認知與腦科學研究中心
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社會科學學院
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FACULTY OF SOCIAL SCIENCES

Social cognition seminar

A.N.D Lab

SOCIAL COGNITION:

From brains to culture

Ch 8 Accuracy and Efficiency in Social Inference

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Outline-Questions

- Why is Rationality Assumed?
- Social Inferences Sometimes Produce Wrong Answers: When?
- Errors and Biases as Consequential: Improving the Inference Process
- Errors and Biases as Incidental: Perhaps They Don't Matter
- Are Rapid Judgments Sometimes Better than Thoughtfully Considered Ones?
- Neuroeconomics: Back to the Future

Why is Rationality Assumed?

Why was the assumption of rationality such a cornerstone of social cognition research? One reason is that research on inference generally assumes either implicitly or explicitly that inferences are goal directed; that is, they are made to achieve some purpose. A person may need to make a decision, choose among several options, or understand a situation before acting on it. If goals dominate the inference process, then clearly some ways of reaching a goal are better than others because they are more thorough and less error-prone. Accordingly, the social perceiver, it would seem, should use them.

Why is Rationality Assumed(1)

Another reason for assuming rationality is more pragmatic. To understand the strategies used by the social perceiver, it is helpful to have a reference point for comparison. Normative models – that is, the optimal ways to use information to reach inferences – provide such reference points. Even when researchers are well aware that social inference does not correspond to normative models, the comparison of naive inference against normative models can help reveal the strategies typically used to make social inferences. Normative models for making judgments and choices are known collectively as behavioral decision theory, and it is against the principles of behavioral decision theory that social inferences have typically been compared (e.g., Dunning, 2012; Einhorn & Hogarth, 1981; Hastie & Dawes, 2001).

Why is Rationality Assumed(2)

Another reason for assuming rationality is more pragmatic. To understand the strategies used by the social perceiver, it is helpful to have a reference point for comparison. Normative models – that is, the optimal ways to use information to reach inferences – provide such reference points. Even when researchers are well aware that social inference does not correspond to normative models, the comparison of naive inference against normative models can help reveal the strategies typically used to make social inferences. Normative models for making judgments and choices are known collectively as behavioral decision theory, and it is against the principles of behavioral decision theory that social inferences have typically been compared (e.g., Dunning, 2012; Einhorn & Hogarth, 1981; Hastie & Dawes, 2001).

Why is Rationality Assumed(3)

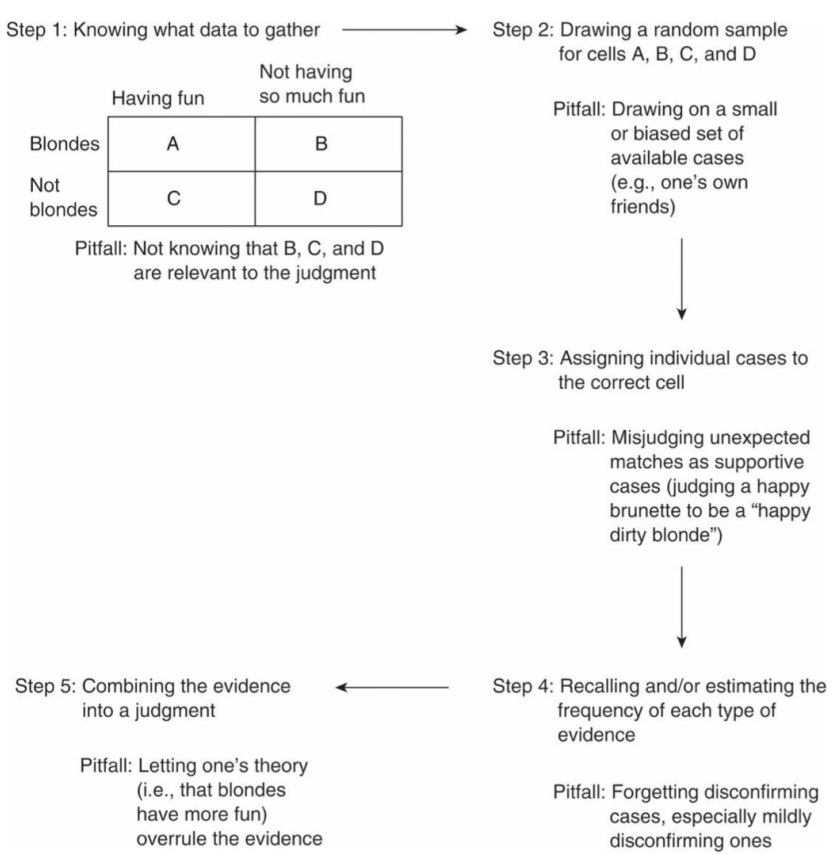
Another reason social inference often fails to match normative models is that the social perceiver operates not only under accuracy pressures but also under efficiency pressures, making inferences quickly in a rapidly changing environment with multiple demands. As such, many inferential tasks are solved with reference to prior expectations or theories, rather than by means of an exhaustive consideration of the data at hand. Although buying the ingredients for a dinner party for one's employer may lead one to devote considerable thought to the purchase of each item, one's typical grocery shopping may be guided by the idea that "cheaper is better" in order to choose quickly from an array of goods. Given the need to process large amounts of information quickly, people's information-processing strategies may lean toward efficiency rather than thoroughness. The criterion of efficiency is not systematically incorporated into normative models of inference, and normative models may not reflect some of the most important pressures that typically operate on the social perceiver.

