Attention and Perception

Lecture 3: Rational Inattention (General Costs)[1]

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[1] A thanks to Mark Dean, whose slides these ones are based on!

Recall

Different approaches to limited attention in economics

1. Limited attention from *mental gaps*
    - Ignore low-salience information (Chetty, Looney & Kroft 2009)
    - Ignore readily available information (DellaVigna & Pollet 2009, Lacetera, Pope & Sydnor 2012)
2. Limited attention from *information frictions*
    - Consideration sets (Caplin, Dean & Martin 2011, Manzini & Mariotti 2014)
    - Rational inattention (Sims 2003, Matějka & McKay 2015)

Modeling Goal and Solution

- Return to general approach to modeling perception in Caplin & Martin (2015) (CM15 hereafter)
  - Recall that perception is summarized by information structures
  - In that paper, take information structures as fixed or given
- Ideally, would like DMs to choose their information structure based on setting
- Why would DMs not choose most informative information structure?
  - Information is costly!

Rational Inattention (RI)

- *Rational inattention*: Choose information to acquire to maximize utility net of information costs
- People are free to choose
  - How much information to acquire
  - What type of information to acquire
- Standard approach to modeling rational inattention:
  - Model as cost for choosing each information structure
  - Costs usually increasing in "informativeness"
- Caplin & Dean (2015) (CD15 hereafter) provide testable conditions for a very general form of this model (will cover this today)

Set Up: Model Objects

- Ω: Objective states of the world (finite)
  - Objective prior probabilities given by $P(\omega)$
  - Subjective prior beliefs given by $\mu(\omega)$
  - Note: CD15 assume μ is correct, so $\mu(\omega) = P(\omega)$
- a: An action
  - $x(a, \omega) \in X$ is prize from action a in state ω
  - Note: CD15 use decision-theoretic $a(\omega)$
- $\mathcal{A}$: Grand set of actions
  - $A \subset \mathcal{A}$: Set of actions (finite)
  - Note: Unlike CM15, CD15 allow action set to change
- u: Utility function over prizes
  - $u(a, \omega) := u(x(a, \omega))$ utility of action a in state ω
  - Note: Unlike CM15, CD15 take u as given for now (relax later)

Set Up: Decision Problems

- Let D be a collection of decision problems, with arbitrary element $i \in D$
- Objective states of the world Ω are fixed across decision problems
- Objective prior can depend on decision problem: $P_i(\omega)$
  - Thus, the subjective prior $\mu_i(\omega)$ can too
- Prizes can depend on decision problem: $x_i(a, \omega)$
  - Thus, the utility function can too: $u_i(a, \omega) := u(x_i(a, \omega))$
- Action set can depend on decision problem: A_i
  - Thus, the decision rule can too: $\sigma_i : \Gamma \to A_i$
- In CD15, just vary the action set across decision problems

The Model

- For each decision problem $i \in D$
  1. Choose π_i: information structure
     - $\pi_i(\gamma|\omega)$ is the probability of receiving each posterior γ from each state ω
     - Note: CD15 calls γ a "signal"
     - Note: Caplin, Dean & Leahy (2022) use Q instead
  2. Choose σ_i: decision rule
     - $\sigma_i(\gamma)$ is the probability distribution over actions in A_i given posterior γ
     - Note: CD15 use C and call "choice function"
     - Note: Caplin, Dean & Leahy (2022) use q instead
- To maximize expected value of actions taken minus cost of information K

$$\sum_{\omega \in \Omega} \mu_i(\omega) \sum_{\gamma \in \Gamma} \pi_i(\gamma|\omega) \left(\sum_{a \in A_i} \sigma_i(a|\gamma) u_i(a, \omega) \right) - K(\mu_i, \pi_i)$$

Value and Cost of Information

- Easy to calculate the *value* of an information structure π in decision problem i

$$G_i(\pi) = \max_{\sigma_i} \sum_{\omega \in \Omega} \mu_i(\omega) \sum_{\gamma \in \Gamma} \pi(\gamma|\omega) \left(\sum_{a \in A_i} \sigma_i(a|\gamma) u_i(a, \omega) \right)$$

