BEHAVIORAL ECONOMICS · LECTURE 5

Bounded rationality I: search and satisficing

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Master Economics – Winter 2026/27

Before we start: find the largest number

Your task

You have **20 seconds**. Which option is worth the most? Keep a finger on your current favourite: I will stop you at a random moment.

1. four plus eight minus four
2. nine minus two plus three
3. six plus seven minus five
4. three plus nine minus one
5. eight plus four plus one
6. seven plus seven minus two
7. five plus nine plus one
8. two plus nine plus three

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Questions

- Who is **sure** they found the best option? Who stopped before reading all eight?
- What was your favourite after 5 seconds? After 10?

Learning objectives

By the end of this lecture you should be able to:

- Describe Simon's **satisficing** procedure and contrast it with maximization.
- Set up the **optimal search** problem and derive the **reservation value** u^*.
- Prove that the optimal stopping rule *is* a satisficing rule, and state the assumptions this needs.
- Derive the **comparative statics** of u^* and compute it in simple examples.
- Explain why satisficing cannot be tested with standard choice data, and how **choice process data** solve the problem.
- Read the evidence of Caplin et al. (2011).

Roadmap

Bounded rationality

Satisficing: the basic idea

Satisficing as optimal search

Testing the satisficing model

Evidence: Caplin, Dean and Martin (2011)

Wrapping up

Where we are in the course

The assumptions of the Robinson model

0. **Consistent preferences:** Robinson's choices can be described by a utility function u
1. **Costless optimization:** he always finds the option that maximizes u
2. **Correct beliefs & expected utility:** he knows p and maximizes expected utility
3. **Absolute, self-regarding consumption:** only his own (b, y) enters u
4. **Stable tastes:** the same u in both periods

Take-away

Part 2 relaxes **Assumption 1**: finding the best option takes time and effort. Today: the decision maker looks at options **one at a time** and stops when one is good enough.

1

Bounded rationality

The decision maker keeps a utility function, but finding its maximum is costly or restricted.

From maximization to bounded rationality

The canonical model

In Part 1 we learned how to test the canonical model

$$C(A) = \arg\max_{x \in A} u(x),$$

and we saw cases where it fails: money left on the table, too much choice, decision difficulty.

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Two ways to extend it

Two ways to extend the model *within* the same framework:

1. **Change preferences:** what goal is the decision maker (DM) trying to achieve?
2. **Change constraints:** add costs and restrictions to the optimization problem.

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1. **Change preferences:** what goal is the decision maker (DM) trying to achieve?
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Bounded rationality follows **route 2**: the DM still has a utility function u, but optimizing over A is costly or restricted.

Many ways to be boundedly rational

Models of bounded rationality

1. **Costs of acquiring or processing information:** Simon (1955), Stigler (1961), Sims (2003)
2. **Limited levels of reasoning:** Camerer et al. (2004), Costa-Gomes et al. (2001)
3. **Thinking aversion:** Ergin and Sarver (2010), Ortoleva (2013)
4. **Bounded memory:** Wilson (2014)
5. **Finite automata:** Piccione and Rubinstein (1993)
6. **Semi-rational models:** Esponda (2008), Rabin and Vayanos (2010), Gabaix (2013)
7. **Heuristics:** Tversky and Kahneman (1974), Gigerenzer (2000)

Part 2 focuses on item 1: the cost of paying attention.

Part 2: the cost of paying attention

Cost of considering options

- Satisficing (**today**, Lecture 5)
- Consideration sets (Lecture 6)

Cost of considering aspects

Cost of considering aspects of a decision:

- Salience (Lecture 8)

Cost of acquiring information

- Bayesian updating: the toolkit (Lecture 7)
- Rational inattention (Lecture 9)

Common thread: the DM has a well-defined u over the menu A, but does **not** evaluate every $x \in A$ for free. *These approaches overlap conceptually.*

2

Satisficing: the basic idea

Simon’s procedure: search until an option is good enough, then stop.