Why is Rationality Assumed(4)

One other reason inference processes often depart from normative models stems from capacity limitations on short-term memory. That is, the ability to process information online is constrained, as Chapters 2–4 noted. At a minimum, the inference process is often marked by a need to use strategies that move information along quickly though not always thoroughly. The label "cognitive miser" was developed to explain the necessary stinginess with which attention and processing time are often allocated to stimuli in the real world (S. E. Taylor, 1981b). Long-term storage in memory, however, is quite cheap, a point easily illustrated by thinking over all the songs you know or the people you can identify by sight. The advantage of so much storage space is that prior information, beliefs, and inferences can be stored as knowledge structures. They are then accessible when new inferences must be drawn. With limited online capacity and a large amount of stored knowledge, how do these factors affect social inference?

Social Inferences Sometimes Produce Wrong Answers: When?

- **Gathering Information**



Nonetheless, in many circumstances, characterizing information on the basis of preexistent theories is unwise. Three such conditions are (Nisbett & Ross, 1980): first, if the theory itself is faulty or suspect. For example, if demons, her parents might at least want a second opinion. Second, if an individual characterizes data on the basis of a theory but believes his or her inferences are objectively based on raw data, problems can result. The physician who sends the girl home after a cursory examination with

believe that the examination was thorough. Third, theory-guided inferences create problems when the theory overrules consideration of the data altogether. The doctor who dismisses the adolescent as an overzealous dieter prior to examining her would be guilty of this error, as well as of gross negligence.

Social Inferences Sometimes Produce Wrong Answers: When?

- **Sampling Information**

  - *sample estimates can be thrown off by extreme examples within the sample.*
  - *Small samples produce poor estimates of a population's characteristics, whereas larger samples are more reliable. This principle is called the* ***law of large numbers****.*
  - *people sometimes attend insufficiently to biases in samples*

Social Inferences Sometimes Produce Wrong Answers: When?

- **Regression to the Mean**

refers to the fact that extreme events will, on average, be less extreme when reassessed at a different point in time.

- *when people encounter extreme values of predictor information, they draw extreme inferences about subsequent behavior*

- *People's insufficiently regressive judgments may represent errors or the misapplication of a normally effective judgmental strategy*

Table 8.1 Regression toward the mean: Taking the GREs twice

Time 1			
Given four students (A, B, C, D) of equal ability, all should score 600 on the Graduate Record Examination:	**But random factors enter in, raising or lowering their scores:**	**Actual scores at Time 1:**	**Conclusion:**
A 600	−10 (slept poorly)	590	B and D look strong;
B 600	+15 (studied examples similar to test items)	615	A and C look weaker
C 600	−17 (gum chewer was a distraction)	583	
D 600	+12 (got a good seat in the test room)	612	
Time 2			
Given same four students taking test again:	**Different random factors are present, raising or lowering scores:**	**Actual score at Time 2:**	**Conclusion:**
A 600	+12 (had a good breakfast)	612	A and C look stronger and
B 600	−10 (sat near the window)	590	B and D look weaker than at Time 1
C 600	−4 (had a slight cold)	596	
D 600	+5 (was "on" that day)	605	

Social Inferences Sometimes Produce Wrong Answers: When?

- **The Dilution Effect**

*when diagnostic information is weakened by nondiagnostic information, inferences are less extreme, a phenomenon known as the **dilution effect** (Nisbett, Zukier, & Lemley, 1981).*

- *Psychologists have developed training techniques to reduce judgmental errors, and ironically, at least some of these efforts actually increase the dilution effect*

Errors and Biases as Consequential: Improving the Inference Process

- **we need methods for detecting and correcting biased inferences.**

preferences, participants inspected four nightgowns displayed on a table and indicated which one they would choose. In fact, a strong serial position effect determines these kinds of tasks, such that people typically prefer the right-most item. (Why this position preference exists is not fully known.) Participants in the experiment showed this serial position effect, but when asked why they made their particular choice, they offered explanations that centered on qualities of the chosen garment itself. When told serial position might have influenced their decision, participants expressed considerable skepticism.

Errors and Biases as Consequential: Improving the Inference Process

- **Should We Turn Inference over to Computers?**

> People's inferential shortcomings are particularly well illustrated when matched against a computer given the same information. The computer always does as well or better (Dawes, Faust, & Meehl, 1989). How can one demonstrate this fact? First, find a judgment task in which roughly the same kinds of information are contained in every case; second, use a decision rule regarding how that information is to be combined to reach a decision for each case. Such judgment tasks are relatively common. A business must replenish stock after considering demand and current inventory. Doctors must diagnose and treat patients given clinical observations, symptoms, and test results. Professors admit or reject students from graduate school on the basis of test scores, grade point average, past work, and letters of recommendation.

Errors and Biases as Consequential: Improving the Inference Process

- **Should We Turn Inference over to Computers?**

A normatively appropriate way of completing such a task is to examine each case (e.g., student), take each of the bits of information relevant to the judgment (e.g., GPA, letters of recommendation, GRE scores), multiply each bit by its weight (e.g., count GREs twice as much as GPA and GPA half again as much as letters of recommendation), add it up for a total case score, and compare the case's score against other case scores to pick the best ones. This process employs a **linear model**, so-called because the total impression is an additive combination of the available information. This task can be efficiently and effectively completed by a properly programmed computer. Various nonlinear combinations can also reliably make decisions: "Weigh GPA twice as heavily as letters of recommendation, unless GPA is lower than 3.0, in which case weigh it evenly with letters." The nonlinear nature of these rules makes them no less readily programmable for a computer, and the computer is more reliable than the human decision maker.

Errors and Biases as Consequential: Improving the Inference Process

- **Should We Turn Inference over to Computers?**

Table 8.3 Comparison of the linear model, the nonlinear model, and a human decision maker: Will Stinch and Crabble be admitted to graduate school?

