taste preference learning

- Training
  - Non-deprived (not hungry)
  - Neutral Flavor 1 + sugar in water
  - Neutral Flavor 2 in water
- Test: Flavor 1 vs 2
  - Non deprived vs deprived tested
- In this case, US is sugar, UR is hedonic response, CR is measured indirectly through rat's consumption. Rat's state affects CS → CR relationship.

For non-deprived state, small mild preference for flavor 1, food deprived strong preference for flavor 1.

- Done with extinction. Extinction means that the actual reward is not delivered for the test case. No sugar in the water in the test case.
- The rat learns to associate Flavor 1 with sugar
- Therefore, when in hungry sate, preference for Flavor 1 over Flavor 2 increases even though during the text stage neither mixture contains sugar.

2.12 Open questions

- What is the range of bodily and neural processes that are capable of exhibiting classical conditioning?
- How much of learning in the brain can be thought of as an instance of classical conditioning?

2.13 Evolutionary advantagegs and constraints on classical conditioning

2.14 Adaptiveness

- The US $\rightarrow$ URs are selected because they are adaptive
- In many settings, it is very useful to prepare the organism to a US by triggering the UR earlier.
- Example: Salivating in advance of food improves digestion.

2.15 Example from the blue gourami experiment

For example, in anticipation of female fish, increased courtship behavior also results in more offspring, which is biologically advantageous

2.16 Biological Preparedness

- Some CSs are more easily conditioned with particular CRs than others
- This reflects the evolutionary situation of the species
- Example: Tastes are more likely to be predictors of poisoning or nutrition than visual or auditory stimuli.

An example experiment:

- Experiment 1: Thirsty rats: taste aversion learning paradigm
  - Phase 1 (pre-test): Salty water consumption
  - Phase 2 (shock): salty water $\Rightarrow$ shock
  - Phase 3 (post-test): salty water consumption is measured

Interesting conclusion: It is not possible to pair salty taste (CS) with shocks (US). However, there are some alternative explanations: maybe the salt concentration wasn't enough. Maybe rats don't learn tastes very well and this conclusion isn't a hint of biological preparedness. So here is a follow-up study:

- Experiment 1: Thirsty rats: taste aversion learning paradigm
  - Phase 1 (pre-test): Salty water consumption
  - Phase 2 (shock): salty water $\Rightarrow$ illness (lithium chloride injection)
  - Phase 3 (post-test): salty water consumption is measured

With illness, rats very strongly preferred not drinking the salty water (aversion). However, one alternative explanation would be now that the shock wasn't enough in strength to influence the rats. So a third experiment is conducted as well to show that rats can learn from a shock as well.

- Experiment 1: Thirsty rats: taste aversion learning paradigm
  - Phase 1 (pre-test): Light + tone
  - Phase 2 (shock or illness):
    * Group S: Light + tone ⇒ shock
    * Group I: Light + tone ⇒ Illness
  - Phase 3 (post-test): salty water consumption is measured

We concluded that rats are indeed receptive to shocks.

2.17 Classical vs Instrumental Conditioning

Instrumental conditioning works on similar principles as classical conditioning but often requires a specific action to get the reward.

- Instrumental conditioning is very powerful and can be used to teach humans and animals to perform a wide variety of behaviors to earn rewards

2.18 How are the CS-US associations learned

- How does the CS acquire or come to predict some value?
- Under what conditions does this occur?

2.19 Rescorla-Wagner learning model

- V_t = size (or value) of the US_t predicted by the CS.
- U_t = size (or value) of the US_t.
- α = learning rate. $\alpha \in (0, 1)$ determines how much each trial impacts future predictions.
- $V_{t+1} = V_t + \alpha(U_t - V_t)$
- If there are multiple CSs 1 - j: $V_{t+1}(i) = V_t(i) + \alpha(U_t - \sum V_t(j))$
- Intuition:
  - Amount of learning is driven by magnitude of surprise
  - Predictability attributed to a CS only if the US is not already predicted by other CSs

α is the learning rate. However, having a high or low learning rate doesn't give you an inherent advantage. It should match the volatility of your environment instead.

- This model makes several predictions that we can test:
  - No learning without surprise or erros in prediction
  - Learning reaches an asymptote when there is no more prediction error.

2.20 Predictions: asymptotic acquisition and extinction

Eventually responses to a CS stabilize and no more additional CRs are give.
The curve is similar for extinction. As the tone is not paired with the airpuff initially, the rats still blink. But, as these are unpaired more and more, they asymptotically stop blinking.

2.21 Blocking

- Phase 1: Some stimulus a $\rightarrow$ US
- Phase 2: A, B $\rightarrow$ US
- However, since B is identical in stimulus to A, in Phase 3 when we show B only, there is no element of surprise, hence, the response is the same.

2.22 An interesting twist on blocking

Blocking of learning for specific outcome is well documented, but what if the outcome isn't a specific event but the level of hedonic utility?

2.23 Trans-reinforcer blocking

Check the study on the powerpoint slide for this.

2.24 Overshadowing

- Phase 1: A and B $\rightarrow$ US. Assume A is a bright light and B is a soft auditory tone.
- Test
- Results: Respond more to A than B as it was a stronger training stimulus.

The more salient stimulus will depend on the context and biological preparedness:
Rats learn from taste and smell, pigeons from hearing. More weight put into the respective categories.

2.25 Bottom Line

Rescorla-Wagner can explain a sizable number of behavioral patterns in learning through classical conditioning. However, there are some aspects that it cannot explain.

2.26 Limitations of the Rescorla-Wagner Model

You can update without experiencing the outcome. Wine example from class.

2.27 Temporal Difference (TD) Learning

- Deals with continuous time rather than discrete trials consisting of stimulus + outcome
- Seeks to predict at each time point all future outcomes given current and previous stimuli
  $V_t(X) = V_{t-1}(X) + \alpha(\text{outcome}(x_i)_{t-1} + \text{prediction}(x_i)_{t-1} - \text{prediction}(X)_{t-2})$

2.28 Basic difference between TD and RW

- RW is discrete, TD is continuous.
- RW updates only when there is an outcome, TD updates whenever there is a change in the state of the world.

2.29 Predictions of TD learning

- Can explain all previous predictions for RW.
- Also explains 2nd order conditioning.

2.30 Second Order Conditioning

- Bell predicts food. And then you introduce a light that predicts the bell. Do you still salivate?
- The answer is yes. Organisms do learn that the light predicts the bell. TD learning incorporates stimuli with direct associations to reward and those that signal changes in the state of the world.

There is ample evidence that the brain uses this mechanism in reward learning.

2.31 An Axiometic Formulation of the Reward Prediction Error Hypothesis

Economists have developed an axiomatic model detailing the necessary and sufficient conditions of a reward prediction error signal (Caplin and Dean 2008 QJE; Caplin et al., 2010 QJE). The axiomatic predictions were subsequently tested with fMRI (Rutledge et al., 2010 J Neuro).

2.32 Axioms for Reward Prediction Error Signals

- Axiom1: Consistent prize ordering
- Axiom 2: consistent lottery ordering
- Axiom 3: no-surprise equivalence
  - Equivalence when there is no surprise

3 Reward Learning II

3.0.1 Dopamine neurons encode prediction error like signals

- Dopamine is a neurotransmitter
- Neurons that release dopamine can be found in the substantia nigra and ventral tegmental area and project to many other brain regions.

Single unit neuron recording: putting electrodes and recording their electrical activity individually

3.1 TD learning and DA in nonhuman primates

Monkeys were deprived of water and placed in front of a screen with electrodes in their brains and shown cues. Initially, juice was given only, without any cues, and dopaminergic neurons showed increased activity. Later, when the cue and the juice were paired, dopaminergic neurons fired at the conditioned stimulus, but not at the actual juice being delivered, as that was expected and there wasn't a prediction error. Later, a third run was made without the juice being given but a cue being signalled. In this case, CS does increase the firing rate of the dopaminergic neurons but the lack of juice later decreases it, as there is a prediction error.

3.2 Schultz, Dayan, Montague (1997)

- Classic paper in neuroscience showing that midbrain dopamine neurons encode the qualitative predictions of the TD learning model
- Natural question: How well does the dopamine signal fit the quantitative predictions of the model?
  - Error signals should scale with the amount of surprise about the outcome

3.3 DA signals do scale with surprise

High surprise increases the firing rate more dramatically than medium high surprise. Prediction error is not binary, it tells us how much surprise as well.

3.4 DA neurons also generate error signals for reward magnitude

When cues imply different amounts of juice rewards, the more juice rewards yield much greater dopaminergic neuron firing rate.

3.5 DA prediction error signals are context dependent

Dopamine signals shouldn't be outcome signals and the results should always be dependent upon expectations. When all three cues are mixed, DA neuron firing is linear. However, a medium reward after many small rewards will give a larger signal than a medium reward after many larger rewards.

3.6 Prediction error signals and dopamine neurons: Human fMRI studies of reward learning

We want to see if TD learning is monkey specific or if it applies to humans.

3.7 Reward learning in humans

Normal events: You are in a fMRI scanner. A flash lights and six seconds later you are given juice.
Catch events: You are in a fMRI scanner. A flash lights and ten seconds later you are given a juice.
Once people notice that the light predicts the juice, people shouldn't make prediction errors after a while. However, in the test condition, when juice is not given, people can make a negative prediction error.

fMRI shows that when nothing is expected but juice is delivered, the signal change is stronger.

The putamen in the brain gives the strongest responses, however, this isn't the area where the somas of the dopaminergic neurons reside, but instead, it is where they project.

Similarly, omission of juice when it is strongly expected shows a negative prediction error.

3.8 Why are we talking about striatum in humans and VTA in monkeys

It is technically difficult to measure neural activity in the substantia nigra or VTA with fMRI or EEG. Therefore, human studies of reward learning often focus on downstream targets of DA neurons.

3.9 Measuring PE signals in human VTA

This requires special MRI sequences that are linked to the person's heart and breathing rates. The point is that it is technically challenging and limits your availability to collect data from the rest of the brain.

3.10 Human VTA does show prediction error signals

With the same light desing, D'ardenne et. al 2008 showed that unexpected positive rewards showed a statistically significant change in activity, whereas the omitted reward conditioned also generated a response but wasn't statistically significant.

3.11 Human striatum also shows prediction error signals

This time, the omitted reward condition shows a statistically significant difference but the unexpected reward doesn't.

3.12 VTA and striatum are correlated

VTA := generator
Striatum := receiver

3.13 VTA encodes PE for primary and secondary rewards

Primary rewards include those that are necessary for the survival of species, such as food and sexual contact. Secondary rewards derive their value from primary rewards.
Both the VTA and the striatum shows that the results can be generalized to secondary rewards like money and doesn't have to solely be useful in the condition of primary rewards.

3.14 Summary so far

- BOLD activity in the ventral striatum seems to qualitatively encode for positive and negative PEs
- This fits well with monkey electrophysiology data since the vStr is a target of midbrain dopamine neurons
- We can also show that human VTA encodes PE signals that correlate with the striatal signals
- Natural follow-up question: Does the BOLD activity in the striatum encodes the PE quantitatively ?

3.15 Striatal signals match quantiative predictions over time (learning)

Definitions:

- CS+: High probability of reward
- CSneut: High prob of neutral outcome
- CS-: High prob of negative outcome

3.16 PE signals and DA neurons: Human fMRI studies of reward learning and choice

- So far we have been discussing passive learning paradigms
  - The people have not been making any choices, only passively learning about stimulus-reward contingencies
- This leads to the question, are the same systems involved in actual choices?

3.17 PE and Instrumental learning

- In instrumental learning, the rewarding outcome is contingent upon a specific response.
- The 'goodness' or 'badness' of specific stimulus-action pairings is learned with repeated experience.
- Somewhat similar to classical or Pavlovian conditioning, except that the learner must make a response (i.e. must choose a certain action)

3.18 PE signals for instrumental and classical conditioning

Conclusion: Ventral striatum reflects PE signals for both types of conditioning

3.19 Do neural reward learning systems show evidence of behavioral phenomenon associated with classical conditioning?

3.20 Blocking Paradigm

3.21 Neuroimaging Results

The authors examine the BOLD signal in an independent ROI within the striatum from previous reward-learning study.
Seeing Y in extinction is associated with greater BOLD signal, consistent with ha positive prediction error.
Seeing X is associated with a decrease in BOLD signal. This is consistent with the fact that it does not predict the reward and is therefore bad news relative to A or Y, which are other symbols that they see in the task.

3.22 Do learners and non-learners exhibit different PE signals in the striatum?

Decks were either high paying or low paying. You had to learn which ones were High probability of winning decks and which ones were low probability of winning decks.

3.23 Learners vs Non-learners

For learners, a strong and robust correlation with PE signals whereas non-learners don't show the same correlation.

3.24 When shouldn't you learn?

3.25 Learning with explicit instructions

- Humans often learn about costs and benefits through explicit instructions rather than trial and error.
- – Question: How do explicit and TD learning systems interact? What happens when they are in disagreement?

3.26 Explicit vs experience learning

Two conditions: Pure feedback vs instructed session. In pure feedback, we receive trial-by-trial feedback on the value of the green rectangle to try to predict its expected value. On the instructed run, we are given the probability of the anonymous variable being greater than 5.

Unsurprisingly, subjects performed better in the instructed session. The instructed group was also less susceptable to trial-by-trial feedback.

PE like signals are also reduced in instructed sessions.

In the instructed session group, dorsal lateral Pre- Frontal Cortex activation was more compared to the feedback group. The dlPFC is associated with complex thinking and memory. dlPFC and vmPFC are inversely correlated.

Interpretation: Regions with access to the instructed knowledge suppress the trial-by-trial learning systems that rely on PE signals.

3.27 Interim Summary

Human and non-human primate brains express PE signals consistent with the implementation of TD algorithms during reward learning.
These TD learning systems aid learning when explicit knowledge is unavailable
However, these learning systems can be suppressed when explicit learning systems are available.

3.28 Sample Exam Question

Dopamine is a learning and motivation molecule, not a reward and pleasure molecule.

3.29 Testing the RPE axioms

Different gambling options were given to the subjects and they were asked to choose some.

3.30 Standard regression analysis reveals ventral striatum activiy correlated with expected RPE signals

3.31 Testing the RPE axioms

Tests of the magnitudes and slopes in ventral striatum show that activity there does not significantly deviate from the criteria laid out in the RPE axioms. Thus it satisfies the necessary and sufficient conditions for encoding an RPE signal.

3.32 A word of caution on reverse inference from neuroimaging results

- – We have discussed several studies where activity in portions of the striatum correlates with RPE signals. However, one should not infer that all striatal activity reflects RPEs.
- Most brain areas are involved in many different functions and one should always be cautious when making statements such as “There was activity in brain area A so the subject was thinking/feeling XYZ”

3.33 An example of why caution is needed

Basic motor functions are among the easiest, clearest, and most robust patterns of activity that we can observe with fMRI. fMRI shows that both hand movement and imagined hand movement light up VERY similar areas in the brain.

4 Lecture 4: Methods in Neuroeconomics

4.1 How can we measure brain activity

- Functional magnetic resonance imaging (fMRI)
- Positron emission tomography (PET)
- Magnetoencephalography (MEG): measures the magnetic changes due to currents.
- Electroencephalography (EEG): Measure electrical activity directly.
- Electrophysiological recordings. We don’t use humans for obvious reasons but we use non-human primates or other organisms.