Search and satisficing

A very simple and intuitive choice procedure, first described by Simon (1955).

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You will probably

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3. check: does it satisfy the needs from step 1?
   - if **yes**, buy it;
   - if **no**, look at the next car and repeat step 3;
4. if you have seen every car and none satisfies your needs, go back and buy the **best** one.

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Two questions for today

1. *Is satisficing a mistake?* Simon saw it as "procedurally rational". We show that it can be **optimal**.
2. *Is it testable?* Not with standard choice data. We need **richer data**.

3

Satisficing as optimal search

With a cost per look, the optimal way to search is to stop at the first item above a reservation value.

Satisficing as optimal stopping

An optimal stopping problem

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The model rests on three ideas

1. Before looking at a car, you do **not know** how good it is.
2. Once you look at it, you know **exactly** how good it is.
3. Each look has a **cost**.

The model: primitives

Primitives

- A menu $A = \{x_1, \ldots, x_M\}$, inspected **one at a time**: x_i is the alternative observed at step i. Utility $u : A \to \mathbb{R}$.
- **(S1) Unknown values:** before inspection, the value of each alternative is unknown: the values $V_1, \ldots, V_M$ are i.i.d. random variables with known distribution F (density f, finite mean).
- **(S2) Costly inspection:** inspecting alternative x_i costs $k > 0$ and reveals its value $V_i = u(x_i)$ exactly.

Which order? It does not matter: before inspection all alternatives look alike (same F), so the DM has no reason to look at one before another.

The model: decisions

Decisions

After each inspection, the DM either

- **stops** and takes the best alternative seen so far, with value $\bar{u}$,
  - **(S3) Perfect recall:** earlier alternatives remain available;
- or **inspects** one more alternative and pays k,
  - **(S4) Constant marginal cost:** k is the same for every look (no curiosity, no fatigue).

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Payoff = value of the chosen alternative $- \; k \times$(number of inspections).

Solving the model: the last inspection

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Payoff of stopping

$$\underbrace{\bar{u}}_{\text{best item}} - \underbrace{(M-1)k}_{\text{search cost}}$$

Expected payoff of searching

$$\underbrace{\mathbb{P}(V \leq \bar{u})\,\bar{u} + \mathbb{E}\left[V\,\mathbf{1}_{\{V>\bar{u}\}}\right]}_{=\,\mathbb{E}[\max(\bar{u},V)]} - Mk$$

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$$\mathbb{P}(V \leq \bar{u}) = \int_{-\infty}^{\bar{u}} f(v)\,dv, \qquad \mathbb{E}\big[V\,\mathbf{1}_{\{V>\bar{u}\}}\big] = \int_{\bar{u}}^{+\infty} v\,f(v)\,dv.$$

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Inspect if

$$\bar{u}\int_{-\infty}^{\bar{u}} f(v)\,dv + \int_{\bar{u}}^{+\infty} v f(v)\,dv - Mk \;\geq\; \bar{u} - (M-1)k.$$

The value of one more look

Expected gain of one more look

Write $\bar{u} = \bar{u}\int_{-\infty}^{+\infty} f(v)\,dv = \int_{-\infty}^{\bar{u}} \bar{u} f(v)\,dv + \int_{\bar{u}}^{+\infty} \bar{u} f(v)\,dv$. The condition becomes

$$G(\bar{u}) \;\equiv\; \mathbb{E}\big[\max(V-\bar{u},0)\big] \;=\; \int_{\bar{u}}^{+\infty} (v-\bar{u})\, f(v)\,dv \;\geq\; k.$$

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Properties of G

- $G(\bar{u})$ = **expected gain** of one more look: you only gain when the new draw beats $\bar{u}$.
- G is continuous and **decreasing**: $G'(\bar{u}) = -\big(1 - F(\bar{u})\big) \leq 0$.
- $G(\bar{u}) \to \infty$ as $\bar{u} \to -\infty$, and $G(\bar{u}) \to 0$ as $\bar{u} \to +\infty$.