	Case A: Gerald Stinch	**Case B: Amanda Crabble**
	GRE: 650 Verbal, 710 Math	GRE: 620 Verbal, 590 Math
	GPA: 3.8	GPA: 2.9
	Letters of recommendation:	Letters of recommendation:
	Hard-working, diligent	A bit of a dreamer, hasn't come into her own
Linear model (as applied by computer)	Score = 2 (GREs) + 1 (GPA) + .5 (Letter of recommendation)	
Decision:	Admit Stinch.	Reject Crabble.
Nonlinear model (as applied by computer)	Score = 2 (GREs) + 1 (GPA) + .5 (Letter of recommendation), unless GPA is less than 3.0, in which case Score = 3 (GREs) + 1 (Letter of recommendation)	
Decision:	Admit Stinch.	Reject Crabble.
Human decision maker	Aha. Another Smedley. Not a creative bone in his body.	Aha. Another Woodley? She was a great theoretician – got off to a slow start, though.
Decision:	Reject Stinch.	Admit Crabble.
Probable outcome given reliable and valid admissions criteria	Stinch will do well.	Crabble will do less well.

Errors and Biases as Consequential: Improving the Inference Process

- **Teaching Reasoning**

Table 8.4 Statistical, methodological, and conditional reasoning in everyday life

Statistical reasoning – Everyday life

After the first two weeks of the major league baseball season, newspapers begin to print the top ten batting averages. Typically, after two weeks, the leading batter has an average of about .450. Yet no batter in major league history has ever averaged .450 at the end of a season. Why do you think this is?

1. A player's high average at the beginning of the season may be just a lucky fluke.
2. A batter who has such a hot streak at the beginning of the season is under a lot of stress to maintain his performance record. Such stress adversely affects his playing.
3. Pitchers tend to get better over the course of the season, as they get more in shape. As pitchers improve, they are more likely to strike out batters, so batters' averages go down.
4. When a batter is known to be hitting for a high average, pitchers bear down more when they pitch to him.
5. When a batter is known to be hitting for a high average, he stops getting good pitches to hit. Instead, pitchers "play the corners" of the plate because they don't mind walking him.

Methodological reasoning – Everyday life

The city of Middleopolis has had an unpopular police chief for a year and a half. He is a political appointee who is a crony of the mayor, and he had little previous experience in police administration when he was appointed. The mayor has recently defended the chief in public, announcing that in the time since he took office, crime rates decreased by 12%. Which of the following pieces of evidence would most deflate the mayor's claim that his chief is competent?

1. The crime rates of the two cities closest to Middleopolis in location and size have decreased by 18% in the same period.
2. An independent survey of the citizens of Middleopolis shows that 40% more crime is reported by respondents in the survey than is reported in police records.
3. Common sense indicates that there is little a police chief can do to lower crime rates. These are for the most part due to social and economic conditions beyond the control of officials.
4. The police chief has been discovered to have business contacts with people who are known to be involved in organized crime.

Conditional reasoning – Permission schema

You are a public-health official at the international airport in Manila, capital of the Philippines. Part of your duty is to check that every arriving passenger who wishes to enter the country (rather than just change planes at the airport) has had an inoculation against cholera. Every passenger carries a health form. One side of the form indicates whether the passenger is entering or in transit, and the other side of the form lists the inoculations he or she has had in the past six months. Which of the following forms would you need to turn over to check? Indicate only those forms you would have to check to be sure.

Transit	Entering	Inoculated against: cholera hepatitis	Inoculated against: typhoid
Box 1	Box 2	Box 3	Box 4

(a) Boxes 2 & 3

Errors and Biases as Consequential: Improving the Inference Process

- *Errors and Biases as Incidental: Perhaps They Don't Matter*
- *Are Inferential Errors Inconsequential or Self- Correcting?*
- *Biases may matter little when decision alternatives are of near equal value.*
- *Some intuitive strategies are relatively robust against certain errors, and in other cases one shortcoming may cancel out another (Nisbett & Ross, 1980).*
- *Some sources of error will correct themselves through repeated encounters.*

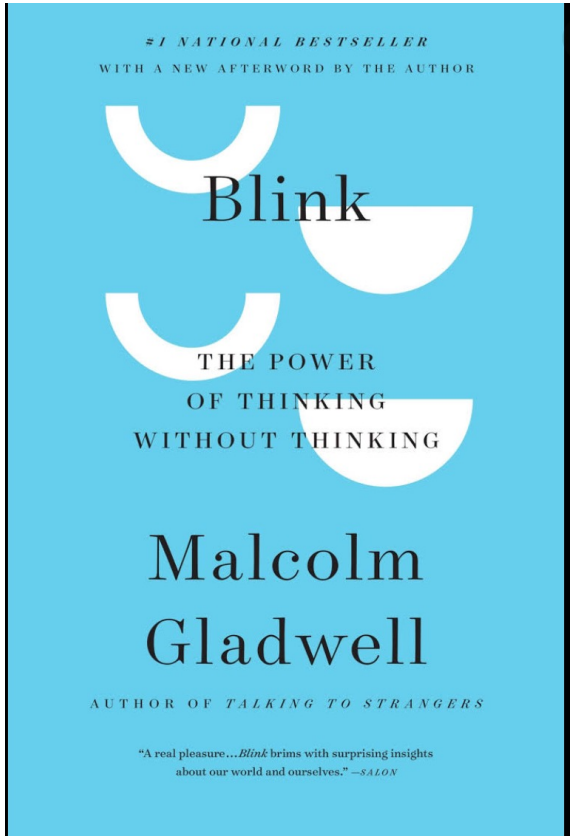
--------- world require people to be sufficiently smart but not optimally smart.

solved. Whereas people may make quick-and-dirty choices and decisions for inconsequential matters, they may be more thorough and circumspect for important decisions. That is, intuitive strategies accommodate pragmatic concerns. Under certain conditions, faulty inferences will be corrected by subsequent evidence through conversation with others (Hirst & Echterhoff, 2012). Thus, one answer to the question "If we're so bad at judgmental tasks, how do we do as well as we do?" is that rapid approximations of normative strategies yield a good-enough way to relate to the world much of the time.