- But what is the correct way to determine the *cost* of an information structure?
- Several proposals:
  - Costly sequential search (e.g. McCall 1970)
  - Cost to reduce variance of normal signal (e.g. Verrecchia 1982)
  - Shannon mutual information costs (e.g. Sims 2003)

Aim

- As usual, have two possible approaches
  1. Make further assumptions
  2. Ask if there is *any* cost function that can explain the data
- Today we take approach 2
- Later we will follow approach 1

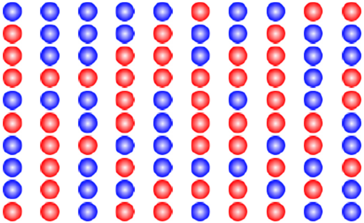
A Caveat

- We **will** assume throughout that costs are additively separable from utilities
- Is this assumption restrictive?
- Yes, see Chambers, Liu & Rehbeck (2020)'s "Costly Information Acquisition"

Observability

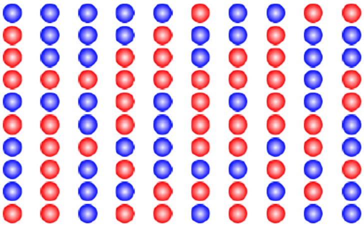
- What do we observe for all decision problems $i \in D$?
- States Ω, Actions A_i
- **State-dependent stochastic choice data** P_i
  - $P_i(a, \omega)$ probability of choosing action a and being in state ω
- Also assume we observe:
  - Subjective prior beliefs μ_i (relax observability later)
    - And assume fixed across decision problems: $\mu = \mu_i$ for all $i \in D$
  - Utilities u_i (relax observability later)
    - And assume fixed across decision problems: $u = u_i$ for all $i \in D$
- Do **not** observe
  - Information structures π_i
  - Posteriors γ
  - Information costs K

An Experimental Example



- In Dean & Neligh (2023), subjects were presented with 100 balls
- State is determined by the number of red balls
- Prior distribution of red balls is told to subjects

An Experimental Example



Action	Payoff 49 red balls	Payoff 51 red balls
a	10	0
b	0	10

- No time limit: trade off between effort and financial rewards

An Experimental Example

- Data: State-dependent stochastic choice
  - Probability of choosing each action $a, b \in A$ and being in each state of the world

	State = 49 red balls	**State = 51 red balls**
Action = a	$P_i(a, 49)$	$P_i(a, 51)$
Action = b	$P_i(b, 49)$	$P_i(b, 51)$

- Observe subject making "same" choice 50 times
- Can use this to estimate P_i
  - But we will not be able to observe P_i perfectly
  - Will only be able to make probabilistic statements
- Can collect this type of data in the lab
  - What about outside?

Question

- What data are consistent with optimal costly information acquisition (with RI)?
  - i.e., for which there exists a cost function K
- For each decision problem $i \in D$, need an information structure π_i and decision rule σ_i s.t.
  - σ_i is optimal for each γ
  - π_i is optimal given K
  - σ_i and π_i are consistent with P_i

$$P_i(a,\omega) = \mu(\omega) \sum_{\gamma \in \Gamma} \pi_i(\gamma|\omega)\sigma_i(a|\gamma)$$

- Also, restrict π_i to be "Bayes plausible" (follow Bayes' rule)
- So satisfies the same conditions as the BEU representation (Data Matching, Bayesian Updating, and σ_i Maximization) plus a new one: π_i Maximization

Notes

- This approach is very flexible
- Nests *many* models of information acquisition
  - Fully flexible
  - Fixed signals
  - Partitions
  - Fixed capacity
  - Sequential search
- How nest hard constraints?
  - e.g., a model in which subjects choose the variance of a normal signal, set the cost of all other information structures to ∞