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Take-away

Inspect the last item **iff** the expected gain $G(\bar{u})$ covers the cost k. The better what you already hold, the less a new look is worth.

The reservation value

Reservation value

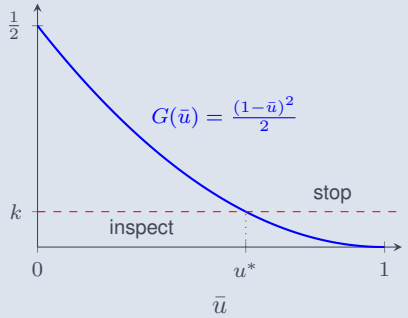
Since G is decreasing from $+\infty$ to 0, there is a value u^* with

$$G(u^*) = \int_{u^*}^{+\infty} (v - u^*)\, f(v)\, dv = k.$$

- u^* need **not** be the value of an available item.
- **Last-step rule:** inspect if $\bar{u} < u^*$, stop if $\bar{u} \geq u^*$.

A **reservation (stopping) rule**.

Example



Values uniform on $[0, 1]$, $k = 0.08$.

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2. $G(u^*) = k \iff (1-u^*)^2 = 2k = 0.16 \iff u^* = 1-\sqrt{2k} = 0.6$.

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4. With many items, each look succeeds with prob. $1-F(0.6)=0.4$: on average $1/0.4 = 2.5$ looks, and the chosen value is $\mathbb{E}[V \mid V \geq 0.6] = 0.8$.

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Take-away

Expected net payoff: $0.8-2.5\times 0.08=0.6=u^*$. The DM accepts an item worth 0.6 although the best item on a large lot is worth almost 1: **not finding the best is optimal** here.

Moving back: the rule is the same at every step

Claim

At period $M - n$, you have inspected $M - n$ items, hold best value $\bar{u}$, and $n \geq 1$ items are left. Whatever n, it is optimal to **stop iff** $\bar{u} \geq u^*$.

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Proof by induction on n: backward in time, from period $M - 1$ to period 1

$n = 1$ **(period** $M - 1$**):** the last-step rule. **From** n **to** $n + 1$ **(one period earlier):** assume the claim at period $M - n$; prove it at period $M - n - 1$.

- **If** $\bar{u} < u^*$**: continue.** "Inspect one item, then stop" already gives $\bar{u} + G(\bar{u}) - k > \bar{u}$; the optimal continuation does at least as well.

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The optimal strategy is **stationary**: the same threshold u^* at every step, whatever the number of items left.

The optimal strategy is satisficing

The optimal strategy

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Take-away

Satisficing is not necessarily irrational: it is the **optimal** response to a per-item search cost. The aspiration level of Simon is the reservation value u^*.

Caveat: the assumptions do a lot of work

The optimal rule is satisficing because of rather specific assumptions:

F is known, not learned (S1)

After four low draws in a row you may revise your beliefs about F: the threshold should then move.

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Perfect recall (S3)

In a flat search, the good flat you saw on Monday may be gone on Friday.

Comparative statics

Why derive satisficing as an optimal strategy? Because it delivers **testable predictions**: u^* solves $G(u^*) = k$, with G decreasing.

How u^* responds

- **Falls with the cost k:** higher k needs a lower u^* to raise $G(u^*)$.

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- **Rises one-for-one with the mean:** shifting all values by δ shifts G by δ, so u^* rises by δ.
- **Does not depend on the menu size M:** the marginal value of one more look does not depend on how many items are left.

Comparative statics: numbers

Benchmark: values uniform on $[0, 1]$, $k = 0.08$, so $u^* = 0.6$

(The spread keeps the mean at 0.5.)