Are Rapid Judgments Sometimes Better than Thoughtfully Considered Ones?

Early social cognition research viewed heuristic inferences as flawed, a position that gave way to observing that, to meet efficiency pressures, sometimes rough approximations to the normative model may suffice for accuracy and be vastly superior for meeting efficiency needs. A more radical view is coming into acceptance at the present time; namely, at least under some circumstances, rapid heuristically based judgments may yield superior inferences compared to deliberative conscious efforts.

Are Rapid Judgments Sometimes Better than Thoughtfully Considered Ones?



The immensely popular book, *Blink*, by Malcolm Gladwell (2005), draws on compelling examples from social psychology to make the case that, for many complex decisions or choices, the brain performs a series of rapid calculations that lead to instant and often correct assessments. For example, very knowledgeable art historians evaluating a kouros reputed to have been carved in 6th-century-BC Greece rapidly concluded that the sculpture was a fake, although none of them could articulate quite why.

决断2秒间

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豆瓣评分

6.8 354人评价

5星 13.3%
4星 32.5%
3星 41.2%
2星 8.8%
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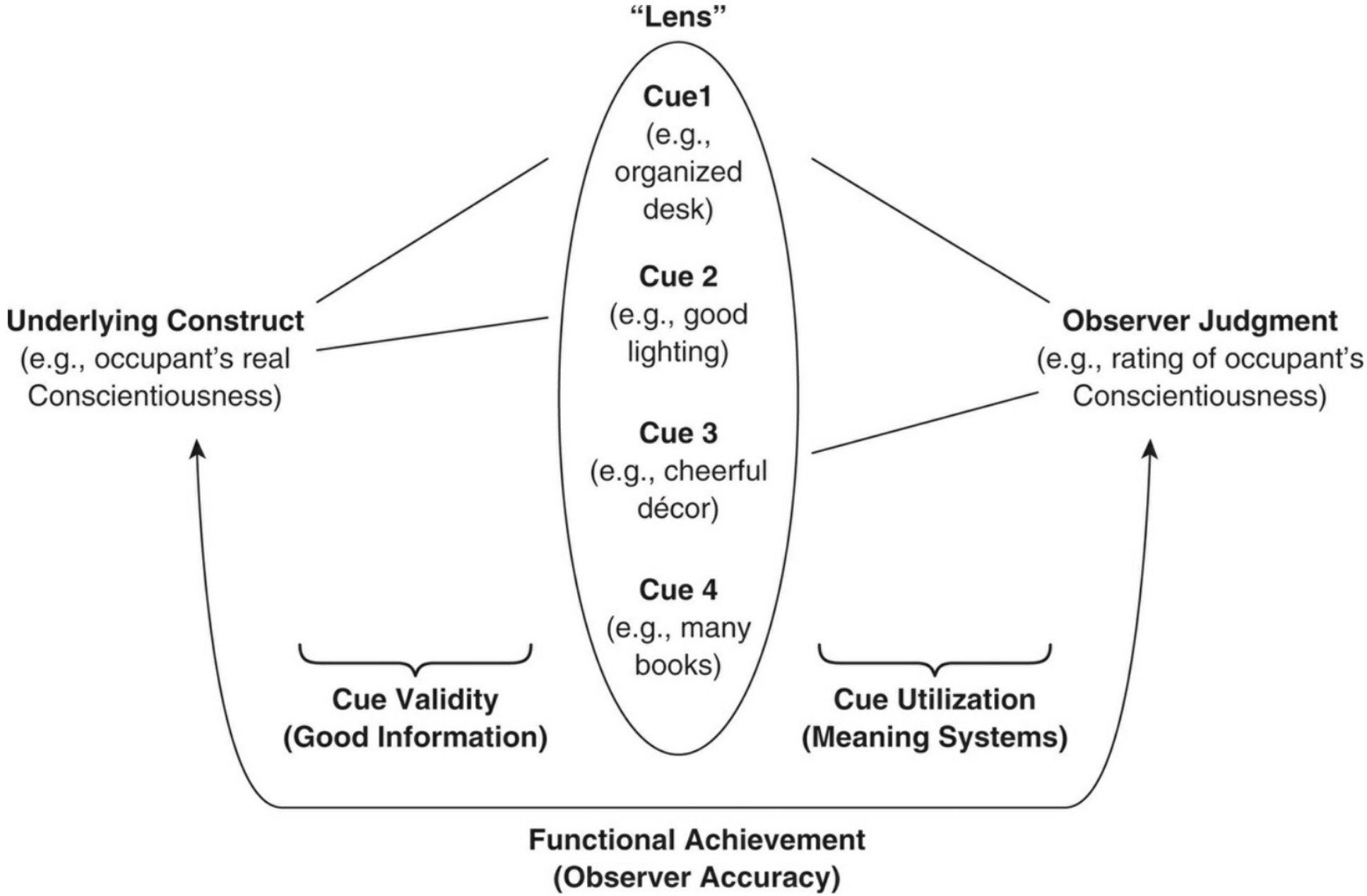
内容简介 · · · · · ·

《决断2秒间》讲述在《引爆点》中，马尔科姆·格拉德韦尔为我们揭示了认知世界的过程，现在，他的另一力作《决断2秒间》，革命性地为我们展示了如何明了我们自身的内心世界。为什么有些人天生就是充满睿智的决策者，而其他人却错误频出?为什么有些人跟随直觉的指引便能抵达成功的胜境，而有些人却在艰难的泥沼中不能自拔?再有，为什么有些英明的决策常常是那些无法向人解释的决策呢？《决断2秒间》是一本关于“不假思索”的著作，是一本让我们无需冥思苦想、在转瞬之间便作出决策的著作，不过，这个过程并不简单。在办公室，在教室，在厨房，在卧室，你的大脑到底是如何运转的呢?《决断2秒间》让我们见到了这样的心理学家——只需观察几分钟的时间，就能预测一对夫妇是否能白头偕老；我们还遇到了这样的网球教练—— 在网球与球拍接触之前，就能断定这次发球是不是双误……当然，《决断2秒间》也让我们看到...