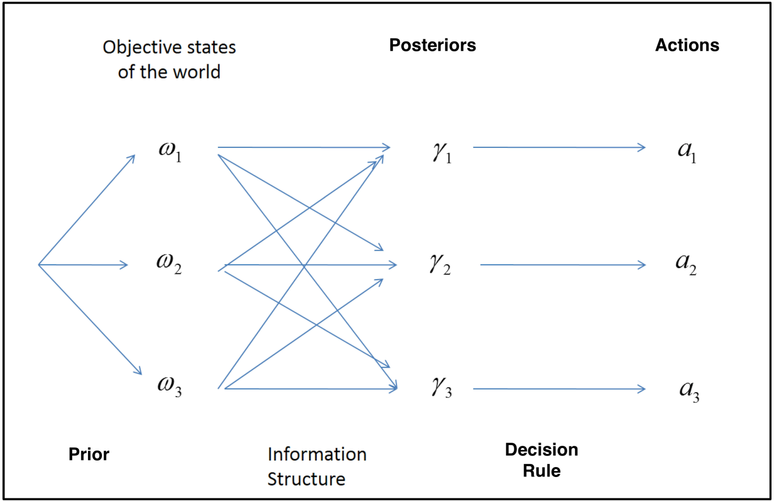
Observing Information Structures

- Key observation: State-dependent stochastic choice data tells us a lot about the information structure a decision maker has used
- What if the decision maker is 'well behaved'?
  - Chooses each action in response to at most one posterior
  - No mixed strategies - one action per posterior
- Information structure can be observed directly from this data
  - For each chosen action a there is an associated "revealed posterior" $\bar{\gamma}^a$
  - Probability of posterior $\bar{\gamma}^a$ in state ω is the probability of choosing a in ω

$$\bar{\pi}(\bar{\gamma}^a|\omega) = P(a|\omega)$$

- Call $\bar{\pi}$ the "revealed information structure"

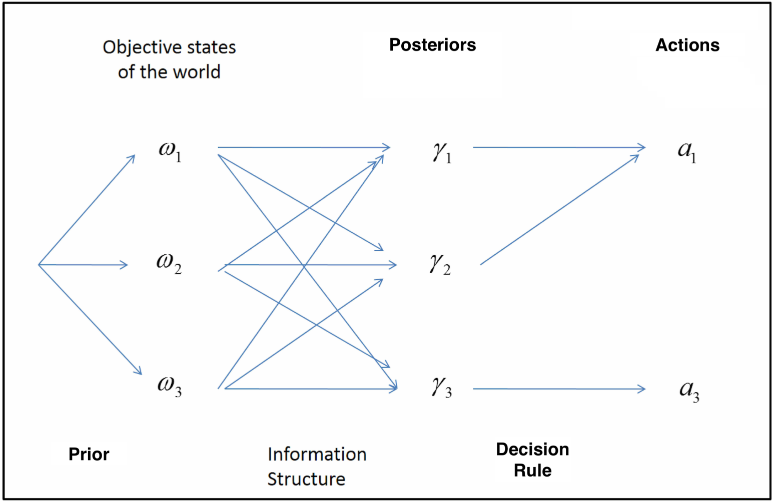
Revealed Information Structure



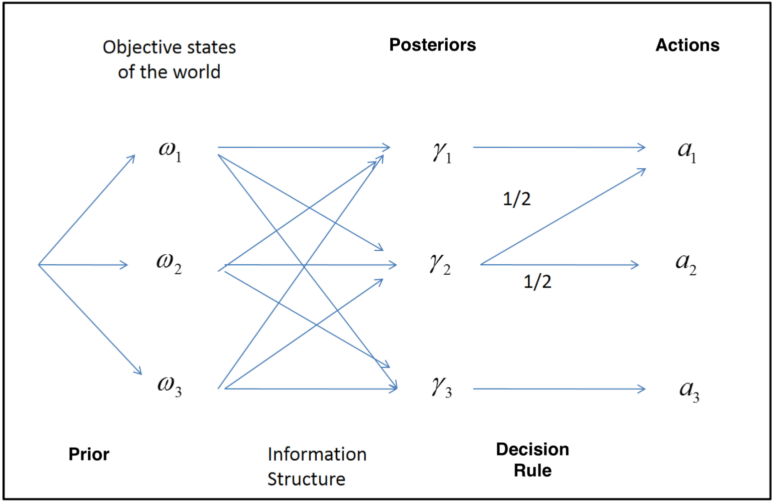
Observing Attentional Strategies

- What if decision maker is not well behaved?
  - Chooses some act in more than one subjective state
  - Mixed strategies - more than one act in an subjective state