4.2 How can we measure brain structure?

- Structural MRI
  - Measure grey or white matter
    - Grey matter = neurons
    - White matter = glia cells and myelin
- Diffusion weighted imaging
  - Primarily measures myelinated axons that convey neural signals between neurons

We can measure the way water moves in diffusion tensor imaging to see which areas contain fibers, since white matter structures are impermeable to water, so the water goes around them.

4.3 Brain Stimulation Methods

- Brain stimulation methods temporarilty alter brain acivity
- They do not measure brain activity, rather bbehavior is tested during or after stimulation.

4.4 Brain Stimulation Methods

- Common techniques include:
  - Transcranial Magnetic Stimulations (TMS)
  - Transcranial Direct Current Stimulation (tDCS)
  - Transcranial Altering Current Stimulation (tACS)
    - Can be used to bring distant regions into or out of phase
  - Depp brain stimulation
    - Implanted electrodes - most commonly as a treatment for Parkinson's Disease

4.5 MRI Machine

Creates a very strong magnetic field. 3 to 7 Teslas. You lie on your back, it is usually dark, loud, and there is a screen for Neuroeconomics studies. You have to lie very still. You respond to questions on the screen using a button box under your fingers.

4.6 Synopsis of MRI

1. Put subject in strong magnetic field
2. Transmit radio waves into subject
3. Turn off radio wave transmitter
4. Receive radio waves re-transmitted by subject
5. Convert measued radio frequency data into an image

4.7 MRI images are composed of voxels

Voxels: 3D pixels
The resolution: 2-3 mm^2.

4.8 Brain structure segmentation and measurement

We can calculate what portion of the brain is white matter, grey matter, or CSF by calculating voxels.
Studies usually take raw images and segment it into only grey matter, only white matter, and only CSF image stacks.

4.9 Cortical thickness from 5-22 years of age

Typically grey matter density decreases from childhood to young adulthood and decreases most steeply from young adulthood to seniority.

4.10 Association between grey matter and risk taking in the UK biobank

Long term goal: how changes in biology is related to early life behavior.
They are trying to see how grey matter volume is related to risk taking behavior. The more the grey matter density in certain regions (page 18 figure b), the less you are prone to taking risks.

4.11 fMRI with Endogenous BOLD Contrast

- Blood Oxygenation Level Dependent Contrast
  - We can measure changes in blood flow and oxygegnation levels with BOLD fMRI
  - Neural activity is associated with changes in blood flow and oxygen and nutrient consumption
  - Changes in BOLD are a proxy for neural activity

Neural activity is associated with changes in blood flow as a part of the brain that is working consumes more oxygen. It also overcompensates.

4.12 BOLD fMRI as a vascular response

- Blood (hemoglobin) carries oxygen and glucose to the brain - and possesses different magnetic properties before and after neural consumption of oxygen.
- Hemoglobin exists in two states:
  - HbO2 (oxyhemoglobin) has little effect the magnetic field
  - Hb (deoxyhemoglobin) significantly effects local magnetism as it is attracted to the main magnetic field.

This is good because we don't need to inject outside labels to create contrast.

4.13 What does the BOLD signal look like

- A slow signal: increases about 2s after neural activity, plateaus around 6-8s, returns to baseline 8-11s after activity.

Note that the response is delayed. This slow response is the major drawback to fMRI as a research technique.
This is why we have to space out multiple tasks properly so that the BOLD signals don't overlap and interfere with one another.
If we want aggregate responses this might not be so bad; however, if you want individual responses, you have to space them out.

4.14 fMRI analysis overview

We want to look at fMRI images in two levels: First, we want to see the individual responses and then we want to aggregate responses between the individuals.

1. If we want to analyze fMRI data over a population, we would first take image time-series.
2. Then, we would normalise our data to align them with one another. Normalisation means we average the looks of the brain across all individuals, and then try to match individual brains to fit the template of the average normalized brain. We use a computer algorithm to do this.
3. Then, we would smooth them.
4. We run a regression model to predict. Most commonly, a general linear model is used. We then correct it and then statistically analyze our data.

4.15 Independent variables can include task events or predictions of behavioral models

4.16 IVs can also be time series from other brain regions in the same or different participants

You can take the time series from one region and correlate it with other regions. For example: if you want to see what happens to the regions outside of the hippocampus when the hippocampus is active, you can take the time series from the hippocampus and use it as an independent variable to regress against all of the other regions in the brain. You can conduct experiments across individuals as well.

4.17 Multi-voxel pattern analysis-an alternative and increasingly popular way to analyze fMRI data

Brain regions and neurons don't respond to stimuli in isolation. They are very interconnected. We can use this distributive code to get a more accurate signal of whatever the subjects are trying to do.

- The basic idea is to explain, distinguish, or predict behavior as a function of distributed brain activity patterns.
- The extent of this distribution could be a fairly local area of few millimeters, the entire brain, or anything in between.
- The patterns can serve as input to regression models or machine learning algorithms.

4.18 Multi-voxel pattern analysis- a summary

The idea is to take two or more voxels and try to use those to explain how different stimuli or task conditions may differ between them. These voxels can be neighbouring voxels or completely distant/irrelevant voxels.

4.19 Types of MVPA

- Classified-based MVPA: Activity in voxel 1 and activity in voxel two are graphed on x and y axis. Once you realize that the data is in clusters, you can put a line in between and discern which cluster is, for example, a face and which one is a scene.
- Similarity-based MVPA: Rating the representations and quantifying the similarity between them.

4.20 How can we use fMRI in Neuroeconomics

- Plassman, O'Doherty, and Rangel (2007)
- Research Question: What brain areas reflect the stimulus value in simple choices between primary rewards (e.g. foods)?

4.21 Plassman et al., Experimental Design

Participants would not eat for four hours before the experiment.

- Two experimental groups: 50 free trials vs 50 forced trials
- Free trials: you would see the picture of a food item (butterfinger candy bar) with a question mark below the image. Question mark means that they would be able to bid for this item freely. After this, there would be a short bid to contemplate how much they would pay for this food.
- Afterwords, there is the bidding, and the feedback round.
- Forced condition: no question mark, there is a number, they have to bid that much.

Once they are done with the scanner, the participants leave the scanner and hang around the lab for thirty minutes more. If their bids were the winning bid, they got to eat the item, if not, they remained hungry for thirty more minutes.

4.22 Using BDM auctions to measure stimulus values

- Critical to have a real-time and incentive compatible measure of stimulus values
- Becker-DeGroot-Marshack auctions widely used in economics for this purpose
- BDM auction rules
  - random price (p) drawn from urn
  - if bid $\geq$ p, get food item and pay p dollars
  - if bid $<$ p don't get food and pay 0
- Think of the bid as a monetized measure of the stimulus value

4.23 Relevant features of the experiment

- Free vs Forced trials: the brain may automatically react to pictures of food you typically like or dislike that may not be related to the computation. This way, by adding the forced condition, you can subtract the activity that is not helping with the computation of the bid.

4.24 BOLD signal magnitude is greater in Free vs Forced

More activity in the ventromedial prefrontal cortex or orbitofrontal cortex (OFC). More lateral regions and the middle regions are more strongly lit in the free condition than the forced. Peak response at 5 seconds due to the fMRI delay. THIS RESULT IS THE AVERAGE ACTIVITY

4.25 Is there a representation of the stimulus value on each trial

They want a trial-by-trial variation on the willingness to pay for the food item. They wanted to see if the trial number and stimulus value correlated with the activity of any individual part of the brain.

4.26 vmPFC and dlPFC encode for WTP in free trials, but not in forced trials

vmPFC and dlPFC reflect stimulus values during decision making situations. They are correlated with actively making a situation instead of just taking a given price for a food item.

4.27 Positron Emission Tomography (PET) Imaging Overview

Unlike fMRI, we need to inject something (radiotracer) into the bloodstream of the participant.

- Synthesize radiotracer
- Inject radiotracer
- Measure gamma-ray emissions from isotope (20-60 min)
- Reconstruct images of radiotracer distribution

4.28 What can PET do that MRI can't?

- PET can measure the location and relative levels of specific molecules in the brain.
- These molecules can be anything labeled with a radioligand (something that undergoes beta decay)

Since we synthesize the radiotracers, we can make them to specifically bind to certain regions and analyze where they aggregate.

4.29 PET limitations

- Requires radioligand injection
- Relatively poor spatial resolution (1 to 5 mm)
- Expensive
- Similar temporal resolution to fMRI for functional analysis
  - Still relying on blood flow

4.30 Are there any neuroscience techniques with good temporal resolution

- yes
  - EEG
  - MEG
  - Electrophysiological recordings

4.31 Electroencephalography (EEG)

You have someone sitting on a chair in a dark room with sensors on the head and a screen in front of the participant. Voltages of the sensors might change. The number of sensors on the scalp would change as well.
Preferably, the subjects wouldn't blink (which is why the room is darker) so that there wouldn't be eye-blinking artifcats (which are significant, since the blinks have high amplitude).

4.32 EEG

- Very old, first used in humans by Hans Berger (1924)
- A tracing of voltage fluctuations versus time recroded from electrodes placed over scalp in a specific array
- Represents fluctuating dendritic potentials in superficial cortical layers

EEG is limited to neurons arranged in a certain orientation. With EEG, we get a time-series of voltage change

4.33 Event-related potentials (ERP)

- It is common to viualize/analyze the EEG siggnals time-locked to specific task events (decisions)
- These time-locked patterns are known as event related potentials
- Averaging ERPs improves signal to noise
- Can compare responses to specific events at a given latency

Essentially, if you are time-locked to a specific event, when you average them, you get a representative average on how the evoked signals may look like, whereas the noise, once it gets averaged, gets reduced, which allows for a comparison of signals.

4.34 Where do EEG signals or ERPs Come From

Excitatory neurotransmitter released on apical dendrites causes positive charges to flow into dendrites -small electrical currents
Any neuron on its own would be very hard to measure, however, luckily in the cortex, lots of neurons are lined up in the same orientation. Thus, we can sum the signals in the neurons of the same orientation.
To be recorded at a distance, large numbers of neurons must have similar voltage fields (ie be pointed in the same direction).
We measure the sum of currents from an equivalent dipole

4.35 Where Do ERPs Come From

Scalp-recorded potentials are possible only for layered structures with consistent orientations. Primarily, this happens in the cerebral cortex.
Open Field:= The neurons are organized similarly with very similar orientations (the outer parts of the brain)
Closed Field:= The neurons are organized chaotically, mostly the inner parts of the brain, such as the striatum. We can't aggregate the signals in these neurons because the signals would cancel out.

We can easily tell when a signal arrives in the sensor array, but its harder to say exactly where it is coming from

- Voltages spread through the brain by "volume conduction"
- Nearly speed of light
- Voltage everywhere except at postive-negative transition
- Skull causes lateral spread (like spraying a hose on cardboard). The skull blurs the signal a bit, making it even harder to know where the signal came from.

4.36 Magnetoencephalopgraphy (MEG)

There is always a magnetic field perpendicular to an electric field.

- Magnetic fields travel around electrical dipoles
- The skull is transparent to magnetism – less blurring compared to EEG
- easier to localize signals compared to EEG, but still very a difficult problem

4.37 The Superposition Problem

Limits the ability to determine where the signal comes from

4.38 What types of Neuroeconomics questions can EEG or MEG address?

Page 57 of Lecture 4 slides.
Come to the lab hungry. An initial BDM Bidding. Then, the EEG scanning round. We are going to rate if you would actually eat this food item. 3 preference rounds of 15 minutes. BDM Outcome part, wait for 10 minutes.

4.39 ERP evidence of stimulus value timing

We can see how the brain signals evolved in certain brain regions.
In the study on page 58, the preferences start to differ very early on in visual cortices. 400 to 550 ms shows that there is a difference in signals in the frontal areas of the brain. Even greater separation between the different levels of stimuli.
Positive and negative deflections in the EEG don't depend on activity, they depend on orientation. Estimated cortical sources for ERP signals on slide 58.

4.40 Must there always be a trade off between spatial and temporal resolution

Yes and no

- Electrophysiological recordings have very precise spatial and temporal resolution
- Unfortunately, these techniques are also very invasive.

4.41 Single unit recording of amygdala neurons during food decisions

Electrophysiological study of human patients do exist (Jenison et al., 2011). Neurons in amygdala encode stimulus value with increasing and decreasing firing rates.
Some neurons increase firing when the amount of money they are going to pay increases. Some neurons decrease firing when the amount of money they are going to pay increases. Positive and negative slopes in this study does show increasing and decreasing firing rates.

4.42 Electrophysiological Recording

- Similar recordingsg can be made in animal models

- However, there are limits to what types of behaviors animals can be trained to do.

It is a bit more difficult, since animals aren't as intelligent as humans, so you have to train them in a certain way so that they understand the task like we do. For example, you cannot ask a rat how much they would pay for a chocolate bar so you need to measure desire in a different way and you need to train the animals a certain way as well.

5 Lecture 5: Shortcuts and Biases in Decision-Making

5.1 Main points in this lecture

Human decision makers have limited cognitive resources and often use heuristic strategies to reduce computation effort and speed choices
Evidence for/against different reasons for decision biases from behavioral and brain data

5.2 Decision strategies and heuristics

There are numerous strategies for selecting an option in choices over complex goods.

- Most rational choice models assume that choosers acquire as much information as possible in order to make the best choice.
- This strategy is exemplified by the weighted action method
- One other version of the strategy: add attribute values regardless of importance
- Lexicographic strategy: take the item with the highest value on the most important item.
- Elimination by aspects: eliminate items from choice set that don't meet criterion on an attribute in order of importance.
- Satisficing: Consider items sequential in order of choice set and choose as soon as one is good enough.

5.3 Do people satisfice

Humans especially satisfice in time constraints.

5.4 The best option was selected less often in more complex situations

The probability of finding the best option decreased with increasing complexity and the number of options.

5.5 What is the level of good enough?

Tracking clicks in the Caplin, Dean, Martin (2011) study.
There does seem to be a level of good enough but it also depends on the total number of options.
It also depends on the work that needs to go into evaluating those options.
There is both a trade-off between the outcome/rewards of a search and the complexity of the search.

5.6 The efficiency of a heuristic depends on the choice conditions

Environments also factor into picking the most efficient heuristic. Slide 15, Lecture 5
The difference between the two environments is that there is a higher correlation between attributes in B than A. This means an option high in attribute 1 will be higher in attributes 2-n so lexicographic becomes fast and accurate.

5.7 The efficiency of a heuristic depends on the choice conditions

There is empirical evidence that people readily adapt their choice strategies to contexts and time constraints.

5.8 Interim Summary of the lecture until now

- Heuristics CAN facilitate quick and reasonably accurate decisions, but the accuracy of heuristics depends on the decision context.
- People will use simplifying heuristics and shortcuts to avoid the effort involved in complex cognitive tasks.
  - Naturally, preferences over mental effort vary across individuals.

5.9 Framing effects as an example of bias

- Choices are susceptible to the manner in which options are presented
  - Violates axioms of rationality
- Framing effects are frequently attributed to emotional influences (eg fear of losses) and thought to be the result of dual-process (System 1 vs System 2) conflicts
  - Question to ask: Is there good evidence for this?
- Framing effects can be attenuated by enchancing engagement or elaboration on the decision problem.