Figure 8.2 Brunswik lens model showing how observers infer conscientiousness from a "Room with a Cue"



Motivated Inference

- *inferences serve purposes other than accuracy and efficiency;*
- *people hold blatantly false beliefs is that such beliefs may be motivating;*
- *Such robust inferential biases persist probably because they succeed in getting people to accomplish more than if their assessments of their likely accomplishments were more realistic.*
- *Certain robust inferential biases may persist not only because they fuel positive emotions and self-esteem, but also because they minimize perceived risk*

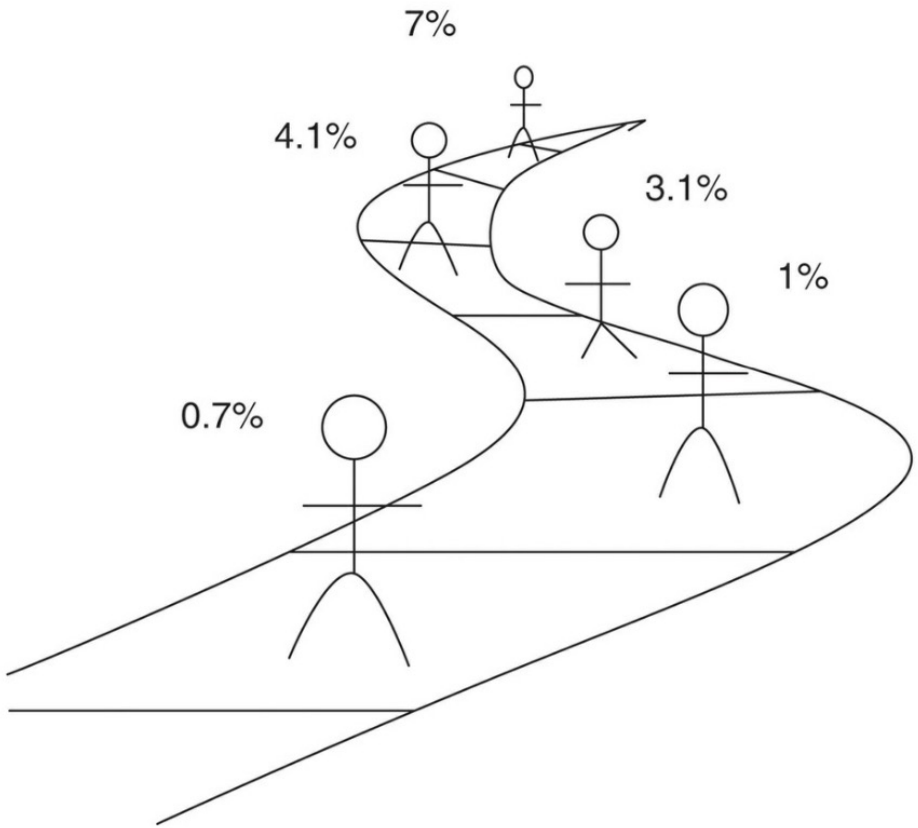
Open-minded 0—1—2—3—4—5—6—7—8—9—(10)

Understanding 0—1—2—3—4—5—6—7—8—(9)—10

Loyal 0—1—2—3—4—5—6—7—8—(9)—10

Caring 0—1—2—3—4—5—6—7—8—9—(10)

Helping partner through rough times 0—1—2—3—4—5—6—7—8—9—(10)



Source: Knäuper, Kornik, Atkinson, Guberman, & Aydin (2005)

Motivation Influences the Underestimation of Cumulative Risk

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McGill University, Montreal

Rachel Kornik
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Katherine Atkinson
University of Lethbridge

Carly Guberman
University of Toronto

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Past research has shown that people typically underestimate the cumulative risk of events. This effect has mainly been interpreted as resulting from the use of cognitive heuristics and judgment strategies, such as availability or anchoring and adjustment. The authors suggest that motivational processes can be an additional force in the generation of cumulative risk estimates. Using an experimental design, Study 1 shows that people underestimate the cumulative risk of infection with sexually transmitted diseases of appealing prospective sexual partners by using risk-irrelevant information for their judgment. Using a correlational design, Study 2 demonstrates that people underestimate the cumulative risk of being infected with a sexually transmitted disease and that commitment to the present partner is directly related to a low cumulative risk estimate as well as indirectly through its effect on the perceived risk of the present partner. Together, the two studies demonstrate that motivation influences the underestimation of cumulative risk.

(e.g., see Shaklee & Fischhoff, 1990). In a simil
the likelihood of contracting a sexually transmit
ease (STD) in one unprotected sexual encount
seem small enough to ignore, but the chances
considerably over repeated unprotected enco
creating a substantial overall risk in the long ter
research has shown that people typically undere
the cumulative effect of events (e.g., Bar-Hille
Cohen, Chesnick, & Haran, 1972). This effect has
been interpreted as resulting from the use of co
heuristics and judgment strategies, such as availal
anchoring and adjustment (Kahneman, Slo
Tversky, 1982; Tversky & Kahneman, 1973, 197
suggest that motivational processes can be an ad
force in the generation of cumulative risk estimat
present research examines this proposition.

