

# Heuristics & Biases

## The Nobel Prize (2002)

Daniel Kahneman  
Field of Economics  
<http://www.nobelprize.org/mediaplayer/index.php?id=916>  
Prize Lecture on Maps of Bounded Rationality

## The Nobel Prize

Motivating questions:

- Why are certain properties directly available while others require computation?
- Can we apply what we know about perception to decision making?

## The Nobel Prize

What properties from perception generalize?

- Surround antagonism?
- Attentional effects?
- Adaptation?

## Adaptation!

Kahneman's perceptual system:

- Highlights **changes** and **differences**
- **Insensitive** to the **level** of any state that remains constant
  - Color adaptation
  - Temperature adaptation

## Logic!

If judgment and choice operate on representations that conform to the rules of perception, we expect **changes** to be **salient** and **maintained states** to be mostly **ignored**

## Two Gambles

You have a 50% chance to **win \$15,000**

OR

to **lose \$10,000**

## Two Gambles

You own some amount of wealth, call it  $W$   
50% chance that you get  **$W + \$15,000$**

OR

You get  **$W - \$10,000$**

## Two gambles

The difference lies in evaluating something as **win / lose** versus **gain / loss**. Outcomes evaluated as gain and loss lies at the heart of risky choice in prospect theory

## Bernoulli vs. Kahneman

Ultimately, Kahneman's Prospect Theory is interested in **change**, even small, myopic change. Bernoulli's sense of value persists (particularly in economics) in looking at **long-term value**.

## The Nobel Prize

- System 1
  - Intuition
  - Good at averages of distributions
- System 2
  - 'Effortful' thought
    - i.e. marked by evidence of effort (pupil dilation)

## Takeaways

- Humans often make decisions based on **change**, not long term value
- Modeling their behavior in certain mathematically, economically 'rational' ways misses some of these behavioral choices
- What we know about perception can inform us in other domains of cognitive science

## Heuristics!

- **Availability**
- Representativeness
- Anchoring and adjustment

## Availability

A heuristic for assessing frequency and probability

i.e. do more words (over three letters) start with the letter r, or have r as their 3rd letter?

## Kahneman and Tversky

What affects our judgements that 'shouldn't'?

- Familiarity (celebrity)
- Salience
- Recency
- 'Ease' of access
- Imageinability

## In other words

- Kahneman's notion of availability seems to rely on **readout** of certain properties associated with frequency
- The claim is that we are willing to rely either on poor readout, or on readout of an overly easily altered / influenced property

## Gigerenzer

Not much to say about availability, except that this is seriously post-hoc

## Base-Rate Fallacy

If a test to detect a disease whose prevalence is 1/1000 has a false positive rate of 5%, what is the chance that a person found to have a positive result actually has the disease, assuming you know nothing about the person's symptoms or signs?

## Bayes Rule

$$P(\text{Sick} | \text{Hit}) = \frac{P(\text{Hit} | \text{Sick}) * P(\text{Sick})}{P(\text{Hit})}$$

$$P(\text{Hit} | \text{Sick}) = (0.95)$$

$$P(\text{Sick}) = (0.001)$$

$$P(\text{Hit}) = (0.95)(0.05)$$

## Representativeness

Probabilities are evaluated by the degree to which A is representative of B. In this case, the extent to which a patient with a hit on a test is representative of a patient with a disease.

<http://individual.utoronto.ca/somody/quiz.html>

## Why neglect the prior?

If a test to detect a disease whose prevalence is 1/1000 has a false positive rate of 5%, what is the chance that a person found to have a positive result actually has the disease, assuming you know nothing about the person's symptoms or signs?

## Single Event Prediction

Bayesian inference allows for prediction of single events. Whereas, the frequentist tradition only predicts confidence in differences.

## Frequency Prediction

One out of 1000 Americans has disease X. A test has been developed to detect when a person has disease X. Every time the test is given to a person who has the disease, the test comes out positive. But sometimes the test also comes out positive when it is given to a person who is completely healthy. Specifically, out of every 1000 people who are perfectly healthy, 50 of them test positive for the disease. Imagine that we have assembled a random sample of 1000 Americans. They were selected by a lottery. Those who conducted the lottery had no information about the health status of any of these people. How many people who test positive for the disease will actually have the disease? \_\_\_ out of \_\_\_.