Change	New G on the support	New u^*
Cheaper search: $k = 0.02$	$(1 - \bar{u})^2/2$	$1 - \sqrt{0.04} = 0.80$ (↑)
Shift: values uniform on $[0.5, 1.5]$	$(1.5 - \bar{u})^2/2$	$0.6 + 0.5 = 1.10$ (↑ by 0.5)
Spread: uniform on $[-0.5, 1.5]$	$(1.5 - \bar{u})^2/4$	$1.5 - \sqrt{0.32} \approx 0.93$ (↑)
More items: $M = 10$ or $M = 40$	unchanged	0.60 (unchanged)

Take-away

Prediction to take to the data: harder evaluation (higher k) lowers the aspiration level; a larger menu should **not** change it.

Recap: satisficing as optimal search

Model and solution

- **Model:** i.i.d. values with known F, cost k per look, perfect recall, constant cost.
- **Expected gain of one more look:** $G(\bar{u}) = \mathbb{E}[\max(V - \bar{u}, 0)]$, decreasing in $\bar{u}$.
- **Reservation value:** $G(u^*) = k$; the optimal rule is "stop at the first item worth at least u^*".

Backward induction: the same threshold at every step, so optimal search **is** satisficing.

Predictions

Comparative statics: u^* falls with k, rises with the mean and with spread, does not depend on M.

4

Testing the satisficing model

Final choices cannot tell satisficing from maximization: we need data on the choice process.

Can standard choice data test satisficing?

Suppose satisficing sounds more plausible than maximization. As (social) scientists, we should **test** it.

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1. Same search order in every menu

The DM picks the first item above u^* in this order (or the best one if none is above).

- Then choices look as if she maximized a utility function: the first item above u^* in the order looks "most preferred", the second one "second most preferred", and so on.
- Behaviorally **indistinguishable** from utility maximization.

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- Behaviorally **indistinguishable** from utility maximization.

2. Search order may change across menus

Any data set can be rationalized: say all items are above u^* and whatever is chosen was looked at first.

We need richer data

Two kinds of richer data

1. **Choice process data:** how the provisional choice changes the longer people think.
2. **Search data:** what people looked at before choosing (e.g. web browsing records).

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Choice process data

Follow a shopper buying a stereo; at any time ask *"If you had to choose now, which one would you pick?"* Annoying, but rich:

- standard choice data: $C(A)$, the choice from menu A;
- choice process data: $C(A, t)$, the choice from A **after thinking for time** t;
- plus the **final** choice $C^{\text{fin}}(A)$ and when it is made.

What satisficing predicts for choice process data

Under satisficing

- people search through alternatives **one at a time**;
- at any time t, $C(A, t)$ is the **best** of the alternatives seen so far;
- once they find an item worth at least u^*, they **stop**: that item is the final choice.

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Simplification

To keep things simple, **assume the analyst knows** u (true in the experiment below).

Which choice process data are consistent with this behavior?

Which observations are consistent with satisficing?

We observe the **sequence of provisional choices**, but **not** the order in which items are inspected.

Four observations

Obs.	Values available	Sequence of provisional choices	Final choice
1	$\{1, 2, 3, 4\}$	$3,\ 1,\ 4$	4
2	$\{2, 4, 6, 10\}$	$2,\ 4,\ 6$	6
3	$\{2, 4, 6, 8, 10\}$	$2,\ 4,\ 8$	8
4	$\{2, 4, 6, 8, 10\}$	$2,\ 6,\ 8,\ 10$	10

Think for one minute: which observations, alone or together, contradict the model?

Two testable conditions

C1: no switch to a lower-valued alternative

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C2: one reservation level for all menus

If the DM stopped at value u in some menu A, she must stop whenever she holds a value at least u:

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Take-away

C1 tests **sequential search** (with recall); C2 tests a **fixed** reservation level. Together they characterize satisficing in choice process data, when values are known.

5

Evidence: Caplin, Dean and Martin (2011)

A lab experiment with choice process data: subjects satisfice, but their aspiration level depends on the menu.