5.10 How does the framing effect relate to limited resources or resource allocation?

- Framing effects are sensitive to the level of processing and the population studied
  - More elaboration over the decision reduces or eliminates framing effects
  - There are studies showing that experts don't show framing effects in their field of expertise

5.11 Elaboration and Framing effects

Kahneman and Tversky (1981) and Takemura (1994) show that high elaboration changes choices.

5.12 Are framing effects caused by an emotional reaction to salient loss?

A popular explanation for the framing effect relies on competition between deliberate, rational thought and emotional reactivity. Often this competition is incorporated into a dual-process framework.

5.13 Neural evidence for Emotion vs Engagement in the context of Framing effects

- Initial fMRI studies did find that
  1. Bbrain regions associated with emotional processing, specifically the amygdalae, were more active when people decided in accordance with, versus against, typical framing effects
  2. Brain regions associated with cognitive control and regulation were more active when people decided against compared to along with typical framing effects
- This was interpreted as evidence in favour dual-process models that assumed competition between emotional and rational, deliberative brain systems.
- BUT more recent work calls the completeness of this conclusion into question

5.14 Patients with complete bilateral amygdala lesions show framing effects

Talmi et al., 2010 Neuropsychologia

- Remember that a popular hypothesis is that the framing effect results from emotional signals generated by the amygdalae
  - If this is true, then individuals without these brain structures should show reduced or no framing effects/
  - This is not the case, as we have just seen.
- There are multiple reasons why these patients might show framing effects despite not having amygdalae, but these results certainly call into question amygdala-mediated emotional processing as the core cause of the framing effect.

5.15 Reason's Enemy is not emotion: engagement of cognitive control networks explains biases in gain/loss framing

- Li and colleagues attempted to provide new insights into framing effects by explaining brain-wide patterns of activity instead of single brain regions one at a time.
- Li et al use an automated meta analytic tool (neurosynth) that is continously growing in terms of its scope and research utility.
  - The backbone of Neurosynth is the automated meta-analysis of fMRI results and topics from published papers.
  - At the time Li et al did their work, neurosynth allowed them to compare their results fmo 143 participants to meta-analytic data compiled from over 8000 other studies.

5.16 Neurosynth

Automatically scrapes html versions of published papers to create associations between terms occuring in the text of a paper and reports of activity at specific coordinates
Generates a very large database of term vs activity maps
The automaticity of this process results in some inaccuracies. For example, terms used frequently in a paper may not be what the paper is about or regions showing greater or less activity are treated the same.

5.17 Participants do show the framing effect and the size of this effect varies across people

5.18 Using whole-brain patterns of activity to try and understand framing effects

1. Step 1: Compute the group-level patterns of brain activity for frame-consistent versus frame-inconsistent choices in the sample of 143 participants.
2. Step 2: Run correlations between this whole-brain map and each of the 2592 term-based, z-statistics maps from an association test from Neurosynth.

5.19 Historgram of correlations between the Framing effect pattern and meta-analytic maps of different terms

Slide 36

- Neural profiles for emotion (NPe) are not the ones most strongly correlated with the differences in activity between frame-consistent and inconsisntent choices.
- Instead, we see that
  - NPs for terms related to resting state or default-mode activity are most positively correlated with the framing effect contrast
  - NPs for terms relating to task engagement and executive function or cognitive control are most negatively correlated with the framing effect contrast

5.20 Computing the degree of explained variance for emotional NPs versus task (dis)engagement NPs

NoE, key idea is that they compute partial correlations
Partial correlations with NPe controlling for NP+/- and partial correlations with NP+/- controlling for NPe

5.21 NPs explain relatively little of the shared variance between the framing contrast and NP+/-

5.22 Explaining individual trial outcomes

Procedure: Compute neural similarity between NP+, NP- and NPe on each trial. Then run a logistic regression using these 3 variables plus response time to explain choice outcomes.
Result: NP+ and RT are significant, others are not.

5.23 Relation to previous fMRI findings in amygdala

Note that when examining regions one by one, Li et al replicate findings from previous findings in the amygdala
However, interpreting these results in the broader context of whole brain activity leads to more nuanced conclusions.

5.24 Conclusions from Li 2017

These results don't rule out emotions as a reason for framing effects
They do indicate that emotions are not the sole, or perhaps the primary driver of framing effects.

5.25 Relating this brain-wide pattern analysis to behavioral experiments on elaboration levels and choice

Increasing elaboration during decision making results in diminished framing effects
Making choices that are inconsistent with framing effects is associated with brain activity patterns that are typical for engaged, controlled processing.

- On the other hand, choosing in line with framing effects is assocaited with brain activity patterns typically seen during "resting state" paradigms
  - During resting state paradigms subjects are asked to lay quitely in the scanner and do nothing for 5-1o minutes (shouldn't sleep)
  - What we observe during these paradigms has been described as mind-wandering, default mode or Random Episodic Silent Thought

5.26 Summary until now

- Framing effects have been shown to exist across several domains.
- The size of the effect varies across individuals
- Neural and behavioral data suggest that emotion-based dual-process explanations for framing effects are incomplete
- Cognitive strategies such as elaboration can reduce the influence of frames and the relative level of engagement or effort put into choice may, at least partially, explain why framing effects exist.

5.27 Attention and deviations from Expected Utility in decisions under risk

- Decision makers often deviate from eU
- Cumulative Prospect Theory (CPT) allows for deviations from linear probability weighting and loss aversion (Tversky Kahneman 1992).
  - Better describes human decisions
  - Doesn't directly explain why they show non-linear probability weighting or loss aversion though

5.28 How CPT parameters influence value and probability

You can change the gamma and deltas to obtain different curves

5.29 Decision screen for Experiment 1 in Pachur et al 2018

You have two gambles with outcomes and probabilities. When you click a box, if you want to look at another box, you click on it but the previous box closes. The researchers measure how much time you spend looking at each box. When you're ready to make a decision and choose a gamble, you click on the buttons on the right.

5.30 Attention indices

- Attention_O = the median (across all gamble problems) of the time spent inspecting all outcome information
- Attention_P = the median (across all gamble problems) of the time spent inspecting all probability information
- Attention_{LA} = the median (across all gamble problems with mixed gambles) the ratio of time the participant spent inspecting loss outcomes
  - i.e., O^-/O^+

5.31 Attention is correlated with loss aversion, outcome sensitivity, and probability sensitivity

5.32 Attention is not related to the elevation parameter (delta)

Attention is not altering your baseline preferences but it is shifting how you factor in your gains and losses.

5.33 CPT parameters related to attention

All the values in CPT is related to attention.

5.34 Experiment 2, Does attention play a causal role?

- Three attention manipulation conditions:
  - Loss attention (n = 40)
    * Loss outcomes open for 900 ms
    * All others 300 ms
  - Gain attention (n = 41)
    * Gain outcomes open for 900 ms
    * All others 300 ms
  - Control (n = 39)
    * All boxes open for 300 ms

5.35 The duration manipulation changed looking times and loss aversion

- Attention_{LA}
  - Loss-attention group = 2.82
  - Control group = 1
  - Gain-attention group = 0.34

5.36 Conclusions from Pachur et al 2018

- Attention is correlated with deviations from EU
- Differences in attention to gains relative to losses can cause loss aversion

5.37 Another form of bias -The Endowment Effect

- The Endowment effect refers to the phenomenon that people behave as if they place more value on an item simply because they own it
  - Famous examples of trading/buying/selling mugs or pens given to participants in lab experiments
- The size of this effect is debated, but the difference in buy/sell prices has been found to be consistently significant even when subjects are told about the endowment effect

5.38 Market experience and the Endowment effect

- Engelmann and Holland (2010) designed a series of experiments to test the effect of market experience on the Endowment effect
- The key manipulation is a forced trading condition

5.39 Experimental Design

- All participants endowed with one of two goods
  - Ex. A bag of coffee or rice, package of crisps, can of cola, pen, notepad
- Trading sessions lasted 5 mins
  - Free conditions had no restrictions
  - In forced conditions, participants could not take home the same item that they were originally given (i.e., they were forced to trade).
  - Asymmetric supply of one good was introduced in some sessions to prompt faster trading.
  - Following the trading sessions all participants were given the same good as compensation for participation in addition to what they could keep from the trading session.
    - Essentially the subjects are re-endowed with the good.
  - In the one-on-one debrief session with the experimenter, the participants were given the opportunity to trade that good for another.
    - This trading opportunity is the dependent measure in the following regression. This is the outcome of the experiment.

5.40 Just as forced elaboration can reduce the Framing effect, market experience can blunt the Endowment effect.

5.41 Take home messages

- People generally adapt their strategy to match the context and reduce effort
  - They may not always do this in an optimal manner.
- It is unlikely that emotions are the sole cause of seemingly irrational behaviors.
- There is also good evidence that experience and attention/elaboration reduce Framing effects, Endowment effects, and other seemingly irrational behaviors.

6 Lecture 6: Valuation Systems in Goal-Directed Choice

6.1 What is goal-directed choice?

- Choices where values are assigned to stimuli/actions by computing action-outcome associations and then evaluating the rewards associated with each outcome
- Also known as "value-based" choice

6.2 Stages of goal-directed choice

1. Representation: First, you perceive a question. What are the feasible actions? Internal states? External states?
2. Valuation: What is the value of each action
3. Action selection: Chose actions based on valuations
4. Outcome evaluation: How desirable aer the outcomes and states that followed the action
5. Learning: Update the representation, valuation, and action selecting processes

6.3 Other types of valuation systems

- Pavlovian: assigns values to a small set of behaviors that are evolutionariliy appropriate responses to particular environmental stimuli
  - Salivation
  - Freezing
  - Approaching food
- Can learn to associate unconditioned stimuli (US) with previously neutral stimuli (CS)
- Habitual: can learn, through repeated training, to assign values to a large number of actions
  - Not limited in the same way as Pavlovian learning
- Key characteristics of habitual valuation systems:
  1. Learn to assign values to stimulus-response associations (which indicate the action that should be taken in a particular state of the world), on the basis of previous experience, through a process of trial-and-error
  2. Generally learn to assign a value to actions that is commensurate with the expected reward that these actions generate, using as sufficient practice is provided and the environment is sufficiently stable
  3. In the habitual system, it would take a while to unlearn a habit. For example, you open the lights when you go into a dark room. Now, whenever you go in, assume that an electric grid shocks your feet. You would unlearn the habit of turning on the lights eventually, however, it would take some time. With goal-oriented learning, however, it would be way quicker to unlearn the habit.
  4. Because values are learned by trial-and-error, habit systems learn relatively slowly and can forecast the value of an actions incorrectly immediately after a change in the action-reward contingencies.
  5. Rely on 'generalization' when assigning action values in novel situations

6.4 Learning the value of actions

- Both Pavlovian and habitual systems learn in a manner consistent with Temporal Difference (TD) models
- Goal-directed system can use this information too, but is not limited to it.
  - It can learn by observation as well

6.5 Outline of questions today

1. Are there neural systems that reflect the value of stimuli/actions at the time of choice?
2. Can the same system represent positive and negative values?
3. Is there evidence for a system that uses a 'common currency' to represent different types of goods?
   - An example for this is: how would you compare the utility you would receive from a new bike with a new laptop? Does your brain have a common currency to compute your preferences?

6.6 Evidence for value encoding in single neurons

Experimental setup: Monkeys are in front of a screen. They will receive a juice reward for their answers.
This study is conducted by eye movements.
In the screens in front of the monkey, there are colored squares. Each color tells him the flavor. The number of squares shows the amount of juice it will receive.
Once the square in the center turns grey, the monkey needs to saccade its eyes towards the reward. Once the monkey selects the option, the juice is delivered, and then it will move to the next question.

6.7 How is the stimulus value measured in non-human primates

Determine the marginal substitution rate
The data shows that the monkey would take 4.1 drops of water to one drop of juice A

6.8 Recording sites in non-human primates

Data on following slides from: Orbitofrontal cortex. Related findings from: ACC, or LPFC

6.9 Some OFC neurons encode stimulus values of particular stimuli (independent of location

Some neurons fire for A, some neurons fire for B.

6.10 Some neurons encode the identity of the chosen item

These neurons will signal what I chose, not how much reward it gives me. In panel f, we see a neuron that fires when B is chosen. It doesn't encode how good B was, it just encodes that B was chosen.

6.11 Some OFC neurons encode the value of the chosen item regardless of identity

Some neurons fire more with value of the item increasing, some fire less with increasing value. They show concave or convex patterns.

6.12 Notes

- There is a representation of stimulus-specific value at the level of single neurons in the brain
- Single neurons also encode choice variables such as chosen value, and stimulus identity

6.13 Meta-analyses of subjective value at the time of choice

vmPFC, striatum, and the dPCC seem to encode for the value of choices.

6.14 Outline of questions today

1. Are there neural systems that reflect the value of stimuli/actions at the time of choice?
    - yes
2. Can the same system represent positive and negative values?
3. Is there evidence for a system that uses a 'common currency' to represent different types of goods?
    - An example for this is: how would you compare the utility you would receive from a new bike with a new laptop? Does your brain have a common currency to compute your preferences?

6.15 How are negative values encoded at the time of choice?

- Which brain areas encode for aversive goal values?
- Can the same areas encode for aversive and appetitive goal values?
    - There are long-standing debates in neuroscience about whether there are separate systems for positive and negative values

6.16 Experimental Design

Two conditions: one food is appetitive, one food is aversive (you would pay to avoid it). If you don't win the auction, you eat the food, if you win, you don't eat the food for the aversive condition.

6.17 Areas encoding for aversive goal values in free trials

fMRI studies show that positive and negative do overlap at certain points in the brain.

6.18 Outline of questions today

1. Are there neural systems that reflect the value of stimuli/actions at the time of choice?
   - yes
2. Can the same system represent positive and negative values?
   - yes
3. Are negative values always associated with less activity?
   - No
4. Is there evidence for a system that uses a 'common currency' to represent different types of goods?
   - An example for this is: how would you compare the utility you would receive from a new bike with a new laptop? Does your brain have a common currency to compute your preferences?

6.19 Goal congruency signals in vmPFC

Participants are making choices between different combinations of goods. Before going into the scanner, they will rate how much they would like to have these goods. In the scanner, they are asked to choose the good they want the most, and second, they are asked to choose the good they want the least.

6.20 Goal congruency signals in vmPFC

Negative things encoded as high activity when chosen the worst option and low activity when chosen the best option. The reverse is true for positive things. The firing isn't dependent on the value of the items but more so dependent on the value of the items with respect to our goal.

6.21 Common Currency

- How/where does the brain represent different types of stimulus value?
- Can different reward types be compared in the same brain regions?

6.22 Tests of common value representation

- Pre-scannnig: free response time, BDM auction. The person must choose between bookstore trinkes vs food.
- During scan: they try give you an item vs money and let you choose to see what encodes the value for different items.

The results show that there are differences between which region in the brain expresses these items; however, there are some overlaps as well.
vmPFC seems to correlate with the overlap and seems to activate commonly for all choices against a fixed monetary bid.

