Search and Satisficing

Mark Dean

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Search and Satisficing

- We will begin by studying one of the oldest and most famous models of bounded rationality
  - Satisficing
  - Originally described by Herbert Simon [1955]
- A very simple and intuitive choice procedure

Search and Satisficing

- Say you are trying to buy a car
- Here is what you do
  1. Decide what features your car needs to have
     - Automatic, 5 star safety rating, go faster stripes, price less than $10,000
  2. Go to the car lot and look at the first car
  3. Does this car satisfy the needs you identified in (1)?
     - If yes, buy the car
     - If not go on to the next car and repeat (3)
  4. If you have looked at all the cars in the lot, and none of them satisfy your needs, go back and buy the best one

Search and Satisficing

- The procedure was called 'satisficing' to differentiate it from 'maximizing'
  - i.e. looking at **all** cars and choosing the one with the highest utility
- You won't necessarily end up with the best option
  - Maybe you bought a car that satisfied your desires, but if you had searched one more you would have got the same model $1000 cheaper
- But is a much easier procedure than utility maximizing
  - Don't in general have to look at all the cars

- We are going to cover two things with regard to Satisficing

1. Satisficing as optimal choice
    - Simon introduced Satisficing as a 'psychologically rational' theory of choice
    - Turns out it can be optimal under some circumstances
2. Testing the Satisficing model
    - Turns out that testing the satisficing model using standard choice data is hard
    - We will discuss some different data sets that we can use

Satisficing as Optimal Stopping

- Imagine that you are back in the car lot
- You have seen a car which is pretty good
- But there are 1000 other cars in the car lot you could look at
- It takes time and effort to look at the next car to see how good it is
- Should you stop and buy the car you are looking at, or keep searching?
- This is an **optimal stopping problem**

Satisficing as Optimal Stopping

- We want to write down a model that captures the following idea
  - Before looking at a car, you don't know how good it is
  - Once you look at a car, you know exactly how good it is
  - But there is a cost to looking at each car
- Should you keep searching, given the cars that you have already seen?

Formal Set Up

- A set A containing M items
- A utility function u: $X \to \mathbb{R}$
  - Value of each option
- A probability distribution f:
  - Beliefs about the value of each option before it is seen
- A cost k :
  - Has to be paid in order to understand the value of the next available alternative.

Formal Set Up

- At any point, decision maker has to choose either to

1. Stop searching, and choose the best available alternative that they have looked at
    - We allow recall, so the DM can choose any of the objects that they have already seen
2. Search another item and pay the cost k

- If they continue searching they will be faced with the same choice after they have looked at the next alternative

Solving the Model

- How could we solve this model?
- Backwards induction!
  - Imagine that you had looked at all but one alternative
  - What would you do?
  - Work backwards from there

After Searching all but one Item

- Let's say that the DM has searched $M - 1$ items
- The best thing they have seen so far has utility $\bar{u}$
- Should they search the Mth item?
- How would you decide?
- Compare the value of not searching to the value of searching

The Value of Not Searching

- What happens if the firm doesn't search?
- Get the item with utility $\bar{u}$ and pay costs of all the searching done so far

$$\bar{u} - (1 - M)k$$

The Value of Searching

- What happens if the firm searches?
- Will have to pay, so search costs now Mk
- What are the benefits?
- Depends on the value of the new alternative you look at u
  - If $u < \bar{u}$ then will choose old item and get $\bar{u}$
  - If $u > \bar{u}$ then choose new item and get u
  - Integrate up over possible values of u
- Total value of searching is

$$\int_{-\infty}^{\bar{u}} \bar{u} f(u) du + \int_{\bar{u}}^{\infty} u f(u) du - Mk$$

- So continuing to search is better if

$$\begin{aligned} & \int_{-\infty}^{\bar{u}} \bar{u} f(u) du + \int_{\bar{u}}^{\infty} u f(u) du - Mk \\ \geq \quad & \bar{u} - (1 - M) k \end{aligned}$$

- Notice we can write

$$\bar{u} = \int_{-\infty}^{\bar{u}} \bar{u} f(u) du + \int_{\bar{u}}^{\infty} \bar{u} f(u) du$$