Same Act in Different States



Mixing



Objective states of the world
Posteriors
Actions
ω_1
ω_2
ω_3
γ_1
γ_2
γ_3
a_1
a_2
a_3
1/2
1/2
Prior
Information Structure
Decision Rule

Observing Information Structures

- Can still recover revealed information structure $\bar{\pi}$
- Not necessarily the same as true information structure π
- But will be a garbling of the true information structure
  - i.e., π is statistically sufficient for $\bar{\pi}$
- There exists a stochastic $|\Gamma(\pi)| \times |\Gamma(\bar{\pi})|$ matrix B such that if we
  - Apply π
  - For each γ^i move to $\bar{\gamma}^j$ with probability B^{ij}
  - We obtain $\bar{\pi}$

$$\begin{aligned} \sum_j B^{ij} &= 1 \; \forall \; i \\ \bar{\pi}(\bar{\gamma}^j|\omega) &= \sum_i B^{ij}\pi(\gamma^i|\omega) \; \forall \; j, \omega \end{aligned}$$

An Aside: Blackwell's Theorem

- Recall $G_i(\pi)$ is the *gross value* of using information structure π in decision problem i

$$G_i(\pi)$$
$$= \max_{\sigma_i} \sum_{\omega \in \Omega} \mu(\omega) \sum_{\gamma \in \Gamma} \pi(\gamma|\omega) \left(\sum_{a \in A_i} \sigma_i(a|\gamma) u(a, \omega) \right)$$

- Blackwell's theorem (Blackwell 1953): information structure π' is a garbling of information structure π if and only if

$$G_i(\pi) \geq G_i(\pi') \; \forall \; i$$

Observing Information Structures

- $\bar{\pi}$ may not be the agent's true information structure
  - But the $\bar{\pi}$ must be a garbling of the true information structure π
  - So π will be at least as valuable as $\bar{\pi}$ in any decision problem
- Turns out that this is all we need for now
- But Caplin, Martin & Marx (2025) show how to recover the full set of possible information structures

Characterizing Rational Inattention

Rational inattention has two parts:

- Choice of act optimal given information structure
- Choice of information structure optimal

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Condition 1

Condition 1 (No Improving Action Switches) For every chosen action $a \in A_i$

$$\sum_{\omega \in \Omega} P_i(a,\omega)\left(u(a,\omega) - u(b,\omega)\right) \geq 0$$

for all $b \in A_i$

- Introduced in CM15
- Intuition: Cannot improve utility by making a whole switch from any chosen action
- Note: Same as

$$\sum_{\omega \in \Omega} P_i(a,\omega) u(a,\omega) \geq \sum_{\omega \in \Omega} P_i(a,\omega) u(b,\omega)$$

Characterizing Rational Inattention

Rational inattention has two parts:

- Choice of act optimal given information structure
- Choice of information structure optimal

- $G_i(\pi)$ is the gross value of using information structure π in decision problem i
- Assume two decision problems: $A_1 = \{a_1, b_1\}$ and $A_2 = \{a_2, b_2\}$
- Cost function must satisfy

$$\begin{aligned} G_1(\pi_1) - K(\pi_1) &\geq G_1(\pi_2) - K(\pi_2) \\ G_2(\pi_2) - K(\pi_2) &\geq G_2(\pi_1) - K(\pi_1) \end{aligned}$$

- Which implies

$$\begin{gathered} G_1(\pi_1) - G_1(\pi_2) \geq \\ K(\pi_1) - K(\pi_2) \geq \\ G_2(\pi_1) - G_2(\pi_2) \end{gathered}$$