6.23 Common Currency

- In both of the previous examples, we saw that some brain regions represent only one type of reward. In other words, there was not complete overlap between food, money, etc.
- This is important to remember, but id doesn't speak against the idea of a common currency representation.
- The common currency hypothesis only requires that the brain can represent various reward types on the same scale.
- A stronger test of the common currency hypothesis is if we can "read out" value from brain activity across different categories of goods.
- The following study uses a design similar in Chib et al, but adds a machine learning analysis to test if they can predict the value of goods across categories
- It will try to predict the value of one type of good, by being trained on another type of good.

6.24 Category-dependent and category-independent goal-value codes

Can a classifier trained on activity from one category predict values in other categories?
The answer is yes, you can accurately predict across goods.

6.25 Interim conclusion

- vmPFC can represent the value of many concrete rewards at the time of choice
  - Juice/food
  - Money
  - Consumer goods
- What about more abstract rewards? How do we compute values when the task is not about ourselves.

6.26 Value computation in moral dilemmas

Shenhav and Greene: Moral dilemma readings first similar to the trolley problem. You are on a rescue team heading to one direction to save a toppled boat. Then, you hear that another larger boat toppled at the opposite direction but there's a probability that a second rescue team can get to it. The probability varies by trial. What do you do? After reading the dilemma, trial 1 commences. Then ten more trials are conducted.
Here, the stimulus of expected value (EV) is computed as: Number of lives x probability of death.

6.27 Value computation in moral dilemmas

The study showed that increasing moral expected value correlated with increasing activity in the vmPFC. Obviously, there are other regions that contribute to this as well, but the vmPFC seems to be the overlap/common region.

6.28 vmPFC represents the relevant value signal

Another question is whether this valuation system is inherently linked to value for yourself.
They brought people into the lab, estimated their temporal discounting functions, and then paired them up with a person that has a temporal discount function that allows the experimenters to create a series of choices that are relatively distinct between the two people, but also with enough overlap where you would make the same choice so that the estimated value functions are relatively uncorrelated between the two of you.
Every trial you get an instructor that you are either choosing for yourself or your partner.
Each trial has two options: Option A today or Option B at some random time.
If you are choosing for your self or your partner, you have to choose the best option.

6.29 vmPFC represents the relevant value signal

The "expected value" is the one relevant to the current choice.
We see from the results that in the vmPFC, the voxels shift from executed value to modelled value.
Executed: the one that is relevant for the person who you're supposed to be choosing for on that trial. So if you're choosing for yourself it's you, if you're choosing for Mary, it's Mary.
The modelled is the alternative choice on that trial.
You always compute executed and modelled values, but which one you compute where depends on the trials. The red portion on slide 47 show the choices you make for yourself.
The value system isn't locked into your own values but it is about whoever is choosing.

6.30 vmPFC represents the relevant value signal

Self value is correlated with the vmPFC when it is choosing for self. When choosing for the other person, the other value is more relevant.

- vmPFC reflects the values you would assign when choosing for yourself
- vmPFC reflects the values you have learned another would assign when choosing for him/her
- The values computed are those that are appropriate for the choice situation

6.31 Notes

- vmPFC represents stimulus or subjective values across a wide range of reward types
- vmPFC is not the only region that represents stimulus value, but it is one of the most consistent regions to do so

6.32 Is vmPFC necessary for goal-directed choice

- We have consistently seen vmPFC reflecting the value of stimuli/actions at the time of choice
- However, other areas (e.g. striatum appear to do so too)
- Also, all of the data shown so far are only correlational

6.33 Testing the generalized axiom of revealed preference in patients with vmPFC damage

Camille et al 2011, page 53, the image shows the damaged areas overlapped in the 9 patients of the study. There are 22 controls.
Large overlap of damage in the vmPFC region.

- Remember, the basic notion embodied in GARP is that a person's choices should be internally consistent and transitive. For example,
  - If someone picks X over Y, then they should not at another point select Y when X was also available.
- This study presented brain damaged patients with choices for different bundles of chocolate bars and juice boxes.
- On average, control subjects had 1.41 GARP violations with a majority making no GARP violations.
- VMF patients had a mean of 4.89 GARP violations, with a large majority making two or more GARP violations. Small samlpes and high variability, so take it with a grain of salt still.
- Variance in the behavioral effect may relate to variance in the lesion location or severity as well.

6.34 Conclusion

- vmPFC lesion patients' choices violated GARP significantly more often than controls
- Suggests that vmPFC is necessary for optimal decision making
  - Note that vmPFC lesion patients still make choices, they just don't compute or compare values as consistently

6.35 Can we use neural representations of value/goal relevance in economics

- Predicting micro-lending
- Efficient allocation of public goods

6.36 Predicting Micro-lending

Nora needs three thousand in micro loans to buy a truck to take her goods to the local market

6.37 Initial internet study design

- Actual lending data provided by the micro-lending site Kiva
- Borrowers' text was assessed for valence using a standardized system
- Borrowers' photographs were rated for valence by people "hired" through Amazon Mechanical Turk

6.38 Internet study results for funding rate (how quickly they reached the goal)

If the photo creates positive arousal and the photo is identifiable, it facilitates reaching the goal. Repayment term is negatively correlated with rate of funding.

6.39 Affective ratings predicted lending rates

Photographs in the top decile of positive-arousal ratings were funded at 8.04 dollars more per hour than were photographs in the bottom decile; they achieved full funding in 11.5 percent less time

6.40 Neuroimaging experimental design

This gave an idea to the researchers. Affective responses in the brain might be useful in predicting rates of funding.
Experimental design: Replicating the online experiment in the fMRI scan.
Step-by-step:

1. Show photograph
2. Show loan page
3. Subject makes a decision on whether to fund the loan or not
4. After scanning, subjects made ratings about their affective responses to the pictures and text descriptions.

6.41 Neuroimaging study results

Nucleus accumbens activity is correlated with aggregate lending rate.

6.42 Neuroimaging study results on predictions of actual lending rates on the Kiva site

6.43 Notes

- Affective ratings predict micro-lending rates better than actual choices
- Neural responses in the nucleus accumbens (a region linked to affective responses) can improve on predictions from affective ratings alone
- The increase in predictive power fom NAcc activity is significant, but rather modest.

Can predictions of value from brain activity contribbute more in other choice contexts?

- Mechanism design for public goods creation

6.44 Public Goods

- Examples: National defense, environmental protection, local parks
- The utility dervied from such goods vary across individuals
- The benefits are non-excludable
  - Ex: once a public park is created, everyone can go and enjoy it

6.45 The free-rider problem

Because a public good is non-excludable, self-interested individuals have an incentive not to contribute to its creation, but still enjoy its benefits.

6.46 Mechanism Design

The goal of mechanism design is to create situations or institutions that make it advantageous for self-interested individuals to reveal their true values-and pay accordingly

6.47 4 Desirable Mechanism Properties

1. Social efficiency
   - requires that the optimal amount of the public good always be produced, meaning that the net benefit to the group is maximized.
2. dominant strategy incentive compatibility
   - requires that the wealth-maximizing strategy for each member of the group is to reveal his or her true value, regardless of others' values or behavior.
   - ensures that every subject has a financial to tell the truth regardless of this or her beliefs about the other group members.
3. balanced budget
   - requires that the cost of the public good be completely covered by the members of the group
4. voluntary participation
   - requires that the expected value from participating in the mechanism be nonnegative for each individual, so that members do not have to be coerced into participating

A central result in economic theory is that there is no set of rules satisfying all four desired criteria simultaneously.

6.48 Neurally Informed Mechanism Design

Work in neuroeconomics has shown the efficacy of a neurally informed mechanism in creating institutions with optimal social efficiency
The key aspects of the NIM are

1. The ability o accurately read out participants values from brain activity
2. A set of taxes creating a dominant strategy to report your true value

You report your values in the Krajbich study. There is a payoff/tax matrix. If the MRI says you have a low value for the good but you contradict it and say you have a high value, you get penalized. The MRI prediction and your own ideas must be congruent to be paid.
Attention check occasionally so that you don't trick the system
The classifier used by Krajbich and colleagues had an accuracy of 0.6
Calibration study: how good is the classifier
Main experiment: Observed accuracy in main experiment
Guess: participant' guess of how accurate the classifier was.
The performance of the NIM is indistinguishable from the theoretical optimum and much better thant he best mechanism available based on choice alone.

6.49 Notes/Conclusions

- Predicting an individual's value for a given good with fMRI measures of brain activity is possible
  - accuracy is significant, but modest at this point
  - even modest prediction rates can be combined with institutional mechanisms that result in better efficiency than is possible by observing choices alone
    * This combination highlights the potential utility of combining brain-derived indicators of states or beliefs (high vs low value for a public good) with the tools of mechanism design or other more standard branches of economics.
- The studies by Krajbich et al and Genevsky et al are intriguing proofs of principle
- However, given the expense of neuroimaging and public opinion of "mind reading" you should not expect neurally informed mechanism designs to be implemented by governments any time soon.

7 Attention

7.1 Premise: Values are constructed at the time of choice

In economics, we don't know when the value is perceived or retrieved, but it is also not very important in those domains.
But in neuroeconomics, it becomes more relevant.

- The brain has infinite resources
- Resource allocations during this construction process will influence valuation and comparison processes (decisions)

7.2 The brain use efficient coding schemes

- Thebrain uses information about regularities in the environment to represent stimuli and states efficiently
- Although efficient codes are the optimal solution under resource constraints, they can cause biases and imprecision in decision making
  - eg Woodford, M (2020). Modeling imprecision in Perception, Valuation, and Choice.

7.3 Efficient codes and risky choice

- There are multiple forms of efficient coding used in the brain
- Codes that determine how we perceive numerical quantities depend on the distribution of quantities in the environment
  - Perhaps surprisingly, this includes numbers written as words or shown as digits
- Computation or representation is easier with numbers that are around us more. Different language speakers make different mistakes due to how much those numbers are prevalent in their native languages.

7.4 Stimulus distributions influence the precision of efficient codes

The optimal representation with a fixed output range is proportional to the CDF of the prior stimulus distribution

- The exact relationship between the CDF and the efficient code depends on quantity being maximized (accuracy, information, reward)
- The Frydman and Jin study discussed nex t use a uniform distribution so that the efficient code is identical for all 3 goals

7.5 Testing resource-limited representation of numbers

- Task = decide if the number on the screen is above or below 65
  - The low volatility context has a uniform distribution of 56-74
  - The high volatility context has a uniform distribution from 31-99
- Researchers will try to manipulate your previous probability distribution
- Assume we can distinguish only 19 magnitudes (this is an example, we don't know the true resource limit)
  - This gives a precision of
    * 1 for low volatility trials
    * 3.6 for high volatility trials
    * This means that we should have trouble judging whether a number is greater than or equal to 65 in the high volatility context than the low volatility context, if the idea of efficient coding impacts our idea representations
  - Performance is compared in the common range, 56-74
    * Performance is compared in the common range, 56-74
  - Payoffs are calculated as 15 $\times$ accuracy - 10 $\times$ average seconds
    * Incentivize accuracy and speed to increase the effect of resource constraints. We want the subjects to do it quickly, as doing it slowly would allow the subjecs to easily compare the numbers.

7.6 Accuracy is lower in the high volatility condition

The graph shows that, for numbers less than 65 especially, the low volatility condition performed better as their chance to classify numbers less than 65 as greater than 65 was lower.

7.7 Response Times

- RTs increase near 65 for both conditions
  - Behavior shows the ubiquitous discriminability or difficult effect
- RTs are longer with high volatility
  - suggests less precise representations

7.8 Risk lottery task

How does efficient coding impact risk decisions. Again two conditions: high volatility condition and low volatility condition.

7.9 Predictions

pX - C sigmoidal curve is steeper for the low volatility condition. This is a qualitative prediction.

7.10 Results

The data matches the prediction: the low volatility group had a lower chance of accepting the gamble when the yield was lower than the sure option, and a higher chance of accepting the yield, when it was higher than the sure option.

7.11 Attention

- Attention is the process of flexibly controlling limited computational resources. Selective attention is good, as it allows us to focus on the aspects of our environment that our important and not take in irrelevant information. It can also impact the way we make decisions, if we are not focusing equally on all relevant information (giving the relevant information different weights).

7.12 Attention and choice

We have seen one example of how visual attention influences risky choices and loss aversion in a previous lecture.
Pachur study
Attention is correlated with loss averison, outcome sensitivity, and probability sensitivity

7.13 Gaze bias both reflects and influences basic preferences

Shimojo: Which face is more attractive study. It found that as we get closer to making a decision, it is likelier for you to inspect the face you would be choosing.

7.14 Attractiveness of abstract shapes

Curve shapes are the same, more or less.

7.15 Gaze also reflects perceptual decisions

Similar curves for this condition as well, except the "indicate disliked face" condition flattens out quicker and is less steep.

7.16 Indicate the disliked face instead of more attractive

The probability of looking at something compared to the probability of choosing it also depends on the way the question is framed. Indicate the disliked face is less steep and flattens quicker. The subjects looked at it less.

7.17 Attention patterns when choices change

When the same subjects were called back and asked the same question, the trend of looking longer continued, the closer the subjects were to deciding again, the likelier they were to look at the face they were going to choose. However, surprisingly, sometimes they diverged from their initial choice. One reason for this potential divergence is that they looked at the other picture longer this time. But, this is just a correlation.

7.18 Casual manipulations of gaze

New experiment. Two conditions: Longer and Shorter.
As you increase the amount of repetitions, percent preference for longer shown face increases.
The no gaze shift manipulations are inconsistent with a "mere exposure" effect.

7.19 Visual attention and purchasing

Three time periods: BDM bids, purchase choice, feedback
The results show that the more you look at an item, the likelier you are to buying it, the more you look at the price tag, the less likelier you are to buying it.

7.20 Does attention amplify value or have a constant effect on choices?

- Many studies have shown that people are more likely to choose the item they fixated on longer
  - There is debate about whether the influence of attention is additive or multiplicative
    - Multiplicative: $\theta\times$ attended item value - (1 - θ) $\times$ unattended item value
    - Additive: θ + attended item value - unattended item value

7.21 Predictions for decision time from each model

- Decision times are faster when options are more distinct.
  - For perceptual judgements, this means more perceptually different
    - Clearly bigger or smaller for example
  - For value-based choices this means more different in value
- A multiplicative effect would amplify differences between sets of high valued options

7.22 Multiplicative vs Additive influence

Multiplicative: as the value increases, the response time would go down.
Additive: as the value increases, the response time would be stagnant overall but the individual responses give a U shaped curve.

7.23 6 datasets all show a negative correlation with a multiplicative effect

Attention would multiply the values of the attended option vs the unattended option and make response times faster.

7.24 Attention effects may vary as a decision unfolds

Recent studies have indicated that, the multiplicative and additive effects may depend on which portion of the decision we are in. We might be shifting from an initial multiplicative effect towards an additive effect.

- Westbrook et al examined the effects of a common dopamine agonist drugs on the willingness to engage in cognitive effort. In this study, they measured effort with a working memory task. They increased the difficulty of the working memory task.
  - selective dopamine D2 receptor antagonist. This leaves more dopamine in the synapses.
- Found that baseline dopamine levels in the brain were correlated with willingness to engage in cognitive effort
- Methylphehnidate increased willingness to complete a harder version of a memory task
- Results show that, as difficulty increases, both antagonist and no antagonist group decrease in willingness to complete the task, but the antagonist group's willingness decreases slower compared to the non-antagonist group. This is correlated with the amount of dopamine in the striatum.