- So continuing better if

$$k \leq \int_{\bar{u}}^{\infty} (u - \bar{u}) f(u) du$$

Solving the Model

$$k \leq \int_{\bar{u}}^{\infty} (u - \bar{u}) f(u) du$$

- Notice that the left hand side does not change with $\bar{u}$
- The right hand side **decreases** in $\bar{u}$
  - Value of continuing to search falls as the value of the best thing you have already seen increases
- Thus we can find a u^* such that

$$k = \int_{u^*}^{\infty} (u - u^*) f(u) du$$

- Optimal strategy
  - Keep searching if the best item you have seen is worse than u^*
  - Stop if it is better than u^*
- This is called a **reservation stopping rule**

Moving Back One Period

- This tells us what to do when we have searched $M-1$ items
- What about when we have searched $M-2$ items?
- First, let's think about what you should do if the value of the best item you have seen $\bar{u}$ is less than u^*
  - The reservation level from last period
- Should definitely keep searching
  - We know from before that if $\bar{u} < u^*$ it is worth searching at least one more period
  - If there are 2 items left to search, can always just search one of them and stop

Moving Back One Period

- What if $\bar{u} > u^*$
- Should definitely stop searching!
  - Will definitely stop searching after looking at the next alternative
  - We know that from the optimal strategy in $M - 1$
  - But that also told us that if $\bar{u} > u^*$ it is not worth searching one more item
- Can repeat for $M - 3$, $M - 4$ etc

The Optimal Strategy

- The optimal strategy is the same in each period!
  - Stop searching if you uncover an object with value greater than u^*
  - Carry on searching otherwise
- If you get to the end, just choose the best option
- But this sounds exactly like satisficing!
  - Keep searching until you find something that is 'good enough'
  - Good enough means better than u^*
- Caveat: We have made some rather specific assumptions to make sure optimal strategy is satisficing
  - e.g. no learning about f

- What is the advantage of deriving this as an optimal strategy?
- Allows us to make predictions about how behavior changes with the environment

$$k = \int_{u^*}^{\infty} (u - u^*) f(u) du$$

- The satisficing level is
  - **Falling** with the cost of looking
  - **Rising** in the variance of f (for a fixed mean)
  - **Rises** one for one with the mean of f (for a fixed variance)
  - **Does not change** with the size of the choice set

Testing the Satisficing Model

- Let's say I have persuaded you that the satisficing model sounds more persuasive than utility maximization
- What should you do next?
- Figure out how to test this hypothesis!
  - We are, after all, scientists
  - Even if we are only social scientists
- How can we do this?

- Approach 1: using standard choice data
- Unfortunately this isn't going to work
- Why?

1. Assumption 1: always search through choice sets in the same order
    - Same prediction as utility maximization
    - See homework
2. Assumption 2: Change search order in each choice
    - Can rationalize any data set
    - Just assume everything is above the satisficing level
    - Whatever is chosen is the thing that was

Standard Choice Data

- We need a richer data set
- Will consider two
  1. Choice process data
     - Records how people's choices change the longer they think
  2. Search data
     - Records what it is that people have looked at before making a choice

Choice Process Data

- Imagine we were interested in the behavior of someone buying a stereo
- We could follow them around the shop
- At any given time, we could ask
    - "If you had to choose now, which stereo would you pick?"
- This would be pretty annoying, but would give us very rich data
    - Standard choice data: $C(A)$ choice from set A
    - Choice process data: $C(A, t)$ choice from A **having thought about the problem for time** t
    - Also observe the time at which they make their 'final' choice

Choice Process Data

- We can use choice process data to test the satisficing model
  - People search through alternatives one at a time
  - At any given time, $C(A, t)$ is the best of the things that they have seen
  - When they find something that is better than the satisficing level they stop searching and make a final choice
- What type of choice process data is consistent with this behavior?
  - To make our lives easier, we will assume we know the utility of each alternative

- Which of the following are consistent with Satisficing?