Designing the experiment

Requirements

To test whether satisficing explains choice **mistakes**, the design needs:

1. a ranking of alternatives that is **obvious to the experimenter**;
2. but subjects who still **make mistakes**;
3. a way to collect **choice process data**.

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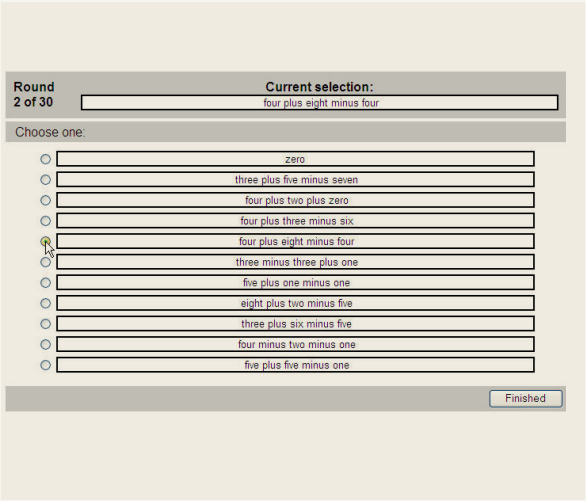
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Choice objects: sums

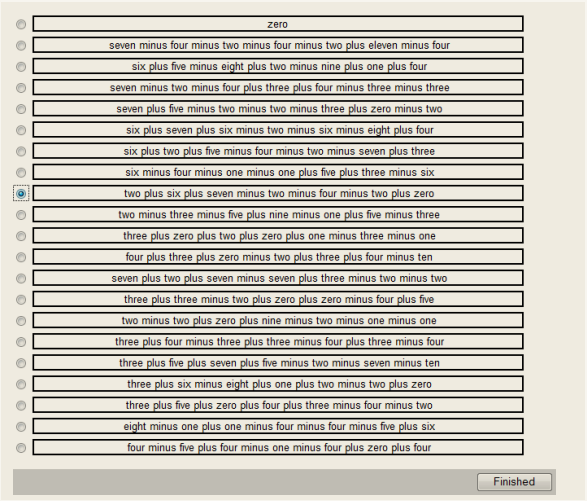
Caplin et al. (2011): “sums”, e.g. *four plus eight minus four*.

- The value of an option is the value of the sum (paid in money).
- The full-information ranking is obvious, but uncovering values takes **effort**.
- 6 treatments: **complexity** (3 or 7 operations) $\times$ **menu size** (10, 20 or 40 options).
- No time limit.

Size 10, complexity 3



Size 20, complexity 7



First result: people do not choose the best option

Standard choice task (22 subjects, 657 choices)

Failure rate (best option not chosen)			**Average loss** ($)		
Set size	Compl. 3	Compl. 7	Set size	Compl. 3	Compl. 7
10	7%	24%	10	0.41	1.69
20	22%	56%	20	1.10	4.00
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Question

Can search and satisficing explain these mistakes? Does it “rescue” revealed preference?

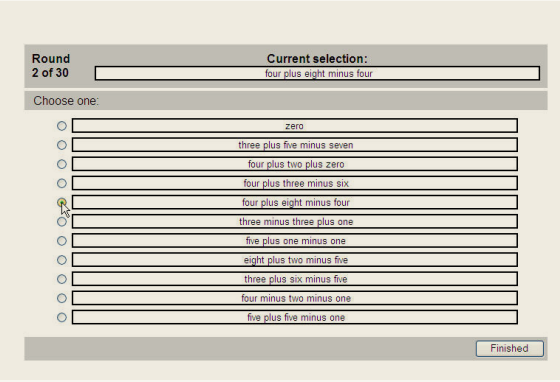
Eliciting choice process data

Procedure

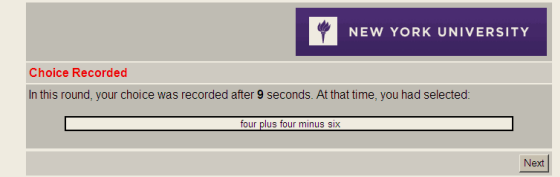
1. Subjects may **select** any alternative at any time, and change their selection as often as they like.
2. The choice is **recorded at a random time** between 0 and 120 seconds, unknown to the subject.
   - Incentive to always keep the current best alternative selected.
   - The sequence of selections = **choice process data**.
3. A round ends after 120 seconds or when the subject presses **“finish”**.
   - Rounds in which subjects do not press “finish” are discarded.