7.25 Differences in dopamine correspond to fixation problems

Westbrook 2020 did a gaze study, where participants had to either do a harder task or an easier task, with the easier task paying less consistently. Both conditions hahd the level of difficulties described on the screen as well. However, the extent of the compensation differences between the two tasks varied from trial to trial. The study concluded that, the more you looked at the costs (level of difficulty) of the hard task, the likelier you were to select it. They realized that, the more you looked at the benefits of the hard task (the monetary compensation), you were also more likelier to select it, however, the graph increases more steeply than the costs graph.
For people who choose the hard task, people look at and compare the benefits and compensations more and focus more on the hard task benefits. This effect is amplified for people who received dopamine antagonists.

- Attention has a multiplicative effect until the bifurcation point
  - Decision made, but not executed yet
- Attention has an additive effect after the bifurcation point.
- This means that, early on, attention has a stronger impact on the value as it multiplies the value, however, as the subject is reaching the decision, after the bifurcation point, you have an additive effect, it will just determine where you will attend.
- This is why, in choices where you have a long delay between you choose and then implement, you would be more likely to see an additive effect: whereas, where the choice time is free, you might see a more multiplicative effect.
- Significant multiplicative effect before bifurcation and significant additive effect after bifurcation.

7.26 Multiplicative vs additive influence of attention

- The debate is not fully resolves
- Thhere do seem to be multiplicative effects
  - They may be limited to early in the decision phase
- Additive effects may kick in later once an option is (nearly) selected

7.27 It's not just about the quantity of attention an option receives

- We have seen examples of how looking longer influences choices
- The order of information acquisition also influences choices

7.28 Information acquisition changes temporal discounting

We are going to look at how people evaluate the magnitude and delays of the options available and how this relates to the probability of the option chosen.
Reeck et al 2018. In the experiment, participants must click each box with the mouse to see the information. Each will give you an amount of money and a delay and you have the right to choose how much you're earning and how much you will wait for it.

7.29 Search strategies

There are two types of strategies that people use to decide: Comparative and Integrative.

- Comparative: This means that you are comparing the two attributes of the decision. This means that you are comparing the amounts to amounts and the delay to the delay. This means that you click on the amounts first and then the delays.
- Integrative: This means that you integrate the response first, and then compare. This means that you would first click on the amount of a choice and then check its respective delay and then do the same thing with the other option.

7.30 Comparative searchers are more patient

They are more tolerant of delays

7.31 Experiment 2: Manipulating search to test causality

This was done to see if the strategy affected the decision or if comparative searchers are naturally more patient.

- Introduce a 1 second delay for discouraged searches
- Easy comparative condition
  - Comparative transitions are immediate
  - Integrative transitions incur a 1 sec delay
- Vice versa for easy integrative condition

7.32 Results for all trials

- Easy Comparative show more patience than Easy Integrative

7.33 Results for trials in which search matched the intended manipulation

Recover the framing effect in comparative searchers

Results are even stronger

7.34 The association between search and patience is task dependent

- Choose between pairs of outcomes
  - One sooner
  - One later
- Text is only visible if you look in a dotted rectangle
  - Analogous to the mouse-tracking studies

This is an eye-tracking study. If you look at one rectangle, the one you look at opens up but the other disappears.

7.35 Payne Index

- PI := Alternative - Attribute $\frac{}{Alternative+Attribute Definitions: alternatives are the two alternatives in an option, attributes are optio}$
- Higher PI means that you do more integrative search

Findings:

- In contrast to the design in Reeck et al, now participants need to integrate sooner and later payoffs to compute the total amount of money
- Does this change the relationship between search patterns and patience?

7.36 In this context, integrative search is associated with more patience

In this study, the average patient choices are positively correlated with the Payne Index.
Also, the implied discount functions for the comparators are more steep than the integrators.

7.37 Integrators' choices are more sensitive to total reward.

Thus the differences between are more complex and context dependent than what we can think

7.38 Summarizing both studies

- Reeck show that information search patterns change temporal discounting
- Khaw show that the information search patterns relate to temporal discounting depends on the choice context

8 Response times contain useful information

8.1 Outline

- Response times (RTs) inform researchers about decision makers' subjective values
- RTs inform experiment participants about one anothers' private information
- Combining RTs and choices in a structured model improves preferences estimates
- RT patterns predicted by sequential sampling models are seen in the field

8.2 Choice RTs are proportional to discriminability

- Thhe field of psychophysics has show that response times are proportional to discriminability (difficulty) in perceptual judgements
  - Replicated many, many times
- If economic decisions are based on differences in utility, then RTs should reveal the strength of preferences, not just preference orders

8.3 RTs should reveal strength of preference, in theory

- Suppose we ask two people, Anne and Bob:
  - "Would you rather have 25 dollars today, or 40 dollars in two weeks?"
  - Both say 40 dollars in two weeks
- These choice outcomes don't tell us who is more patient in general
- Now suppose:
  - Anne made her choice in 5 seconds
  - Bob made his choice in 10 seconds
- Who is more patient?
- A faster choice should indicate a stronger preference, hence we can infer that Anne is more patient than Bob.

8.4 Decision times are proportional to value differences

Monotonic relationship between the response time and the preference.

8.5 Sequential sampling models of decision making

Drift diffusion model on page 7.
The line at the top and the bottom are the threshold. These are the levels of evidence required to make the decision. The more you make these thresholds larger, the longer it would take you to make a decision, but the less errors you would make while doing so as well. In other words, the longer you gather data, the less susceptible to noise your data will be and the higher the signal/noise ratio you will have and the lesser the errors you will make.
The rate at which the lines move towards the thresholds depend on the preferences of the chooser. The more someone likes an option compared to another, the faster the lines will go to the threshold.
Paper by Clithero 2018

8.6 Sequential sampling models of decision making

- Sequential sampling models can have different stopping rules (thresholds)
  - Constant over time
  - Decreasing over time
  - Based on a cost/benefit calculation for future sampling
  - etc

8.7 Why do decision makers take multiple samples of value/utility

8.8 Example, two cheeses

You don't have an inherent table immediately on your mind. You will have to think about your preferences. You will have distributions for the variables.

- You can opt to take a single sample from distributions and compare their values. This is susceptible to incorrect decision making.
- By taking more and more samples, we are more likely to make the correct decisions but it also costs more time.

8.9 Do RTs contain useful information in practice

- If choices are based on a sequential evidence accumulation process, then RTs should be proportional to value differences.
  - Other things influence RTs too
    - Age, health
    - Choice complexity
    - Attention/distraction
    - Etc
- Is the relationship between strength of preference and RT strong enough to be useful?

8.10 RTs do reveal strength of preference in lab experiments

Take three domains for the experiment: Risky, intertemporal, social. Can we use the response times in these three domains to infer something about the underlying strengths of preference.

- In each choice domain, the authors capture choice-derived preferences with the following models.
- Note that they take arguably reasonable steps to simplify the models or experiments such that risk, intertemporal, and social preferences are captured by a single parameter.

8.11 Risky choices were modeled with standard prospect theory

8.12 Intertemporal choices were modeled with a hyperbolic discount function

$$U(x, d) = \frac{x}{1 + kD}$$

where x is the delayed monetary amount, k is the discount factor (higher is more impatient) and D is the delay period

8.13 Social choices were modeled with Fehr-Schmidt

$$U_i(x_i, x_j) = x_i - \alpha \times max(x_j - x_i, 0) - \beta \times max(x_i - x_j, 0)$$

where x_i is he dictator's payoff, x_j is the receiver's payoff, α reflects disadvantageous inequality aversion, and β reflects advantageous inequality aversion. Each trial was designed to either measure

α or β, so we treated this experiment as two separate datasets.
In the choice sets we have, we either have disadvantageous or advantageous decisions but not mixed sets.

8.14 Establishing a negative correlation between strength-of-preference and RT.

In the subsequent graphs “indifference X”
We are going to plot RT on the Y axis.
The lower the strength of preference, the higher the RTs.

8.15 One trial preference rankings

- Participants choose between
  - A 50/50 lottery with a gain of 12 dollars and a loss of 7.5 dollars or
  - 0 dollars for sure
- A loss aversion coefficient of $\lambda = 1.6$ would make someone indifferent in this case (assuming risk neutrality)
- This one choice outcome only tells us if $\lambda \geq 1.6$ or $\lambda <$
  - We can only form two groups of people
- With RTs we can rank subjects that accept or reject the gamble
- Hypothesis: subjects with loss aversion closer to 1.6 have longer RTs
- We divide people into two groups: Risky option chosen vs Safe option chosen
- Graph made from λ estimated from choices on x axis and RTs on y axis

8.16 Uninformative choices

- RT-based inference could also be used when an experiment is flawed in such a way that most subjects give the same answer to the questions.
- Konovalov and Krajbich mimic this situation
  - Use 4-10 trials from each data set in which most people gave the same response
  - Only use participants that gave the modal responses
  - Use RTs on 1-N trials to estimate strength of preferences

8.17 RTs from uninformative choices correlate with preferences estimated from all choices

8.18 Beyond ranks to parameter estimates

Can you use RTs to estimate a parameter value such as the loss aversion coefficient or the discount rate

- Konovalov and Krajbich propose a method to use RTs alone to estimate parameter values
  1. identify trials with RTs in the upper 10% (the slowest decile)

- These should be trials where participants are close to indifference
2. Calculate the value of the preference parameter that would make the subject indifference between the two alternatives on each trial
3. parameter estimate = average of the values from step 2

- Note that this gives a bounded estimate
  - Upper (lower) bound: mean of highest (lowest) 10% of all possible indifference values

8.19 Preference parameter estimated from the top decile method

Take aways:

- Clearly RT estimates are not a 1:1 match with choice estimates
- However, there is useful information in RTs

8.20 Summary

- Response times alone can reveal strength of preference in controlled lab settings
- These results once again support the idea that value-based decisions are made from preferences constructed at the time of choice.

8.21 Do people use information present in response times?

- There are various pieces of data showing that they do
- E.g. the length of time between an interview and job offer
  - This interval could carry information about the strength of the employer's preference for the applicant
  - This extra information can influence the applicant's decision to accept the offer
    - Assumption: employees prefer to work at a firm that highly values them
- Becker et al (2010) find that job applicants are more likely to accept a job offer if it is delivered quickly (contolling for ex post employee performance ratings)
- Van de Calseyde et al (2014) provide similar evidence in a laboratory setting where decision times are exogenously manipulated.
- From a theoretical perspective, if response times (RTs) reveal an agent's private information, then many economic environments will contain richer information structures than are typically modeled.

8.22 RTs reveal private information in information cascades

- Experimental Design
  - There is an uncertain state of the world (binary probability = 0.5)
  - Each subject (n = 8) receives a private conditionally independent signal
  - Subjects sequentially provide a prediction about the state of the world that everyone coming after them can observe
  - Finally, the state becomes public to all
    - Correct predictions pay 1 dollar

        * Incorrect predictions earn 0 dollars

- The first person in the game has only their signal
- The second person has their signal and the first signal

8.23 Key manipulation is the presence or absence of RT information

- Participants entered their predictions within a 10 second window.
- The prediction was only shown after 10s regardless of how soon the subject responded.
- Two conditions: in one condition, participants only saw the decisions of the previous subjects. In the other, they saw the decisions and the response times.

8.24 Information cascades

- Suppose that
  - Player 1 sees A
    * signals A
  - Player 2 sees B
    * infers that the state is A with 0.5 probability
    * Signals A
  - Player 3 sees B
    * infers that the state is A with 0.66 probability
    * Signals A
- This triggers an information cascade, with players 4-8 adopting the same logic and selecting action A regardless of their own private signals
- The normative prediction in such games is
  - If one state of the world has 2 net decisions in its favor
  - Then all subjects should choose this state of the world
  - It is optimal for all participants to cease their belief updating at this point

8.25 Predictions for adding RT information

- if a previous subject's RT is "long," then she likely has private information that conflicts with the preceding signals
- Do participants use RT information to break out of information cascades?

8.26 Do participants use RT information to break out of information cascades

Slide 41 graph x axis are the conditions and y axis is following private signal percentage.

- RTs are long/short if they are above/below the median RT of 2.03 seconds
- Data are restricted to positions 4-8 and restricted to trials in which the private signal does not match the previous move
- They didn't tell people what RT meant

8.27 RT information increases payoffs

8.28 Conclusion

- Study participants can infer conflict and private information from response time information without explicit instructions to do so

8.29 Applying the DDM to value-based choice

Clithero 2018. Food choice task. In the first stage: participants are shown one food and asked to give a yes or no answer to the question "would you like to eat this at the end of the study?" People are just responding without RT constraints but regardless they answer very quickly. The answers were fitted using a DDM or Logit methods. The aim is to predict binary choices when two foods are shown in the second task. The DDM produces the same sigmoid curve but it uses RTs in addition to outcomes to make a more precise estimate.

8.30 Could the DDM generate better out-of-sample predictions about choice than traditional logistic regression models?

8.30.1 Notes

- The predictions derived from the DDM should be better than hose frmo a logit when trained on finite datasets
  - When the mean RT curve is steep, the probability of choice curve is flat, when the mean RT curve is flat, the probability of choice curve is steep. Hence, they are complimentary.
  - Especially when choice probabilities are around 0.25 or 0.75

8.31 Observed results for the DDM

- Fits to Yes/No Task
- Fits to predictions about choices and RTs in the 2-alternative forced choice task

8.32 DDM vs Logit predictions for the 2AFC

DDM is better overall. Page 48, for data above the 45 degree line, DDM is better. It is especially better where the logit curve is flatter.

8.33 Combining attention influences and response time

The more you look at an item, the more you value it and are likelier to buy it. We will incorporate this into the RT model.

8.34 Greater fixation sensitivity leads to worse choices

Fixation sensitivity:= change in slope
People who are more likely to fixate their attention are less likely to choose their subjective best option.

8.35 Combining attention influences and response times

8.36 Response times in the wild

- eBay recently produced a dataset with all exchanges for listings created from June 2012 to June 2013. The dataset consists of millions of bargaining exchanges
- Cotet and Krajbich test if RTs from eBay sellers follow the patterns predicted by sequential sampling models of constructed preferences

8.37 Accept and Reject RTs are proportional to $\frac{p1}{p0}$

8.38 Generality across goods

This is true for a large variety of goods

8.39 Experience

Sellers show the same pattern of RTs across levels of experience

8.40 Summary

- Response times are useful for
  - Researchers trying to estimate/understand strengths of preference
  - Individuals interacting with one another
- Response times carry information for
  - Decisions mad in controlled laboratory settings within seconds
  - The pattern also appears to hold in real life as well
    * Data from eBay sellers
    * Other potential domains: Political endorsements, IPOs, returning phone calls or texts, etc

9 Social Preferences and Economic Choice

9.1 Outline for the notes

- Models of social preferences
- Empirically measuring social preferences
- Neural substrates of social preferences
- Associations between hormones and social preferences

9.2 Social Preferences

- Social preference theories try to incorporate some or all of the concepts listed below into models of choice:
  - Altruism

- Fairness and inequity aversion
- Reciprocity
- Group welfare

9.3 Models of social preferences

- Models of social preferences assume that people are generally self-interested but also concerned about the payoffs of others
- Three types of models
  - Inequality aversion
  - Social welfare
  - Reciprocity

9.4 Inequality aversion

- Inequality aversion models assume that people are averse to unequal outcomes
- The strength of this aversion to inequality may or may not be allowed to differ in advantageous vs disadvantageous contexts depending on the model

9.5 Fehr-Schmidt model (1999)

- Subtract weighted payoff difference from own payoff
- Allows for different weighting or discount factors in advantageous vs disadvantageous domains
- In multiplayer games, the largest inequality is implemented

$$U_A(\Pi^A, \Pi^B = \Pi^A - \beta(\Pi^A - \Pi B), if \Pi^A > \Pi^B)$$
$$U_A(\Pi^A, \Pi^B = \Pi^A - \alpha(\Pi^B - \Pi B, if \Pi^A < \Pi^B)$$

Π^A:=Payoff for self
Π^B:=Payoff for other
β:= Advantageous inequality aversion
α:= Disadvantageous inequality aversion

9.6 Social welfare models

- Social-welfare models assume people like to increase social surplus, caring especially about helping those with low payoffs
- Explains case where people chose to reduce the level of their own payoff if it will increase the sum of payoffs to all members
- Say option 1 pays you 3 and the other 5 and option 2 pays you 2.8 and the other 8. In this case, most would choose option 2, even though it increases inequality and decreases your welfare. This cannot be explained by the F-S model.