Observation	Available options	Sequence of 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

- We require two conditions to ensure that data is consistent with satisficing

1. Subjects must always switch to higher value alternatives
2. There must be some u^* such that search stops if and only if the utility of the chosen value is above u^*

- We will now talk through an experiment that will allow us to test whether the satisficing model explains choice mistakes
- We need three things in our design
  1. Ranking of alternatives is clear to us as experimenters
  2. But subjects still make mistakes
  3. Need to be able to collect choice process data

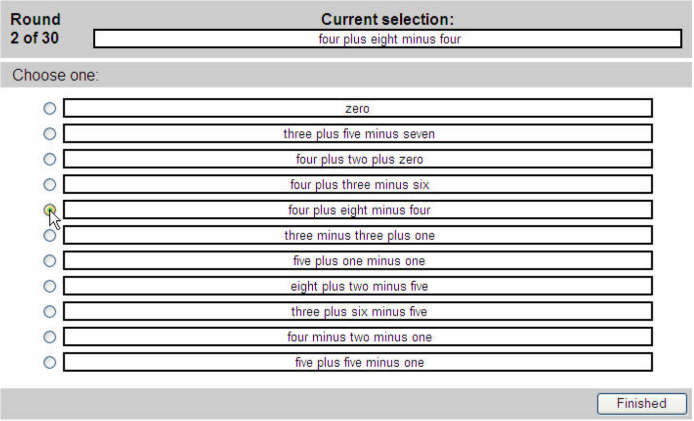
Choice Objects

- Subjects choose between ‘sums’

four plus eight minus four

- Value of option is the value of the sum
- 'Full information' ranking obvious, but uncovering value takes effort
- 6 treatments
  - 2 x complexity (3 and 7 operations)
  - 3 x choice set size (10, 20 and 40 options)
- No time limit

Size 10, Complexity 3



Size 20, Complexity 7

- zero
- seven minus four minus two minus four minus two plus eleven minus four
- six plus five minus eight plus two minus nine plus one plus four
- seven minus two minus four plus three plus four minus three minus three
- seven plus five minus two minus two minus three plus zero minus two
- six plus seven plus six minus two minus six minus eight plus four
- six plus two plus five minus four minus two minus seven plus three
- six minus four minus one minus one plus five plus three minus six
- two plus six plus seven minus two minus four minus two plus zero
- two minus three minus five plus nine minus one plus five minus three
- three plus zero plus two plus zero plus one minus three minus one
- four plus three plus zero minus two plus three plus four minus ten
- seven plus two plus seven minus seven plus three minus two minus two
- three plus three minus two plus zero plus zero minus four plus five
- two minus two plus zero plus nine minus two minus one minus one
- three plus four minus three plus three minus four plus three minus four
- three plus five plus seven plus five minus two minus seven minus ten
- three plus six minus eight plus one plus two minus two plus zero
- three plus five plus zero plus four plus three minus four minus two
- eight minus one plus one minus four minus four minus five plus six
- four minus five plus four minus one minus four plus zero plus four

Finished

Failure rates (%) (22 subjects, 657 choices)

Failure rate		
	Complexity	
Set size	3	7
10	7%	24%
20	22%	56%
40	29%	65%

Average Loss ($)		
	Complexity	
Set size	3	7
10	0.41	1.69
20	1.10	4.00
40	2.30	7.12

Results

- In this environment, people do not choose the best option
- Choice does not imply revealed preference
- Can behavior be explained by search and satisficing model?
- Do these models resurrect the concept of revealed preference?

Eliciting Choice Process Data

1. Allow subjects to select any alternative at any time
   - Can change selection as often as they like
2. Choice will be recorded at a random time between 0 and 120 seconds unknown to subject
   - Incentivizes subjects to always keep selected current best alternative
   - Treat the sequence of selections as choice process data
3. Round can end in two ways
   - After 120 seconds has elapsed
   - When subject presses the 'finish' button
   - We discard any rounds in which subjects do not press 'finish'

Stage 1: Selection

Round
2 of 30

Current selection:

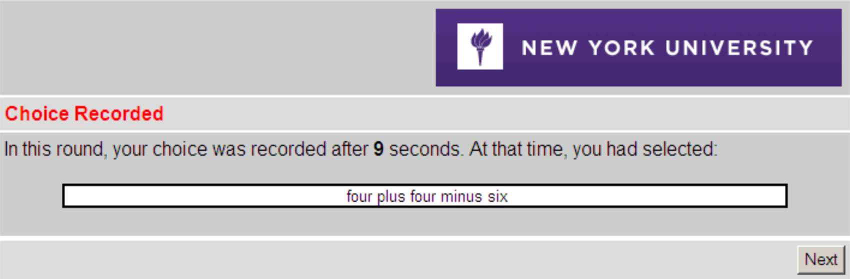
four plus eight minus four

Choose one:

- zero
- three plus five minus seven
- four plus two plus zero
- four plus three minus six
- four plus eight minus four
- three minus three plus one
- five plus one minus one
- eight plus two minus five
- three plus six minus five
- four minus two minus one
- five plus five minus one

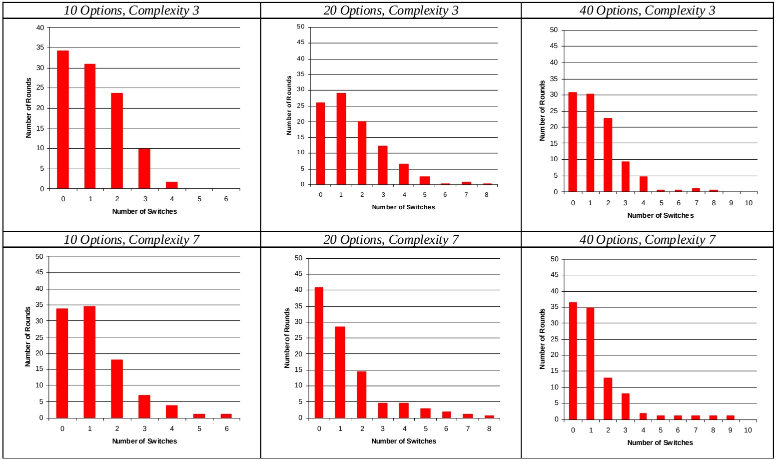
Finished

Stage 2: Choice Recorded



Do We Get Richer Data from Choice Process Methodology?

978 Rounds, 76 Subjects

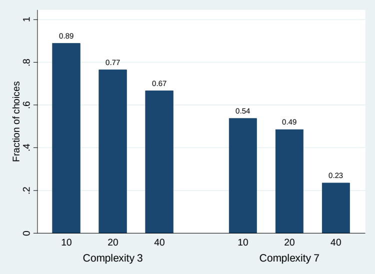


Testing Condition 1

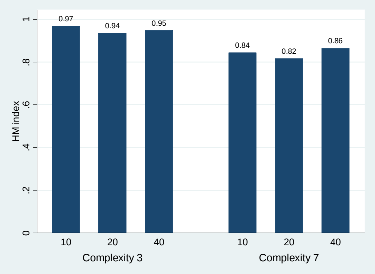
- Subjects must always switch to higher-valued objects **(Condition 1)**
- Graph the fraction of switches that satisfy condition 1
- Compare to the fraction of choices that satisfy 'standard' revealed preference

Traditional vs ABS Revealed Preference

Traditional



ABS

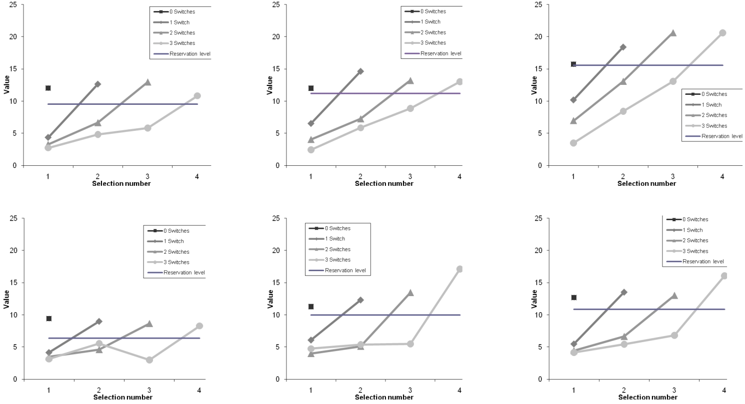


Satisficing

- Broadly speaking, subjects are searching sequentially
- Are they Satisficers?
- Can we find a utility level u^* such that they stop search if and only if they encounter a utility above u^*?

Satisficing Behavior a la Simon [1955]

10 20 40



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Estimating Reservation Levels

- Choice process data allows observation of subjects
  - Stopping search
  - Continuing to search
- Allows us to estimate reservation levels
- Assume that reservation level is calculated with some noise at each switch
- Can estimate reservation levels for each treatment using maximum likelihood

Estimated Reservation Levels

Set size	**Complexity**			
	3		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)

Estimating Reservation Levels

- Reservation levels decrease with complexity
  - As predicted by theory
- Increase with choice set size
  - Not predicted by theory