The interface

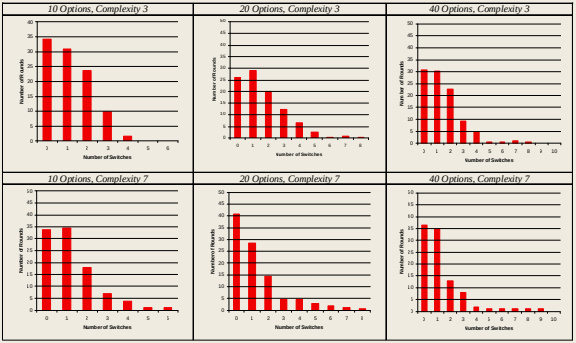
Stage 1: selection



Stage 2: choice recorded



Do we get richer data? (978 rounds, 76 subjects)

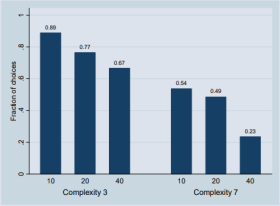


Number of rounds by **number of switches**, for each treatment. Most rounds contain at least one switch: the process is observable.

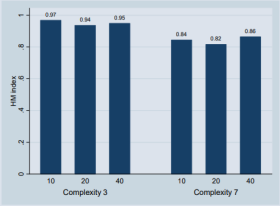
Testing C1: sequential search

Data

Traditional



ABS

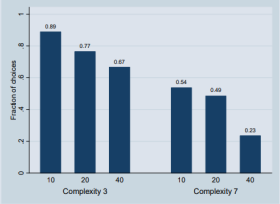


Left: share of choices consistent with standard revealed preference (best option chosen). Right: share of switches consistent with **C1** (alternative-based search, ABS; Houtman–Maks index).

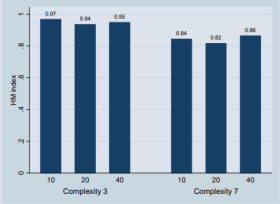
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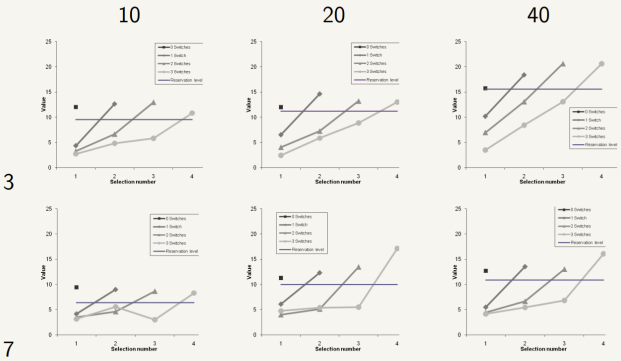
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Result

Broadly, subjects search **sequentially**.

- Violations of C1 come from miscalculation: more frequent with complexity 7 than 3,
- but they do **not** increase with the size of the choice set.

Testing C2: a reservation level



Value of successive selections, by number of switches; rows: complexity 3 and 7; columns: set size 10, 20, 40. Horizontal line: estimated reservation level.

Search tends to stop once a value above the line is found.

Estimating reservation levels

Method

- Choice process data show when subjects **stop** and when they **continue** searching.
- This allows estimating a reservation level per treatment:
  - assume the reservation level is drawn with some **noise** at each switch (a noise model, as in Lecture 3);
  - estimate by **maximum likelihood**.