9.7 Charness and Rabin (2002)

- Includes parameters for reciprocity
  - Reciprocity models assume that the desire to raise or lower others' payoffs depends on how fairly those others are behaving
- Formulation is same as the Fehr-Schmidt model in advantageous situation if the other has not "misbehaved"
- Different from Fehr-Schmidt model in disadvantageous situation
  - includes preferences for overall welfare
- Payoff for self is denoted as B
- The parameters , , and capture various aspects of social preferences
  - inequality averse preferences (¡ 0 ¡ ¡ 1) mean that utility for B increases with B and decreases with the difference B A.
  - ¡ 0 assumes disutility for A when B ¡ A
  - competitive preferences (¡ 0) mean that the utility for B increases as B increases relative to A
  - narrowly self-interested preferences (= = 0) mean that the utility for B depends only on B
  - social welfare preferences (0 ¡ 1) mean that utility for B increases with B and A.

9.8 Notes

Different models of social preferences incorporate different motivations for other-regarding preferences

- Inequality aversion
- Social welfare
- Reciprocity

9.9 Empirically measuring social preferences

- Very brief overview of two common lab paradigms:
  - Dictator game
    - Measures altruism, generosity, and inequity aversion
  - Ultimatum game
    - Proposer: Inequity aversion and beliefs about expectations
    - Responder: Inequity aversion and reciprocity

9.10 Dictator game

- Player A (dictator) can decide how much money (or any good) to split between herself and Player B (recipient)
- It could be a free or restrictive dictator game (dictator is restricted to a few given choices)
- The outcome is exactly the split that the dictator decides on

9.11 Dictator game

- Prediction for purely self-interested agent = give zero
- Typical findings as reported by Levitt and List (2007) JEP:
  - More than 60% of dictators give a positive amount of money with the mean being 20% of the endowment
- By design, the dictators don't see the other person, don't know the person.

9.12 Ultimatum game

- Player A (proposer) can decide how much money (or any good) to split between herself and Player B (responder)
- The responder can accept the split or reject it and then both players get nothing
- Dictator choice can still be motivated by altruism, generosity, or fairness but must also consider reciprocity.
- The responder's actions influenced by fairness and reciprocity preferences
- Predictions for purely self-interested agents:
  - Proposer: give zero or minimum positive amount
  - Responder: indifferent to zero, accept any positive offer
- Typical findings as reported by Levitt and List (2007) JEP:
  - Majority of proposer offers in the range of 25-50%. Few below 5%
  - Responders frequently reject offers below 20%

9.13 Modified Ultimatum game

- Removing reciprocity preferences
  - The responder's actions influenced by fairness, but not reciprocity because player 1 did not act.

9.14 Notes

We can isolate different motivations that people have by making them play both the dictator and ultimatum game. We can isolate their pure social preferences in the dictator game, and see how they adjust their preference with the ultimatum game.

- Different games measure different motivations in social interactions
- Pure altruism and fairness are measured by unidirectional interaction
- Reciprocity is measured by bidirectional interactions

9.15 Neural substrates of social preferences

There is a large degree of individual variance in social preferences for fairness, altruism, reciprocity, etc. for example (Slide number 21). We are wondering how the variability in the histogram could relate to brain structure and function.

9.16 A restricted binary dictator game

The dictators have two options in the fMRI. They are restricted, since choosing more options would make the subject move more and hurt the image. One option is a fairer split than the other.
There are two trials: advantageous and disadvantageous. In the advantageous trial, in both options, you will earn more, however, in one option, you will earn vastly more than the other person, where in the other, your payoffs will be more similar. It is the vice versa for the disadvantageous trial.

9.17 No correlation between advantageous and disadvantageous preference parameters

The lack of correlation suggests that preferences may differ between advantageous and disadvantageous contexts
So there is some difference between how you make these decisions between the two cases.

9.18 Stability of preferences

- Studies on social/risk/time preferences have shown that preferences of an individual are relatively stable across time within domains
- Could brain structure -which is relatively stable- support stable social preferences? So rather than looking at brain function, these authors will try to analyze the stucture of the brain.

9.19 Measuring brain structure with voxel based morphometry

Take a high resolution structural image of the brain. Use a computer algorithm to separate white matter and gray matter. Then, normalize and smooth the image. Aggregate the subjects and apply GLM.

9.20 Grey matter density in right TPJ correlates with advantageous altruism

The more grey matter you have in this region, the more you are willing to accept the cost for making an altruistic act.
Interestingly, density in this region does not correlate with other parameters such as disadvantageous altruism, positive reciprocity, and negative reciprocity.

9.21 Social preferences in charitable donations

This result seems to be in-line with another study on charitable donations and social preferences.
Experiment: On each trial you are shown an image and a title of a particular charitable donation and you are asked how much of your 100 dollars would you like to give to this cause. If you give some money, the experimenters will match your donations. In the second case, you are forced to donate a certain amount to the charity, regardless of your preferences.
The idea is to compare trials where you actually need to compute how much you want to give to where you are forced to donate but still probably have bottom-up reactions to the image used for the cause.

9.22 Donation amounts correlate with vmPFC activity

The more you give, the stronger the activity there. When we take the intersection of Donation amount and food purchases, we see that vmPFC has an overlap between the two actions.

9.23 TPJ activity is also associated with willingness to give to charity

A measure of your willingness to give to charity is positively correlated with activity in the TPJ.

9.24 Inhibitory brain stimulation via TMS over the TPJ increases selfish behavior

Soutschek study conducted with a modified dictator game. Unlike other dictator games, participants knew some of the other people they played with, as they gave a list of family members or friends to the experimenters. The subjects could also be paired with random people too. There is a social distance scale between the pairs from 1-100. The family members or friends don't even know you are doing this task if you don't inform them, but the experimenters will actually pay them if you are paired with them since you gave the experimenters a list.
There are two conditions: In condition B, you either get 100 CHF or a 75-75 split between you and the person who is X social distances away from you.
In condition A, you are shown a delay of the payment first, and then you get an amount that you can take today.
Choices are modeled with a hyperbolic discount function

$$SV_{delay} = \frac{V_{delay}}{1 + k_{delay} \times D_{delay}}$$

$$SV_{social} = \frac{V_{social}}{1 + k_{social} \times D_{social}}$$

parameter k:= how much you will discount future payoffs D:= actual delay

9.25 Results of the Study

In both intertemporal and interpersonal conditions, the TMS lowers your discount rate.

9.26 Why test temporal discounting and social preferences in the same experiment?

- Hypothesis: both decisions involve theory of mind and/or perspective taking
  - Social decisions: take perspective of another person
  - Intertemporal decisions: take perspective of your future self

9.27 Classic test for theory of mind (usually for children)

Theory of mind: you have the ability to realize that your mind differs from another agent's mind. A classic test: the Sally Anne test.

9.28 Testing perspective taking after TPJ stimulation

The experimenters are going to make you change your perspective to another person's perspective. How many dots is the person able to see? Usually people don't make mistakes but with TPJ they do make a statistically significant higher number of errors.

9.29 Brain stimulation (TMS) over the TPJ decreases perspective taking

- Across participants perspective taking errors were correlated with
  - Temporal discounting
  - Social discounting

9.30 vmPFC structural integrity also impacts social choices

Brain damage examination will try to answer this again, as TMS can't usually target this region.

9.31 vmPFC damage alters social choices

For the dictator game: For people with damage to the vmPFC, the offers to the other individual is significantly lower compared to no damage.
For the ultimatum game: People without brain damage would offer more points than they demand. However, vmPFC would demand more than they are offered.

9.32 vmPFC damage alters social choices

- vmPFC damage is associated with
  - more individualistic behavior in the Dictator game
  - No "cushion" for stricter fairness environment by others in the Ultimatum game

9.33 Notes

- Large individual variance in generosity, fairness, altruism preferences
- Individual differences in brain structure and function of TPJ and vmPFC are associated with behavioral differences

9.34 Reciprocity in the Ultimatum game

We are investigating what might cause you to reject an offer.
Experiment: Play Ultimatum game against human subjects and a computer. Decide whether or not to accept or reject offer by those partners.

9.35 Results

Lower rejection rate against a computer

9.36 Neural response to unfair offers

Activity in a range of brain regions. However, dlPFC is activated significantly. The more activity in that region, the less likelier you will accept an offer. But again, this just a correlation.

9.37 Causal role of dlPFC in UG with human partners

We can investigate the causal role of dlPFC activity by stimulation
Inhibition of right dlPFC by TMS increase acceptance of unfair offers
However, it doesn't change fairness ratings

9.38 No effect of right dlPFC in UG with computer partners

TMS doesn't significantly change behavior when the partner is a computer rather than a human being
Computers aren't viewed as being unfair

9.39 Combined TMS+fMRI in the Ultimatum game

Want to investigate if there is an influence in the brain somewhere else when TMS inhibits the right dlPFC.

As expected, TMS reduces activity in the stimulated region
Interestingly, another area was influenced. TMS to rDLPFC also reduced activity in the vmPFC

9.40 Why does the association with vmPFC matter?

- We have already seen that vmPFC represents subjective values for a wide range of goods
  - Primary rewards
  - Secondary rewards
  - Moral values, donations to charity
  - Another person's temporal discounting functions
- Social preferences may be influenced by computations in specific areas of the brain, but if they are ultimately represented in vmPFC activity, then maybe they aren't qualitatively different from any other preference.

9.41 Sample question

Similar brain structures are used to compute/implement social preferences compared to non-social choices- TRUE

9.42 dlPFC and Norm Compliance for proposers in the Punishment Game

Two conditions in this article: Dictator transfers and punishment transfers. Ultimatum game can be modified to become a punishment game, where the receiver can punish the sender by using monetary units from his own endowment, which would be multiplied by 5 and subtracted from the sender, resulting in a -Y MU penalty for the receiver and a -5Y penalty for the sender.

9.43 dlPFC and Norm Compliance in the Proposer

Average transfer rate in the Punishment condition is much higher than the dictator case. Results from slide 55.

9.44 Brain activity

Regions more active in the sanction enforced norm compliance condition are given on slide 56.

9.45 Right dlPFC activity correlates with the average difference between Pun and Control transfer amounts.

More dlPFC activity means higher transfer difference between the punishment and the control conditions

9.46 A causal role for right dlPFC in Norm Compliance

Changing the brain activity by TMS in the dictator and punishment game. If they use inhibitory TMS on right dlPFC for the dictator game, there is less transfer than sham (no affect) and the excitatory TMS conditions. If they use inhibitory TMS on right dlPFC for the punishment game, there is more transfers than no stimulation and the excitatory stimulation conditions.

9.47 dlPFC and Norm compliance in the proposer

TMS did not change fairness ratings or expectations about anger or punishment

9.48 Social and nonsocial contexts differ

Nonsocial= computer

9.49 Notes

- Perceived intention plays a key role in reciprocal social interaction
  - Remember the different behavior with computer partners
- The right dlPFC plays a causal role in making and accepting offers in Ultimatum game
- Inhibition of the right dlPFC changes
  - proposal and rejection rates
- doesn't affect reports of perceived unfairness

9.50 Questions

- If choices and ratings can be changed by TMS independently, which one should we focus on?
- Can we completely write off the self-report ratings because they are not incentivized?

9.51 Why reject UG offers

- Previous behavioral studies show that perceived fairness intention plays a role in rejection of unfair offer in Ultimatum game (computer fairness is perceived as high, which is why rejection rates were much lower)
- TMS experiments show that there is a dissociation between perceived fairness and actual rejection
- However, detection of unfairness $\neq$ Rejection of offer

9.52 Impunity game

Set up the same as the Ultimatum game, but the outcome of rejection differs.
Accept: Bot payoffs as proposed
Reject: Proposer keeps his proposed amount but responder gets nothing

- Standard version-proposer informed of rejection
- Private version - proposer not informed

9.53 Result

Impunity game: Substantial rejection in both impunity and private impunity games

- Reciprocity motivations can not fully explain rejection in Ultimatum game
- Speculation: rejection may be driven in part by a desire to maintain one's self image.

9.54 Hormones and social behavior

Hormones have complex, widespread, context-dependent effects on physiology and behavior

- Examples of context dependence:
  - Dosage (studies ofthen use very high doses, which is not always generalizable to real life)
  - Circadian rhythm
  - Developmental stage
  - Cultural or social context
- Punchy headlines like "Hormone H causes behavior B" are, at best, incomplete stories
  - The same is true for most things in economics or finance too
    - Causal effects depend on initial conditions "dosage"

9.55 Oxytocin and Testosterone examples

These two hormones have a long history of being featured in high profile papers that link them to aspects of social behavior.

9.56 Hormones and social behavior

NoE Oxytocin

- Is a neuropeptide synthesized in hypothalamic neurons
- has a central role in regulating social approach and attachment behaviors in many non-human mammals
  - Mother - infant bonding
  - Adult pair bonding in monogamous mammals
- Non-mammals have hormones with similar chemical structure
- The full body of literature indicates that the effects of oxytocin strongly depend on individual and contextual factors

Testosterone

- Well-known as a sex hormone produced in the testes and ovaries
  - Also produced in the adrenal glands
  - Can be synthesized in the brain too
- Many of the effects of systemic testosterone in the brain occur after it has been converted to estradiol

9.57 Testosterone and social status

Rather than promoting aggression per se, testosterone seems to promote actions that signal social status

- In non-human animals, social status often signaled through aggression
- Humans have more ways of signaling social status

9.58 Testosterone and social status

Nave et al 2018.

- Nave et al randomized male participants to a double-blind RCT
  - 125 received a single dose of testosterone
  - 118 received placebo
- Two Tasks:
  1. Decide between clothes from different brands
     - Brands differed in their association with social rank
  2. Rate attitudes about items
     - Status enhancement
     - Power enhancement
     - Quality

9.59 Experiment timeline and manipulation check

Survey in the morning and hand scan first. Then gel and T-loading period. Then behavioral tasks and then payout.
They will sample the amount of testosterone to make sure that the T didn't dramatically get lower over time.