Optimal Choice of Information Structures

- Surplus must be maximized by correct assignments

$$G_1(\pi_1) + G_2(\pi_2)$$
$$\geq G_1(\pi_2) + G_2(\pi_1)$$

- Problem: Don't observe π_1 or π_2!
- But we know that revealed and true information structure must give same value in DP it was observed

$$G_i(\bar{\pi}_i) = G_i(\pi_i)$$

- Also, as π weakly Blackwell dominates $\bar{\pi}$

$$G_i(\bar{\pi}_j) \leq G_i(\pi_j)$$

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Condition 2

- Can rearrange as no improvements

$$
\begin{aligned}
& G_1(\bar{\pi}_1) - G_1(\bar{\pi}_2) \\
+ \quad & G_2(\bar{\pi}_2) - G_2(\bar{\pi}_1) \\
\geq \quad & 0
\end{aligned}
$$

- To guarantee the existence of a cost function requires a stronger condition

Condition 2 (No Improving Attention Cycles) For an observed sequence of decision problems 1, ..., K and associated revealed information structures $\bar{\pi}_1 ... \bar{\pi}_K$

$$
\begin{aligned}
& G_1(\bar{\pi}_1) - G_1(\bar{\pi}_2) \\
& + G_2(\bar{\pi}_2) - G_2(\bar{\pi}_3) \\
& + ... \\
& + G_K(\bar{\pi}_K) - G_K(\bar{\pi}_1) \\
\geq \quad & 0
\end{aligned}
$$

Taking to Data

- This can easily be rewritten in terms of the data because

$$G_i(\bar{\pi}_j) = \sum_{a \in A_j} \max_{\hat{a} \in A_i} \sum_{\omega \in \Omega} P_j(a, \omega) u(\hat{a}, \omega)$$

Condition 2 (No Improving Attention Cycles) For an observed sequence of decision problems $A_1 ... A_K$

$$\begin{aligned}
& \sum_{a \in A_1} \max_{\hat{a} \in A_1} \sum_{\omega \in \Omega} P_1(a, \omega) u(\hat{a}, \omega) - \sum_{a \in A_2} \max_{\hat{a} \in A_1} \sum_{\omega \in \Omega} P_2(a, \omega) u(\hat{a}, \omega) \\
& + \sum_{a \in A_2} \max_{\hat{a} \in A_2} \sum_{\omega \in \Omega} P_2(a, \omega) u(\hat{a}, \omega) - \sum_{a \in A_3} \max_{\hat{a} \in A_2} \sum_{\omega \in \Omega} P_3(a, \omega) u(\hat{a}, \omega) \\
& + ... \\
& + \sum_{a \in A_K} \max_{\hat{a} \in A_K} \sum_{\omega \in \Omega} P_K(a, \omega) u(\hat{a}, \omega) - \sum_{a \in A_1} \max_{\hat{a} \in A_K} \sum_{\omega \in \Omega} P_1(a, \omega) u(\hat{a}, \omega) \\
\geq \quad & 0
\end{aligned}$$

Testing NIAC

- We test NIAC by looking at the impact of cycling revealed information structures
- For example, consider these unconditional joint distributions of states and actions:

$$P_1 = \begin{array}{c} \begin{matrix} 49 & 51 \end{matrix} \\ \begin{pmatrix} \frac{3}{8} & \frac{1}{8} \\ \frac{1}{8} & \frac{3}{8} \end{pmatrix} \begin{matrix} a_1 \\ b_1 \end{matrix} \end{array} \ \& \ P_2 = \begin{array}{c} \begin{matrix} 49 & 51 \end{matrix} \\ \begin{pmatrix} \frac{2}{6} & \frac{1}{6} \\ \frac{1}{6} & \frac{2}{6} \end{pmatrix} \begin{matrix} a_2 \\ b_2 \end{matrix} \end{array}$$