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Estimated reservation levels (standard errors)

Set size	Complexity 3	Complexity 7
10	9.54 (0.20)	6.36 (0.13)
20	11.18 (0.12)	9.95 (0.10)
40	15.54 (0.11)	10.84 (0.10)

What do the reservation levels tell us?

Findings

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Take-away

Satisficing explains the data **better** than maximization, and its key comparative static (cost) holds. But the aspiration level depends on the menu: the simple optimal-search model is not the whole story.

Search data

A second kind of richer data: what people **look at** before they buy.

Online book buyers

- De los Santos et al. (2012) use web-browsing and purchase data of online book buyers.
- They compare **sequential search** (as in today's model) with **fixed-sample search** (Stigler, 1961): decide in advance how many stores to visit, visit them all, buy the cheapest.
- Their finding: behavior is better described by **fixed-sample** search.

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- Their finding: behavior is better described by **fixed-sample** search.

Take-away

Outside the lab, the evidence for satisficing is weaker. But such field data sets have limited power to tell the two models apart.

6

Wrapping up

Satisficing can be optimal, and choice process data show that people do it.

Recap

Theory

- **Bounded rationality** keeps a utility function but adds costs or constraints to optimization.
- **Satisficing** (Simon): search until an option is “good enough”.
- With per-item search cost, known i.i.d. values and recall, the **optimal** strategy is satisficing, with reservation value u^* solving $G(u^*) = k$.

Testing and evidence

- **Standard choice data cannot test it**: we need choice process data (C1, C2) or search data.
- **Lab evidence** (Caplin et al., 2011): subjects search sequentially and stop at a reservation level that falls with complexity, but rises with menu size.
- **Field evidence** (De los Santos et al., 2012): fixed-sample search fits better.

Exercises (1/2)

1. (Easy)

Values are uniform on $[0, 1]$ and $k = 0.18$. (a) Compute u^*. (b) The first item is worth 0.55: stop or continue? (c) With a very large lot, how many items does the DM inspect on average?

2. (Intermediate)

Each item is worth 0 or 10 with probability $\frac{1}{2}$ each. (a) Compute $G(\bar{u})$ and u^* as functions of k. (b) Describe the optimal rule for $k = 1$. Is u^* the value of an item? (c) What happens when $k > 5$?

Exercises (2/2)

3. (Intermediate)

Values are known. Which observations violate C1 or C2? Which reservation levels u^* are consistent with observations a and b?

Obs.	Values available	Provisional choices	Final
a	$\{3, 5, 7, 9\}$	$3,\ 7$	7
b	$\{1, 4, 6, 8\}$	$4,\ 6,\ 8$	8
c	$\{2, 5, 9, 10\}$	$5,\ 9,\ 10$	10
d	$\{2, 6, 8\}$	$6,\ 2,\ 8$	8

4. (Advanced)

(a) Show that if all values are shifted by δ, u^* rises by exactly δ. (b) Show that a mean-preserving spread of F raises u^*. *Hint:* $G(\bar{u}) = \mathbb{E}[\max(V - \bar{u}, 0)]$ *and* $v \mapsto \max(v - \bar{u}, 0)$ *is convex.*

Questions for discussion

Discuss

- Does bounded rationality differ from simply changing preferences? If so, how?
- Which problem of the canonical model $C(A) = \arg\max_{x \in A} u(x)$ does satisficing address?
- Real-world examples where satisficing seems more plausible than maximizing?
- Why can satisficing not be distinguished from utility maximization with standard choice data?
- Compare satisficing with other models of bounded rationality: rational inattention (Lecture 9), heuristics.

Final take-aways

1. **Bounded rationality** relaxes **Assumption 1**: the DM has preferences, but finding the best option is costly.
2. **Satisficing can be optimal**: with a cost per look, search until an item beats the reservation value u^*.
3. The model makes **sharp predictions** (u^* falls with cost, does not depend on menu size) that need **richer data** than final choices.
4. In the lab, people **satisfice**, but their aspiration level depends on the menu.

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