9.60 Task 1 Results

People who had testosterone highly preferred brands with higher social rank significantly more than the no-T condition; however, both groups gave similar quality preferences.
Researchers specifically disassociated status and quality so that there wouldn't be a confound

9.61 Task 2

Only for goods that emphasized status there was a statistically significant different between the two groups with high-T preferring higher status goods.

9.62 Hormones

Question: Does oxytocin cause feelings of affiliation, trust, and prosocial behavior?
Answer: That depends on the animal, context, and your definition of prosocial.

Question: Does testosterone cause aggressive social behavior or violence?
Answer: That depends on the animal and the context

9.63 Take home message

Robust main effects of any single hormone, within physiologically plausible doses, on something as complex as social behavior are very unlikely
Hormones do influence social behaviors, just in complicated ways we don't fully understand yet

10 Strategic Behavior

10.1 Game Theory

Game theory is about how people interact

- Originally developed to explain how intelligent/rational/emotionless agents should behave
- More recently used to model how average people actually behave

10.2 What type of interactions

- Tennis players serving left or right
- Bakeries lowering prices at the end of the day
- Haggling in the marketplace

10.3 Game Theory

Components

- Multiple players
- Each player has multiple actions
- Each possible combination of actions yields an outcome
- Each outcome yields different payoffs for each player

Nash Equilibra

- Outcomes where no player can increase her own payoff by changing her action while keeping the other player's action constant

10.4 Assumptions

- Rationality (best response)
  - Given a player's belief about what the other player(s) will do, her action maximizes payoff
- Common knowledge
  - Everyone knows that everyone is rational and has fully thought through the game
- Already in equilibrium
  - No learning or out of equilibrium play

If we deviate from one of these conditions, we can't compute NE

10.5 Empirical problems with rationality or best response

- In experiments, we often see subjects playing "close" to equilibrium but not quite in equilibrium
- Many subjects choose the optimal action while others choose the second best action, fewer choose the third best, and so on
- Suggests a probabilistic choice process

10.6 Alternative models that relax assumptions of Nash Equilibrium

Quantal Response Equilibrium (QRE)
Cognitive Hierarchy (CH)

10.7 Quantal Response Equilibrium (QRE)

- QRE relaxes "Best response" while maintaining common knowledge and the equilibrium concept
- Rather than best responding to others' actions, each player "better responds" by choosing the best response with probability P1, the second best with probability P2 ¡ P1, the third best response with probability P3 ¡ P2

- Agents will still choose the best option with the highest probability but you don't HAVE TO
- Each player also knows that the other players are better responding (common knowledge) and so are better responding to a distribution of actions and not a single action

10.8 Logit QRE

Players choose their actions according to probabilities given by:

$$P_{ij} = \frac{\exp \lambda EU_{ij}(P_{-i}}{\sum_k \exp \lambda EU_{ik}(P_{-i})}$$

where P_{ij} is the probability of player i choosing strategy j
EU$_{ij}$ is the expected utility to player i of choosing strategy j given other players are playing according to the probability distribution P$_{-i}$
k is the number of actions in the game
λ is the weighting parameter. Notice that as $\lambda \to 0$ players choose randomly, while as λ ∞ players play in Nash Equilibrium

10.9 Results

λ increases over time. This means that they are better responding.

10.10 QRE Summary

- QRE provides a better fit of human behavior than Nash in some classes of games
  - Especially in relatively simple games with a small number of players
  - Behavior in more complex and/or large group games is often not fit well by QRE
  - In many cases, there is evidence that the common knowledge assumption of QRE is not valid.

10.11 Problems with common knowledge

- Common knowledge is a strong assumption, which assumes that each player correctly knows the other players' strategies
- Often implausible, especially in complicated or unfamiliar games
- Data often show different distributions of choices by different subjects and this violates the equilibrium assumptions of QRE

10.12 Beauty Contest

In the beauty contest game, everyone writes a number from 0-100 and your goal is to pick 2/3 of the average. QRE predicts that most would pick 0 and the relative frequencies would stably fall but that is not what we see due to a lack of common knowledge. Most people choose around 33-36

10.13 Explanations

- Notice that we cannot explain this behavior using QRE or other equilibrium +noise models
  - A rational player;s best response is always to choose low and so equilibrium-like behavior will always peak at 0.

- It must be that players have different beliefs about what the other players will choose
- We must relax the common knowledge assumption!

10.14 Cognitive Hierarchy (CH) model

- Let's assume that different players put different levels of thought into their decision
- Assume discrete steps of thinking where each level indicates one more iteration of analysis of the game
  - Level 0: These players do not understand the game and so choose randomly
  - Level 1: These players believe that everyone else that are playing are Level 0's and best-respond to that belief
  - Level 2: These players realize that there is likely some mixture of Level 1's and Level 0's and best-respond
  - Level K: believe that there is a mixture of Level 0-K-1 players and best-respond accordingly

10.15 Why only up to K-1?

- The intuition behind the model is that each "best response" calculation takes effort and players are labeled by the number of calculations they make
- Level 0's make no calculation and choose randomly
- Level 1's only make 1 calculation, so they can only best-respond to one strategy, namely the Level 0 strategy
  - They can't best-respond to other Level 1's as well because that would require a second calculation, turning them into a Level 2 player

10.16 Beauty contest with learning: Guesses start to move toward zero over repeated rounds

11 Summary

Most people do not play strategic games like completely rational, emotionless geniuses
People display various levels of sophistication in incorporating the actions of others into their strategies
Remember: its not just games! We have examples from tennis, politics, etc...

11.1 How does the brain implement strategic choices?

11.2 Neuroimaging example I

Replicating the beauty contest in the fMRI machine. They are playing against other humans or computers in two different conditions. They don't know anything about the other human, but, they will be notified of the computer's strategy. Computer always chooses uniformly.
There is another calculation task to see if your mental math is good enough to be able to calculate means and medians for the beauty contest task.

11.3 Human vs Computer choice

mPFC and TPJ are regions that have been repeatedly implicated in "mentalizing" tasks that require individuals to consider the beliefs of other.

11.4 mPFC activity and strategic behavior

The more you engage the mPFC, the closer you get to the winning number in the human opponent condition.

11.5 Neuroimaging Example II

Work vs Shirk game Two roles in the game: Employer and Employee. If the employee is working and the employer doesn't inspect, the employer gets 100 and the employee gets 0. If the employee is working and the employer inspects, the employee gets 50. If the employee is shirking, and the employer doesn't inspect, the employee gets 50 and the employer gets 0, and if the employee is shirking and the employer inspects, the employer gets 25 and the employee gets 0.

11.6 Hampton et al, tested an idea similar to CH

- Is behavior best captured by:
    1. Simple temporal difference reward learning
    2. A 'fictitious play' model where the subject chooses the best response based on the past history of the opponent
        - For example, the employee might work more often after being inspected several times
        - An 'influence' model where subjects consider that their own actions will influence the opponent
            * The employer doesn't inspect after inspecting twice in a row under the belief that the previous inspections will cause the worker to work

11.7 Influence model has the best to the choice data

11.8 Good match between model predictions and subject's choices

The probability of work/shirk and inspect/no inspect is predicted well by the influence model

11.9 Fitting model predictions to brain activity

There are very few regions in the brain that correlate with the simple RL model
Fictitious model also has little correlations but
Influence model has way more correlates in the brain compared to the other two

11.10 Influence better than RL

There are certain regions that correlate significantly with certain parts of the brain.

11.11 Switch vs Stay predictions

The three models also make different predictions about the expected reward, and therefore BOLD signal on stay vs switch trials

11.12 Switch vs Stay Predictions

Expected Value Difference = Switch - Stay
Neural activity matched the influence model in mPFC

- Both RL and fictitious play will most likely "stay" after a reward and "switch" after a non-reward. mPFC implicated
- The influence model has a higher incentive to switch even after receiving a reward
  - Expected reward signals associated with a specific action do not necessarily increase after the receipt of a reward when taking into consideration the influence that an action exerts on the opponent's strategy

11.13 What about at outcome

At the outcome phase, you are told the outcome of that trial and you can update your strategy then

11.14 Activity correlated with TPJ in the update signal

It was found that higher activity in the TPJ was correlated with the update portion of the influence equation

11.15 Individual differences in strategy correlate with mPFC (again)

Remember that influence model is equal to the fictitious play plus the impact of self on other's actions and could be interpreted as higher level reasoning similar to levels in CH

11.16 Testing the causal role of TPJ in strategic choice using TMS

Scanned players have a training phase and then are split into two Groups: Placebo group that gets scanned for an irrelevant part of the brain (so that their experimental conditions are similar) and the experimental condition group whose rTPJ gets scanned. They then play against Human opponents outside of the scanner who were trained individually.

11.17 Behavioral Results

The rTPJ stimulation group:

- Switches actions less often
- Is more predictable from one trial to the next
- Has a lower influence parameter (k)

11.18 TMS reduces the influence update signal in right TPJ

11.19 Once again, dmPFC activity correlates with model sophistication

TMS over the right TPJ decreases its functional association with the dmPFC. This again suggests that TPJ is very important for strategic behaviors regarding thinking about what other people might be doing.
One question we have is that, how social is the TPJ? Does it give similar results for non-human interactions or opponents?

11.20 Neural differences between groups

Single card poker game in which the high card wins
Played versus computer and human opponents
All subjects bet on low cards more than 10% of the time.

11.21 Opponent characteristics

The same human opponent played against all participants

  - His base pay was ten dollars
  - He received one bonus of five dollar in-game earnings were sufficiently large
  - He received a second bonus of five dollars for helping his call rate between 45% and 55% over the course of the experiment

- The choice to bluff or fold for the computer opponent was made by random selection with an equal probability of a bluff or fold on each trial

11.22 Using brain data to predict behavior in a strategic game

- To predict bet/fold choices, the brain was divided into 55 separate anatomical regions
- Predictions were made using multivariate analysis techniques using different combinations of these 55 regions
- They are going to try to find unique combinatorial advantage. Meaning, when a region is included and excluded in the analysis, how strong are the predictions?

On the graph on slide 61, we see the computer opponent UCP measures on the x axis and Human opponent UCP on the y axis.
TPJ improved performance more for human opponents compared to computer opponents. The authors refer to this as a "social bias."
Social bias in TPJ predictive power is stronger in subjects who considered the human partner to be the better opponent compared to subjects who believe computers were better than or equal to human opponents

11.23 Notes

Neuroimaging techniques reveal that the patterns of brain activity underlying strategic choices partially overlap with

- Altruistic choices

- Simple choices for the individual alone

Areas involved in reasoning about others' beliefs seem to contribute to higher order thinking in strategic games

11.24 Strategic behavior in bargaining

In this example: Feedback is hidden. Page 65 diagram. Buyer gets value v, sends suggestion s. Seller receives suggestion s, submits price p. If $p \leq v$, DEAL. Seller earns p, Buyer v-p. If p is greater than v, NO DEAL. Both get payoff 0

11.25 Strategic behavior in bargaining

- The tradeable object has no value to either player if a trade does not occur
- However, if a trade does occur, each player prefers a sale price that favors them
  - Buyers prefer lower prices
  - Sellers prefer higher prices
- This misalignment of incentives implies that the only equilibrium solution of the one-round version of this game is for no information transfer to occur
- The buyer should "babble" and send suggestions with no informative relationship to her private value
- The seller should ignore this suggestion and set a price of either 5 or 6 (to maximize the expected revenue)
- However, this is the mutually optimal solution only if both players believe that the other is also playing in equilibrium
- Babbling is only optimal if the seller is in fact ignoring buyer suggestions
- Ignoring buyer suggestions is only optimal if they contain no meaningful information
- In reality, players' beliefs about what others are likely to do are often not accurate
- Therefore, descriptive models of belief formation and adjustment will be relevant
- Models such as cognitive hierarchy predicts the existence of different behavioral types based on the depth to which participants model their opponents

11.26 How do Buyers actually behave?

We can break down the people who play this game into three groups:
– Incrementalists (blue) send suggestions that are highly correlated with their true value
– Strategists (red) send suggestions that are negatively correlated with value. Strategists appear similar to incrementalists and thus reap the surplus from high-value trials.

- This is strategically logical. If the item is low value and the strategist sends in a high value and the seller plays accordingly, the deal won't take place. If the item is high value and the strategist sends a low value and the seller plays accordingly, they will reap the benefits.

– Conservative buyers (green) play closest to an economically rational actor and reveal no information about their value with their suggestions
Histograms on slide 71 showing suggestion frequencies for a single incrementalist and a single strategist. Note that from the perspective, the two look indistinguishable.

11.27 Traits between groups

No difference in IQ or socioeconomic status
Incrementalists earn less than Strategists and conservatives from the experiment.

11.28 The dlPFC is more active in strategists compared to the other two groups

11.29 Right TPJ activity varies as a function of value for strategists, but not conservatives or incrementalists

12 Memory and decision-making

12.1 Types of memory according to retention time

- Sensory memory (milliseconds)
- Working and short-term memory (seconds to minutes)
- Long-term memory (minutes to years)

12.2 Working memory (WM)

A limited capacity storage and manipulation system

- Used to maintaining information over a short time (seconds) in order to manipulate it
- Very limited capacity (4-9 single items at one time)
- Capacity varies across individuals and domains but is relatively stable within a given individual

Active manipulation of information distinguishes working memory from short-term memory (passive storage)

12.3 Long term memory (LTM)

Can be separated into categories

- Declarative: knowledge that you can consciously access
  - Episodic: memory for episodes/experiences in your life. Example: I was at the birthday party
  - Semantic: facts about the world. Example: Monte Rosa is the tallest mountain in CH.
- Nondeclarative memory: knowledge without conscious access
  - Riding a bike, kicking a ball

12.4 WM and LTM sub-categories are at least partially distinct

Studies of patients with brain lesions show that damage to specific brain regions leads to deficits in specific forms of memory.

12.5 The famous case of HM

Clear evidence for the functional localization of declarative long-term memory
Both his hippocampi were surgically removed
After surgery he could not form new memories
He had anterograde amnesia

12.6 HM could still form new non-declarative memories

E.g., he could learn new tasks such as mirror drawing after practicing

- He did not consciously know that he had gained these skills

12.7 Memory, imagination and simulation

Fact: anterograde amnesiacs such as HM also have difficulty imagining the future
Hypothesis: The purpose of memory is to guide current and future decisions and actions

- There is little evolutionary benefit to just remembering the past because we can't change it
- There are obvious benefits to learning from the past to inform or improve subsequent behavior
- Being able to imagine or simulate novel combinations of goods experienced separately in the past could help decision-makers generalize knowledge to new situation

12.8 Evidence that preferences are generalized via memory

Memories are a source of information for constructing preferences about goods that we have experienced in the past
Values spread across things that are associated with one another in memory

12.9 Preference by association

In past lectures, we discussed how temporal difference models can explain the way we learn about va;ue through repeated experiences of reward or punishment
Wimmer and Shohamy tested if this type of learning can generalize across stimuli that are associated with one another in memory
Study took place in three phases

1. Association phase: They would show either a picture of a face, body part, or scene and present that with an abstract fractal image
2. Reward phase: Only shown the abstract images. Some will predict a reward, some won't.
3. Decision phase: The subjects would then get two mandatory choices: They would choose between a reward abstract image and a no-reward abstract fractal image and then they would choose between two scenaries, one of which was associated earlier with the reward image.