- And these utilities:

$$u(a,\omega) = \begin{array}{c} \begin{matrix} 49 & 51 \end{matrix} \\ \begin{pmatrix} 10 & 0 \\ 0 & 10 \end{pmatrix} \begin{matrix} a_1 \\ b_1 \end{matrix} \end{array} \ \& \ u(a,\omega) = \begin{array}{c} \begin{matrix} 49 & 51 \end{matrix} \\ \begin{pmatrix} 20 & 0 \\ 0 & 20 \end{pmatrix} \begin{matrix} a_2 \\ b_2 \end{matrix} \end{array}$$

The Value of Information

- The value of the chosen information structure in A_1 in decision problem A_1 is

$$\max_{a\in\{\mathbf{a_1},b_1\}}[P_1(a_1,49)u(a,49)+P_1(a_1,51)u(a,51)]+\max_{a\in\{a_1,\mathbf{b_1}\}}[P_1(b_1,49)u(a,49)+P_1(b_1,51)u(a,51)]$$

$$\frac{3}{8}10+\frac{1}{8}0+\frac{1}{8}0+\frac{3}{8}10=\frac{60}{8}=7\frac{1}{2}$$

- Switching to the chosen information structure in A_2 gives

$$\max_{a\in\{\mathbf{a_1},b_1\}}[P_2(a_2,49)u(a,49)+P_2(a_2,51)u(a,51)]+\max_{a\in\{a_1,\mathbf{b_1}\}}[P_2(b_2,49)u(a,49)+P_2(b_2,51)u(a,51)]$$

$$\frac{2}{6}10+\frac{1}{6}0+\frac{1}{6}0+\frac{2}{6}10=\frac{40}{6}=6\frac{2}{3}$$

The Value of Information

- The value of the chosen information structure in A_2 in decision problem A_2 is

$$\max_{a\in\{a_2,b_2\}}[P_2(a_2,49)u(a,49)+P_2(a_2,51)u(a,51)]+\max_{a\in\{a_2,b_2\}}[P_2(b_2,49)u(a,49)+P_2(b_2,51)u(a,51)]$$

$$\frac{2}{6}20+\frac{1}{6}0+\frac{1}{6}0+\frac{2}{6}20=\frac{80}{6}=13\frac{1}{3}$$

- Switching to the chosen information structure in A_1 gives

$$\max_{a\in\{a_2,b_2\}}[P_1(a_1,49)u(a,49)+P_1(a_1,51)u(a,51)]+\max_{a\in\{a_2,b_2\}}[P_1(b_1,49)u(a,49)+P_1(b_1,51)u(a,51)]$$

$$\frac{3}{8}20+\frac{1}{8}0+\frac{1}{8}0+\frac{3}{8}20=\frac{120}{8}=15$$

NIAS and NIAC

- P_1 and P_2 satisfy NIAS because no wholesale improving switches of actions
- But do they satisfy NIAC? The change from switching in the first problem is $6\frac{2}{3} - 7\frac{1}{2}$ and the change from switching in the second problem is $15 - 13\frac{1}{3}$, so there is a net improvement
- This means that this data does not satisfy NIAC, so there is no K that rationalizes the data

Theorem 1: CD15

Theorem

For any data set $\{D, P\}$ the following two statements are equivalent

1. $\{D, P\}$ *satisfy NIAS and NIAC*
2. *There exists a* $K : \Pi \rightarrow \mathbb{R}$, $\{\pi_i\}_{i \in D}$ *and* $\{\sigma_i\}_{i \in D}$ *such that* π_i *and* σ_i *are optimal and generate* P_i *for every* $i \in D$

Proof.

$2 \rightarrow 1$ *Trivial*

$1 \rightarrow 2$ *Rochet (1987) (literature on implementation)* □

Costs and Blackwell Ordering

- So far we have been completely agnostic about the cost function
- Perhaps we want to impose that information structures more Blackwell informative are (weakly) more expensive
- Turns out we get this 'for free'
- Say we observe π_i in A_i and π_j in A_j such that π_j is a garbling of π_i (π_i is sufficient for π_j)
- By NIAC must be the case that

$$\begin{aligned} G_j(\pi_j) - K(\pi_j) &\geq G_j(\pi_i) - K(\pi_i) \Rightarrow \\ K(\pi_i) - K(\pi_j) &\geq G_j(\pi_i) - G_j(\pi_j) \end{aligned}$$