Neuroeconomics: Back to the Future

Roughly, the idea is to use the expected utility (EU) model, which predominates in economics, to undertake the following: generate predictions about how inference *should* proceed and what brain regions may accordingly be implicated; integrate those insights with research on how inference actually *does* proceed to identify other neural subsystems likely to be involved (such as brain regions implicated in affective input or automatic processing); and verify these integrative predictions using insights and methodologies from neuroscience such as fMRI, to see if the expected brain regions do, in fact, activate during inference (Sanfey, Loewenstein, McClure, & Cohen, 2006). Although neuroeconomics adopts expected utility theory as its point of departure, a stance that would seem unwise given all the research just reviewed, it qualifies those predictions with insights from the descriptive theory provided by social cognition research on judgment and decision making.

Extended content : Prospect theory

Utility : calculated by summing the subjective values

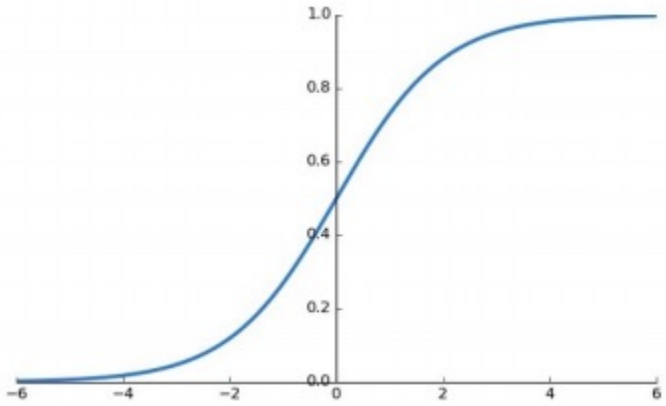
$$V = \sum_{i}^{n} \pi_i v_i$$

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

$$\begin{aligned}
\pi_1 &= w^-(p_1), \\
\pi_n &= w^+(p_n), \\
\pi_j &= w^-(p_1 + \cdots + p_j) - w^-(p_1 + \cdots + p_{j-1}), 1 < j \leq k, \\
\pi_j &= w^+(p_j + \cdots + p_n) - w^+(p_{j+1} + \cdots + p_n), k < j < n,
\end{aligned}$$

Selection probability: using the softmax function to transform the utility of options to the probability of one specific option being selected

$$P(g) = \frac{e^{\phi V_g}}{\sum_i^n e^{\phi V_i}}$$



Application : Prospect theory

Gamble 1

80% chance to win 5 mop

20% chance to win 100 mop

Gamble 2

100% chance to win 24 mop

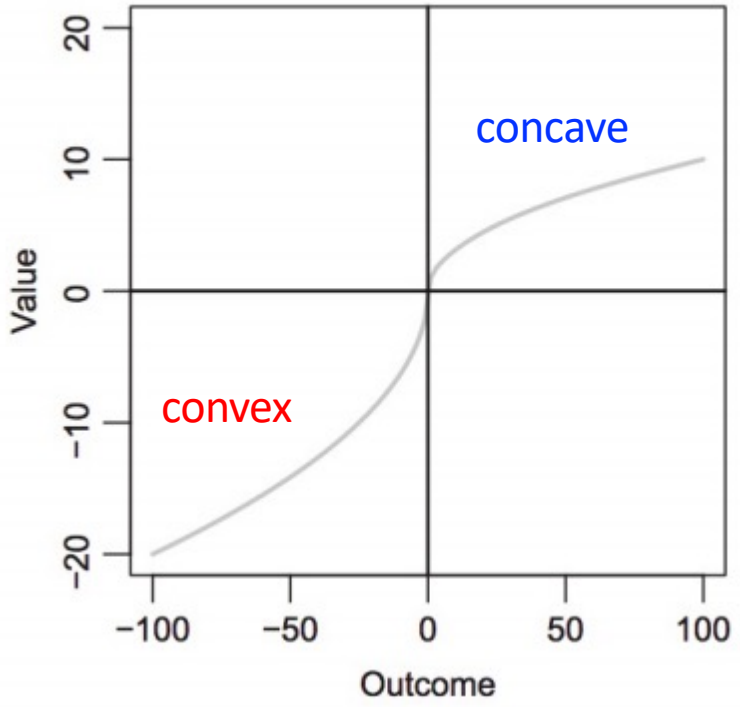
Value function : it maps the outcome values into subjective value.

Subjective value measures how much a person like or dislike the outcome value.

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

Loss aversion : steeper for loss than for gain

$\lambda > 1$



Risk-seeking for loss

Risk-averse for gain

Application : Prospect theory

Probability weighting function : it maps the probability into subjective probability.

We tend to overweight small probabilities, and underweight intermediate and large probabilities