## Frequency Prediction

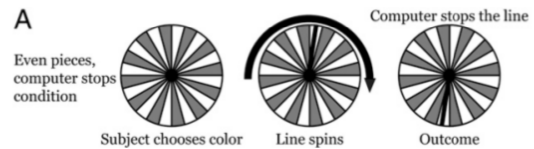
Medical diagnosis problem	N	Bayesian answers (%)
Original single-event version (Casscells, Schoenberger, & Grayboys, 1978)	60	18
Single-event version, replication (Cosmides & Tooby, 1990)	25	12
Frequency version (Cosmides & Tooby, 1990)	50	76
Frequency version, pictorial (Cosmides & Tooby, 1990)	25	92

## Check your assumptions

Are the patients tested randomly sampled?  
You can say so, but do people believe it?

## Green et al (2013)

Temporal dependence



## Heuristics as Assumptions

'Confirmation biases (Austerweil & Griffiths, 2011; Navarro & Perfors, 2011; Oaksford & Chater, 1994), reasoning fallacies (Hahn & Oaksford, 2006, 2007; Harris, Hsu, & Madsen, 2012; Oaksford & Hahn, 2004), framing effects (McKenzie, 2004; Sher & McKenzie, 2008), and probability matching (Green, Benson, Kersten, & Schrater, 2010) can be rational in certain contexts.' -Jern, Chang & Kemp (2014)

## The Conjunctive Fallacy

Linda is 31 years old, single, outspoken and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in antinuclear demonstrations. Subjects were asked which of two alternatives was more probable:  
Linda is a bank teller  
Linda is a bank teller and is active in the feminist movement

## Kahneman and Tversky

Participants agree: Linda is probably a feminist

$$P(x) * P(y) < P(x) | P(y)$$

## Gigerenzer

Frequentists' normality does not make predictions about specific events but rather delineates confidence.

## Breaking the illusion

Linda problem	N	Conjunction violations (%)
<i>Single-event versions</i>		
Tversky & Kahneman (1983)		
Which is more probable?	142	85
Probability ratings	119	82
Probability ratings T*	75	57
Betting	60	56
Fiedler (1988)		
Probability ranking, exp. 1	44	91
Probability ranking, exp. 2	23	83
<i>Frequency versions</i>		
Fiedler (1988)		
How many out of 100?	44	22
How many out of X?	23	17

## Anchoring and Adjustment

The year Washington elected president?  
 The boiling point of water in Denver (F)?  
 The number of US states in 1880?  
 The freezing point of Vodka (F)?  
 Duration of Mars' orbit around the sun (days)?

Epley & Gilovich (2006)

## How did we do?

Estimated Answer, Plausible Range, and Location of the Estimated Answer Within That Range (Skew) in Study 1b

Question	Anchor	Answer		Plausible range		Mean skew
		Actual	Estimated	Near	Far	
Washington elected president	1776	1788	1779.67	1777.29	1784.57	.33
Boiling point of water in Denver (°F)	212	203	203.00	207.31	187.83	.22
Number of U.S. states in 1880	50	38	39.72	38.45	24.45	-.09
Second European explorer to reach West Indies	1492	1501	1507.25	1496.82	1545.59	.21
Freezing point of vodka (°F)	32	-20	7.35	26.31	-9.08	.54
Duration of Mars' orbit around Sun* (days)	365	869	491.67	392.23	1043.00	.15

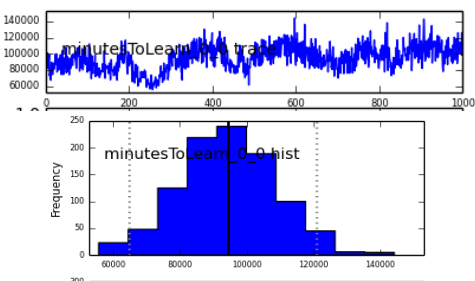
## A Generative Model

$$P(\text{guess}|\text{anchor}) = P(\text{anchor}|\text{guess}) * P(\text{guess}) / P(\text{anchor})$$

Intractable to marginalize  $P(\text{anchor})$   
 How do we get to the posterior?

(Vul et al., 2014)

## Sampling



## Conclusion

Sometimes mathematical models should be followed.  
 Humans do not always follow mathematical models.

## Conclusion

Are biases real or brought on by the task?

Biases are the data. They are generated by the heuristics (or *assumptions*) that we default to when making decisions under uncertainty. Sometimes they are task related, other times they are not.

## Conclusion

Why are we bad at making decisions under uncertainty?

With recent evidence from generative Bayesian Models, it is less apparent that we are “bad” and it is more likely that we behave optimally under the assumptions we hold. How we select our assumptions is an open question.