- And by Blackwell's theorem (Blackwell 1953)

$$G_j(\pi_i) \geq G_j(\pi_j)$$

Restrictions on the Cost Function

- Any behavior that can be rationalized can be rationalized with a cost function that
  - Is weakly monotonic with respect to Blackwell
  - Allows mixing
  - Positive with free inattention
- Reminiscent of Afriat's theorem (Afriat 1967)
- Can also extend to 'sequential rational inattention'

Recovering Costs

- Say $\bar{\pi}_i$ is the revealed information structure in decision problem A
- Assuming weak monotonicity, $\bar{\pi}$ is optimal, so it must be that

$$G_i(\pi) - K(\pi) \leq G_i(\bar{\pi}_i) - K(\bar{\pi}_i)$$
$$K(\bar{\pi}_i) - K(\pi) \leq G_i(\bar{\pi}_i) - G_i(\pi)$$

- If $\bar{\pi}_j$ is used in decision problem B then we can bound relative costs

$$G_j(\bar{\pi}_i) - G_j(\bar{\pi}_j) \leq K(\bar{\pi}_i) - K(\bar{\pi}_j) \leq G_i(\bar{\pi}_i) - G_i(\bar{\pi}_j)$$

- Caplin, Martin & Marx (2025) provide efficient method to generate these costs and a representative cost (see later)

What If Utility and Priors Are Unobservable?

- Can add ‘there exists’ to the statement of the NIAS and NIAC conditions
- Data has an optimal costly attention representation if **there exists** $\mu \in \Delta(\Omega)$ and $u : X \to \mathbb{R}$ such that
  - NIAS is satisfied
  - NIAC is satisfied
- If μ is known but u is unknown, conditions are linear and (relatively) easy to check
- If μ and u are unknown, conditions are harder to check
  - Still not vacuous
- Possible to recover all consistent utility functions using geometric approach introduced in CM21

Rational Inattention vs Random Utility

- Alternative model of random choice: Random Utility
  1. Agent receives some information about the state of the world
  2. Draws a utility function from some set
  3. Chooses in order to maximize utility given information
- Key differences between Random Utility and Rational Inattention
  1. Random Utility allows for multiple utility functions
  2. Rational Inattention allows attention to vary with choice problem
- How can we differentiate between the two?

Monotonicity

- Random Utility implies monotonicity
  - In fact, fully characterized by Block–Marschak monotonicity (Block & Marschak 1960)
- For any two decision problems $A_1 = A$ and $A_2 = A \cup b$ for $b \notin A$

$$P_1(a|\omega) \geq P_2(a|\omega)$$

- Rational Inattention can lead to violations of monotonicity (Matějka & McKay 2015)

Act	Payoff 49 red dots	Payoff 51 red dots
a	23	23
b	20	25
c	40	0

- Adding act c to $\{a, b\}$ can increase the probability of choosing b in state 51 (exists prior where c makes worth paying attention)

Other Approaches

- Special class of RI model: Capacity-Constrained Learning (Caplin, Martin, Marx, Morozova & Xu 2026)
- Variation on RI model: Costly "experiments"
- Special class of RI model: Uniformly Posterior Separable (UPS) (Caplin, Dean & Leahy 2022, Bloedel & Zhong 2025)

$$K(\mu, \pi) = T(\mu) - E_{\pi}\left[T(\gamma)\right]$$

- Special class of UPS model: "Shannon model" with mutual information costs

$$\begin{aligned} K(\mu, \pi) &= \lambda \left(H(\mu) - E_{\pi}\left[H(\gamma)\right]\right) \\ &= \lambda \left(\begin{array}{c} \sum_{\gamma \in \Gamma} \pi(\gamma) \sum_{\omega \in \Omega} \gamma(\omega) \ln \gamma(\omega) \\ - \sum_{\omega \in \Omega} \mu(\omega) \ln \mu(\omega) \end{array} \right) \end{aligned}$$

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