$$w(p) = \frac{p^c}{(p^c + (1-p)^c)^{(1/c)}}$$

1. We separate probability weighting function for loss and gain

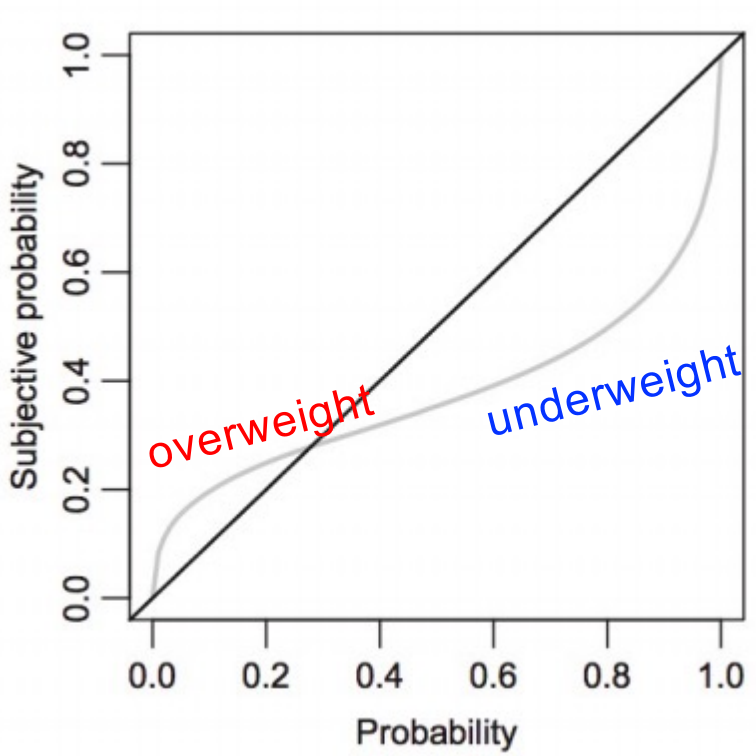
   for gain: w+ with c=gamma

   for loss: w- with c=delta

2. w+ and w− apply to cumulative probabilities

$$\pi_1 = w^-(p_1),$$
$$\pi_n = w^+(p_n),$$
$$\pi_j = w^-(p_1 + \cdots + p_j) - w^-(p_1 + \cdots + p_{j-1}), 1 < j \leq k,$$
$$\pi_j = w^+(p_j + \cdots + p_n) - w^+(p_{j+1} + \cdots + p_n), k < j < n,$$

p_1 : the probability of the most negative outcome
p_n : the probability of the most positive outcome



Neuroeconomics: Back to the Future

- discounted utility (DU) model

Q1 (1) 5*mop* now vs (2) 10*mop* 2weeks later

Q2 (1) 12*mop* now vs (2) 20*mop* 3weeks later

Q3 (1) 12*mop* now vs (2) 30*mop* 4weeks later

Q4 (1) 8*mop* now vs (2) 30*mop* 10weeks later

Q5 (1) 4*mop* now vs (2) 100*mop* 1years later

Q6 (1) 5*mop* now vs (2) 150*mop* 2years later

Q7 (1) 20*mop* now vs (2) 1,000*mop* 5years later

Q8 (1) 20*mop* now vs (2) 10,000*mop* 10years later

Hierarchical modeling for Inter-Temporal Preferences

We value the present more than the future. --> ‘intertemporal ’ preferences

Modeling the decision-making under intertemporal preferences:

Present Subjective Value (PSV) of the option 1 and option 2

$$V^B = B \times \frac{1}{1 + kD}$$

B: monetary amount

D: delay

k: discount function

Choosing Between option 1 and option 2

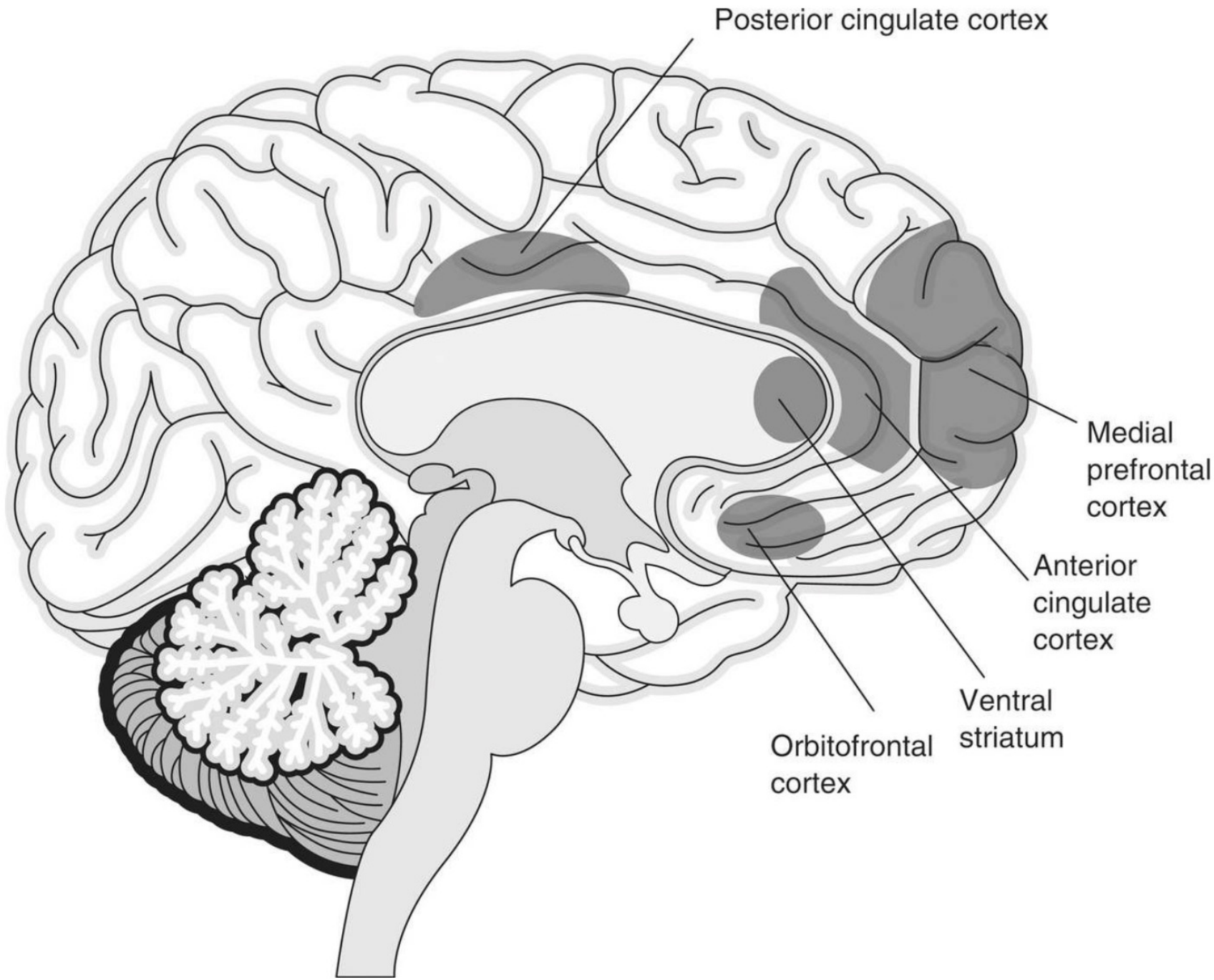
V^A, V^B : PSV of option1 and option2

α: discount function

ϕ : cumulative normal distribution function

Project you can try

1) Fit your own data, and get your discount function
2) Apply the hierarchical models to the data from your classmates, and compare the k (girls vs boys)


Posterior cingulate cortex
Medial prefrontal cortex
Anterior cingulate cortex
Ventral striatum
Orbitofrontal cortex

Summary

- at least under certain circumstances, judgmental errors and biases may produce severe distortions, and therefore it is advisable to find ways to correct the inference process;

- experimental literature makes people look worse than they really are, and that intuitive inferential strategies are actually quite effective in the real world.

- heuristically based judgments are actually better than more thoroughly considered ones. For example, experts may be able to make rapid use of vast stores of nonconscious knowledge to produce judgments that are more accurate than judgments made via conscious deliberation.

Where is the study of social inference headed?

NETWORK SCIENCE

Inference and influence of network structure using snapshot social behavior without network data

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Population behavior, like voting and vaccination, depends on the structure of social networks. This structure can differ depending on behavior type and is typically hidden. However, we do often have behavioral data, albeit only snapshots taken at one time point. We present a method jointly inferring a model for both network structure and human behavior using only snapshot population-level behavioral data. This exploits the simplicity of a few parameter model, geometric sociodemographic network model, and a spin-based model of behavior. We illustrate, for the European Union referendum and two London mayoral elections, how the model offers both prediction and the interpretation of the homophilic inclinations of the population. Beyond extracting behavior-specific network structure from behavioral datasets, our approach yields a framework linking inequalities and social preferences to behavioral outcomes. We illustrate potential network-sensitive policies: How changes to income inequality, social temperature, and homophilic preferences might have reduced polarization in a recent election.

INTRODUCTION

Human behavior, from voting preferences to vaccine sentiments, can depend on the structure of social networks (*1*). While we have huge, high-quality, social-scientific datasets linking the behavior of individuals to their individual circumstances [from censuses (*2*) through health surveys (*3*) to, in fine spatial aggregate, voting outcomes], it is extremely costly, or even impossible, to have direct access to the social networks on which this behavior is articulated. Here, we do not seek to infer individual links with high accuracy but instead seek a behavior-specific network model that is informative of social network structure and is policy relevant. The need to understand social network structure and how it shapes behavior appears acute: There are concerns about both the role of social networks in health from (*11*, *12*). An alternative route to using data from technology platforms is to use conventional surveys. Beyond issues with scalability, it is often a challenge to identify from surveys whether the inferred network structure relates to the true network on which a particular behavior is articulated (*13*–*15*). A third established route is to attempt to infer network models through, e.g., time-series data (*16*–*19*). These approaches typically assume repeated observations of individual-level data; unfortunately, human behavior, such as voting or smoking, is often sampled at a single point in time.

While it might thus seem challenging to access behavior-specific social structure, there is one distinctive feature of social data that assists inference: Unlike many networked systems, censuses provide socially relevant coordinate information for individual nodes. Peter

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Investigation of the neural correlates of mentalizing through the Dynamic Inference Task, a new naturalistic task of social cognition

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ABSTRACT

Understanding others' intentions requires both the identification of social cues (e.g., emotional facial expressions, gaze direction) and the attribution of a mental state to another. The neural substrates of these processes have often been studied separately, and results are heterogeneous, in part attributable to the variety of paradigms used. The aim of the present study was to explore the neural regions underlying these sociocognitive processes, using a novel naturalistic task in which participants engage with human protagonists featured in videos.

A total of 51 right-handed volunteers underwent functional magnetic resonance imaging while performing the Dynamic Inference Task (DIT), manipulating the degree of inference (high vs. low), the presence of emotion (emotional vs. nonemotional), and gaze direction (direct vs. averted).

High nonemotional inference elicited neural activation in temporal regions encompassing the right posterior superior temporal sulcus. The presence (vs. absence) of emotion in the high-inference condition elicited a bilateral pattern of activation in internal temporal areas around the amygdala and orbitofrontal structures, as well as activation in the right dorsomedial part of the superior frontal gyrus and the left precuneus.

On account of its dynamic, naturalistic approach, the DIT seems a suitable task for exploring social interactions and the way we interact with others, both in nonclinical and clinical populations.

RESEARCH ARTICLE

Reduction in social learning and increased policy uncertainty about harmful intent is associated with pre-existing paranoid beliefs: Evidence from modelling a modified serial dictator game

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Abstract

Current computational models suggest that paranoia may be explained by stronger higher-order beliefs about others and increased sensitivity to environments. However, it is unclear whether this applies to social contexts, and whether it is specific to harmful intent attribu-

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Further Readings

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Questions

- Why is Rationality Assumed?
- Social Inferences Sometimes Produce Wrong Answers: When?
- Errors and Biases as Consequential: Improving the Inference Process
- Errors and Biases as Incidental: Perhaps They Don't Matter
- Are Rapid Judgments Sometimes Better than Thoughtfully Considered Ones?
- Neuroeconomics: Back to the Future