12.10 Association phase

Six unique S1 stimuli were always followed by the same S2 circle

- S1 images were initially rated as neutral
- Two S1 images were drawn from each category

Participants were not told about the associations between S1 and S2.

- Task was to respond to occasional inverted faces, body part, or scene images

Each S1-S2 pair was shown 10 times in a pseudo-random order
Faces, body-parts and scenes reliably drive activity in different brain regions
This fact is used to test for reactivation of S1 stimuli in the subsequent reward phase

12.11 Reward phase

Only S2 stimuli are shown (never S1).
One of the two S2 stimuli paired with each category of S1 (face, body part, scene) was assigned as S2+, the other S2-

- S2+ were followed by reward 81% of the time
- S2- were followed by neutral outcomes 100% of the time

Participants had to press a button for every image.

- One button ”collected” dollar bills
- They had to press a different button for all other stimuli

Participants were informed that they might notice predictive associations between each circle stimuli (S2 and reward or neutral outcomes)

12.12 Decision Phase

Participants chose between two S1 or two S2 stimuli
Were told to pick the one they thought would be more likely to win 1 dollar.

- No feedback
- 4 repeats of each pairing

In the absence of any spread of reward,

- participants should be equally likely to choose any of the never-rewarded S1 images activity during the prior reward phase should be unrelated to these decisions.

However, if reward spreads and biases decisions,

- then participants should be biased toward choosing S1 images that were previouslyassociated with the S2 rewarded images more often.
  - “decision bias” = the tendency to chose S1+ items over S1– items,
- decision bias should be related to hippocampus activity during the reward learning phase.

12.13 Results

Participants chose S2+ stimuli more often than S2-
The level of decision bias varied substantially across participants and stimuli

- Mean preference for S1+

The authors use the variability in decision bias to test hippocampal activity
They find more hippocampal activity during the reward phase S2 stimuli who's associated S1 image would later have a strong decision bias
Decision bias did not relate to reported memory accuracy

12.14 Hippocampal activity was compared during the Reward phase not the decision phase

The idea was that seeing S2 should activate representations of the associated S1

12.15 Testing reactivation of S1 during the Reward Phase

Remember that faces, body parts, and scenes activate different portions of the brain's visual processing system
This gives the authors a means of testing for reactivation of S1 representations
Also, remember that S1 is not shown during the Reward phase they are testing in

12.16 Reactivations are stronger for high-bias than low-bias S1 images

Hippocampus plays an important role in connecting the information where it is stored in the brain but may not be the place that actually stores the memory. The more the S1 encoding regions are used, the more bias you will have.

12.17 Conclusion

Activation of memory associations between S2 and S1 during the Reward phase seems to facilitate the generalization of reward learning across related stimuli

12.18 Combining memories to evaluate new things

We often need to decide between goods or actions that we have no direct experience with
Can we simulate possible values for new things based on memories of previous outcomes?

12.19 Preplay

Decision making involves 'preplay' of potential outcomes in the brain

- Multiple studies show this for
  - rodents navigating familiar mazes to reach reward
  - Humans making spatial and non-spatial decisions over familiar items
- Can humans use preplay to represent novel goods

12.20 Repetition suppression

Neuronal populations respond less to a stimulus when it is repeated within a short time frame
Less neural response == less fMRI BOLD signal

Thus, if novel goods are represented as a combination of familiar goods in the brain, BOLD signals should be lower for a novel combined good when it is preceded by one of its components

It is not just about items it is also how much you like the items as well

Experiment will create combinations of food to make a novel good with different familiar component goods. They will also present characters with the foods to create associations. They want to control for any visual associations between the component and the novel item.
13 novel goods created from the combinations of two familiar food types
Novel goods were not previously been tasted together
Two examples are shown here: avocado and raspberry smoothie and tea jelly.

12.21 Learning prior to scanning

The goal is to test for overlap in memories of simulations, not visual characteristics
Train to associate components and combinations with abstract symbols
Accuracy = 97.8 percent after training

12.22 Two tests in the scanner

Choose between novel goods
Imagine sensory properties of novel goods

12.23 Chosen values are correlated with vmPFC and dmPFC

12.24 vmPFC and the hippocampus show repetition suppression

If you have the same chosen value in a row, you would have less signal the latter time

12.25 The extent of the suppression effect is related to a good's value

The more valuable the novel goods are, the higher the repetition suppression in both the vmPFC and the hippocampus
The mechanistic reason for this relationship between a good's value and repetition suppression across components and combinations is as yet, unknown.

12.26 Suppression between components and combinations disappears with experience

The authors tested another group of participants in the same manner, but first gave the one sample of the novel goods.
Suppression was less when the items were familiar as the subjects already tasted it. Hence, potentially, they stopped treating it as a novel imaginary combination item but rather another item that was tried.
Once a novel food is experienced, its representation may be distinct from its component parts.

- E.g., we don't think of ice cream as frozen milk, sugar, salt, water, and air bubbles

12.27 Conclusion

Preplay simulations of outcome values occurs in humans brains

- Mediated by structures that are known to play a key role in memory formation and recall

- Hippocampal damage and value-based choice

–Does damage to the hippocampus impair value-based choices relative to perceptual choices?

- If the hippocampus is used to recall and predict values, then damage there should impair value-based choices
- Perceptual choices are based on current sensory information, not remembered or simulated values
  - Should not be impaired by hippocampal damage

We have hippocampal damaged patients: Two groups: value based choices such as food choices and perceptual choices.
Value based choices

- Bid on 60 food items in a BDM auction item Choose between pairs of foods with a range of value differences
- Pictures of the foods were shown on the screen
  - Memory not required for knowing the choice set
  - may be required for evaluation and comparison

Perceptual task

- Judge if there are more yellow or blue dots
- Dots flicker in and out
  - Degree of flickering determines difficulty

12.28 Perceptual Decisions results

Indeed, perceptual decisions were okay in both groups, and response times were also pretty normal.

12.29 Value-based Decisions Results

Probability of correct answer was less for amnesiacs. Worse accuracy compared to healthy controls Reaction times were higher for amnesiacs

12.30 Amnesic patients show altered accuracy/speed trade offs for value-based choices

Even though they can see the food images on the screen and know that they are choosing between an apple and a banana, due to the damage to their hippocampus, impairs their ability to accurately choose, based on their own subjective values, which of the two items are better.

12.31 Summary

Result: Value construction and comparison is impaired following hippocampal damage
Conclusion: memory and simulation systems are important for constructing precise values at the time of choice

13 Emotions and Decision Making

13.1 Outline of this lecture

- Definitions and key ideas regarding emotion
- Emotions as specific motivators
- Neurobiology of emotion and the limbic system

13.2 What is emotion?

Colloquially, emotion is used to refer to all aspects of affective experience
However, in component process theories of emotion and affect the term "emotion" is proposed to reflect the discrete response to an external or internal event that entails a range of synchronized features, including:

- subjective experience,
- expression
- bodily response
- action tendencies

Emotions may involve all or a subset of the features listed on the previous slide
The key is that this subset be expressed in a relatively synchronized, temporally discrete manner

13.3 Emotion vs Mood

In contrast to emotions as synchronized, discrete responses to an event, moods are diffuse affect states characterized primarily by subjective feelings that are relatively enduring and generally low intensity
However, moods and emotions are not mutually exclusive and can be initiated by the same event

- For example, suppose you find out you did well on an exam, or your favorite football club wins a game.
  - You become happy directly after the outcome and might also maintain a good mood for the rest of the day even when not thinking about the exam or game

13.4 Common Emotions

Positive vs Negative
Positive: Happiness
Negative: Fear, sadness, anger, disgust

Surprise: can be positive or negative

13.5 Emotion feature 1: Subjective experience

Feelings are the consciously accessible and therefore most prominent characteristics of emotions, but they are only one component of emotion.
It is argued that emotions can occur without a change in subjective experience (see Öhman et al ., 2000; Funayama et al ., 2001 ; Winkielman et al ., 2005).

- This debate is not fully resolved
- Regardless, it is true that we can measure aspects of emotion without asking about subjective experience.

13.6 Emotion feature 2: Expressions

Charles Darwin, and others after him, suggested that the patterned facial expressions of emotion evolved for two functions:
The first being as a means of social communication to allow conspecifics to both benefit from the emotional reactions of others., such as fear to a threatening stimulus or disgust to a noxious stimulus, and to determine the intent of others, such as smiling in appeasement or anger when threatening.

13.7 Facial expressions send clear signals

Anger: I am upset and may cause you harm
Fear: There is something dangerous nearby
Disgust: Don't eat this!
Happy: Everything is fine and I approve of what you are doing

13.8 Emotion feature 2: Expressions

The second proposed function of facial expressions is to alter the perceptual experience in adaptive ways by changing the facial configuration.

- widening the eyes to obtain more visual information in fear
- restricting the nasal passages to limit olfactory sensation in disgust

13.9 Emotional expressions prime the body for relevant actions

Fear motivates the acquisition of information in order to escape threat, while disgust reduces sensory exposure to aversive stimuli.

13.10 Emotions prime the body for relevant actions

Changes in the subjective visual field - a fearful face allows you to see more. Even though when not feeling the emotion, when you mimic the expression, you get the benefits.
Disgust reduces your sensory input allowance
Changes in saccade velocity- The eyes move faster when making a fearful face, even when the individual is not actually frightened
Changes in inspiration capacity- a fearful expression allows more airflow to the lungs

13.11 Emotional feature 3: Bodily response

This is often referred to as the fight or flight response
Emotions elicit changes in hormones, heart-rate, and skin conductance
They also promote behaviors like freezing and enhacned startle responses

- Very useful for studying affective responses in animal models. Remember the classical or Pavlovian conditioning studies we discussed before

13.12 Emotion feature 4: Action tendencies

Approach vs avoid

- People and animals tend to move away from threats and disgusting objects
- However, they often move towards stimuli that elicit happiness

13.13 Emotions as specific motivators

Emotions are often separated into positive and negative or aversive domains.
It is commonly assumed that one aspect of decision making is to try and increase positive emotions at the time of outcome
However, emotions can influence decision making even if they are incidental to the choice
Not all negative emotions have the same influence on choices. Each negative emotion is associated with a specific 'adaptive' behavioral response
People may sometimes chose to experience negative emotions if the behavior they motivate is useful

13.14 Using emotion productively

1. Do people choose to experience "negative" emotions if they believe that they will aid performance on a specific task?
2. Do emotions actually improve performance?

13.15 Choosing to be afraid

Method

- Subjects given the opportunity to recall emotional memories under different conditions
- All subjects were told that they would be playing computer games in the next part of the study, but the types and goals of these games differed

Method, computer game descriptions

- Avoidance games: Avoid flying monsters trying to eat you or sneak across enemy terrain
- Approach games: find and grab money as quickly as possible or build a theme park
- Confrontation: Avenge the murder of a spouse or fight an opponent

Before the game, the subjects were asked how much they would like to experience an emotion, either fear, excitement, or anger, during these three aforementioned games
Approach goal: Excitement preferred
Avoidance goal: fear-inducing Confrontational goal: anger inducing

13.16 Goal dependent choice of emotion

Different experiment: Tenant and landlord: collaborate (long term) and confront (short term)
Before interacting with the 2nd player (tenant) the landlords could choose from different emotion inducing activities
Confrontation group got angry more, collaboration group was more happy

13.17 Choices based on expected usefulness

13.18 Congruent emotions benefit performance

Landlords who chose the anger inducing activities collected significantly more rent

- Somewhat incentive compatible in that each player had a points payoff matrix based on amount of rent collected, but these points did not change the cash payout

13.19 Notes

People will sometimes choose to experience negative or 'aversive' emotions if those emotions are expected to convey some behavioral benefit
Again, different negative emotions have different expected affects on decisions

13.20 Incidental happiness and sadness have been reported to change temporal discounting rates

Sadness reportedly increases impatience, happiness reportedly decreases impatience

13.21 The happiness study didn't replicate

Watching films didn't change TD values for people

13.22 Study characteristics associated with replication measures

13.23 For sadness

Emotion induction using 3-min video clips – Sadness: a clip about the death of a boy's mentor (Gross Levenson, 1995) – Disgust: a clip about an unsanitary toilet (Lerner et al., 2004) – Neutral: a clip about the Great Barrier Reef (Lerner et al., 2004)
Following the videos participants wrote essays about experiencing sadness, disgust, or their nightly activities (neutral).
Emotion induction resulted in higher self-reported ratings of the targeted emotion

13.24 Results

Sadness did change temporal discount factors

13.25 But why is that?

Sadness makes the subjects more prone to having impatient thoughts, which alters their TD.

13.26 Query theory predicts affects of thought order

QT proposes that preferences are constructed, rather than pre-stored and immediately retrievable
Construction happens in accordance with the answers to one or more internally posed questions, or queries.
Query order depends on the structure of the choice situation or task, and can influence retrieval of information, leading to different decisions.
The ordering of your items will decide which one you will prefer later.

Sadness seems to change the order of motivations you come up with for having something now or the future, which influences TD

13.27 Sadness also appears to reduce patience for cigarettes

Increases inhalation volume while smoking

13.28 Sadness vs happiness influences on TD

Does sadness have stronger influences on temporal discounting?

- Hard to say based on one set of film clips (i.e., one form of emotion induction)
  - One film clip could induce stronger emotions than the other
  - Interpretation of the films may have changed after ¿ 15 years
- Thought processes induced by the film clips
  - Not measured for happiness
  - Sadness effects mediated by impatient thoughts and/or self-focus rather than negative affect per se
    - The "sad" clip deals with death (critical confound?)

13.29 Emotions as motivators summary

– Discrete motions have specific motivational properties. E.g., approach, avoid, engage, withdraw
– The effects of emotion on choices are driven, at least in part, by the behaviors they motivate

13.30 Neurobiology of emotion

13.31 Emotions are often mediated by the limbic system

13.32 We know that aversive, fear learning is mediated by the amygdala

No amygdala in rats: no fear learning from shocks

13.33 Emotional enhancement of memory is also linked to amygdala activity

Amygdala activation predicts memory for emotional items in one study

13.34 The Amygdala processes emotional signals

Even subconsciously presented emotional signals increase amygdala activity

This might have something to do with the evolutionary response to detecting fear

13.35 Trustworthiness judgements are also impaired by amygdala damage

Approachability of faces can be misjudged
Trustworthiness: Even the faces with the least trustworthy faces are marked as trustworthy by amygdala damaged patients

13.36 Take home message

Patients with bilateral amygdala lesions (JM, SM, RH) rate negative faces as more trustworthy and approachable than healthy and brain damaged controls
Thus, not only is the amygdala involved in processing emotion it also plays a role in evaluating social others

13.37 Another word of caution on reverse inference

– While we know that emotions often involve brain structures such as the amygdala, we CANNOT infer any specific emotion from the presence or absence of binsula, and ventral striatum,rain activity. – For some reason, people are especially tempted to make reverse inferences related to emotional states. – All three structures process information and have cognitive in addition to emotional processing.
These areas are not just active in emotions and will be active in other tasks. Their sole purpose isn't to process emotions
The primary issue is that most brain regions are involved in multiple functions and behaviors and increased activity in a specific region could mean many different things.

Remember the Real vs Imagined movement, they look pretty similar

14 Conclusion