Testing Capacity-Constrained Learning

Spring 2026

The General RI Model

- For each decision problem i
  1. Choose π_i: information structure
     - $\pi_i(\gamma|\omega)$ is the probability of receiving posterior γ from state ω
  2. Choose σ_i: decision rule
     - $\sigma_i(\gamma)$ is the distribution over actions in i given posterior γ
- To maximize expected value of actions taken minus cost of information K

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

- CD15 show characterized by two conditions: NIAS and NIAC

Condition 1 (No Improving Action Switches)

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

Condition 2 (No Improving Attention Cycles)

$$\begin{aligned}
& \sum_{a\in A_1} \max_{\hat{a}\in A_1} \sum_{\omega\in\Omega} P_1(a,\omega)u_1(\hat{a},\omega) - \sum_{a\in A_2} \max_{\hat{a}\in A_1} \sum_{\omega\in\Omega} P_2(a,\omega)u_1(\hat{a},\omega) \\
& + \sum_{a\in A_2} \max_{\hat{a}\in A_2} \sum_{\omega\in\Omega} P_2(a,\omega)u_2(\hat{a},\omega) - \sum_{a\in A_3} \max_{\hat{a}\in A_2} \sum_{\omega\in\Omega} P_3(a,\omega)u_2(\hat{a},\omega) \\
& + \ldots \\
& + \sum_{a\in A_K} \max_{\hat{a}\in A_K} \sum_{\omega\in\Omega} P_K(a,\omega)u_K(\hat{a},\omega) - \sum_{a\in A_1} \max_{\hat{a}\in A_K} \sum_{\omega\in\Omega} P_1(a,\omega)u_K(\mu,\hat{a},\omega) \\
\geq \quad & 0
\end{aligned}$$

Capacity-Constrained Learning

- Today consider an important special case of the general RI model, where $K(\mu, \pi)$ can only take one of two values: 0 or ∞
- This can be interpreted as choosing among feasible information structures (choosing π to maximize $G_i(\pi)$ s.t. π is feasible)
- Because feasibility is an exogenous constraint on Bayesian learning, this model class includes fixed-capacity versions of rational inattention [Sims, 2003] and efficient coding [Woodford, 2012]
- Caplin et al. [2025] show that this model class, called "Capacity-Constrained Learning," is characterized by a single condition: NIS

NIS

[No Improving (Action or Attention) Switches (**NIS**)]
Utility function u satisfies NIS for P if and only if for any set of decision problems $i, j \in D$,

$$\sum_{a \in A_i} \sum_{\omega \in \Omega} P_i(a, \omega) u_i(a, \omega) \geq \sum_{a \in A_j} \max_{\hat{a} \in A_i} \sum_{\omega \in \Omega} P_j(a, \omega) u_i(\hat{a}, \omega) \tag{1}$$

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- *wholesale* switches of actions and attention should not improve utility
- involves both checks "within" each decision problem (when $i = j$)

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- *wholesale* switches of actions and attention should not improve utility
- involves both checks "within" each decision problem (when $i = j$)
- and between decision problems (when $i \neq j$)

NIS

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Utility function u satisfies NIS for P if and only if for any set of decision problems $i, j \in D$,

$$\sum_{a \in A_i} \sum_{\omega \in \Omega} P_i(a, \omega) u_i(a, \omega) \geq \sum_{a \in A_j} \max_{\hat{a} \in A_i} \sum_{\omega \in \Omega} P_j(a, \omega) u_i(\hat{a}, \omega) \qquad (1)$$

- *wholesale* switches of actions and attention should not improve utility
- involves both checks "within" each decision problem (when $i = j$)
- and between decision problems (when $i \neq j$)
- involves checking $N + N^2$ inequalities

Intuition

- Checks “within” each decision problem (when $i = j$)
  - Intuition: Holding learning fixed, can improve utility with switch of actions? (Note: same as NIAS)
- Checks between decision problems (when $i \neq j$)
  - Intuition: Can improve utility with switch of learning?
  - Idea: In principle, any learning that was done in another decision problem was feasible in this one!

NIS $\implies$ NIAS

- Proof: for within decision problem $i = j$, NIS becomes

$$\sum_{a\in A_i}\sum_{\omega\in\Omega} P_i(a,\omega)u_i(a,\omega) \geq \sum_{a\in A_i}\max_{\hat{a}\in A_i}\sum_{\omega\in\Omega} P_i(a,\omega)u_i(\hat{a},\omega) \tag{2}$$

- Note that for all $a \in A_i$,

$$\sum_{\omega\in\Omega} P_i(a,\omega)u_i(a,\omega) \leq \max_{\hat{a}\in A_i}\sum_{\omega\in\Omega} P_i(a,\omega)u_i(\hat{a},\omega)$$

Therefore, (2) implies

$$\sum_{\omega\in\Omega} P_i(a,\omega)u_i(a,\omega) = \max_{\hat{a}\in A_i}\sum_{\omega\in\Omega} P_i(a,\omega)u_i(\hat{a},\omega) \geq \sum_{\omega\in\Omega} P_i(a,\omega)u_i(\hat{a},\omega)$$

Which is exactly NIAS

NIS $\implies$ NIAC:

- For all decision problem j and $j+1$, NIS implies

$$\sum_{a\in A_j}\sum_{\omega\in\Omega} P_j(a,\omega)u_j(a,\omega) \geq \sum_{a\in A_{j+1}}\max_{\hat{a}\in A_i}\sum_{\omega\in\Omega} P_{j+1}(a,\omega)u_j(\hat{a},\omega) \qquad (3)$$

- Therefore,

$$\sum_{j=1}^{J}\left(\sum_{a\in A_j}\sum_{\omega\in\Omega} P_j(a,\omega)u_j(a,\omega)\right) \geq$$

$$\sum_{j=1}^{J}\left(\sum_{a\in A_{j+1}}\max_{\hat{a}\in A_j}\sum_{\omega\in\Omega} P_{j+1}(a,\omega)u_j(\hat{a},\omega)\right)$$

NIS $\implies$ NIAC:

- Plugging in NIAS on the LHS, we get

$$\sum_{j=1}^{J}\left(\sum_{a\in A_j}\max_{\hat{a}\in A_j}\sum_{\omega\in\Omega}P_j(a,\omega)u_j(\hat{a},\omega)\right)\geq$$

$$\sum_{j=1}^{J}\left(\sum_{a\in A_{j+1}}\max_{\hat{a}\in A_j}\sum_{\omega\in\Omega}P_{j+1}(a,\omega)u_j(\hat{a},\omega)\right)$$

Which is exactly NIAC

Summarizing the relationship

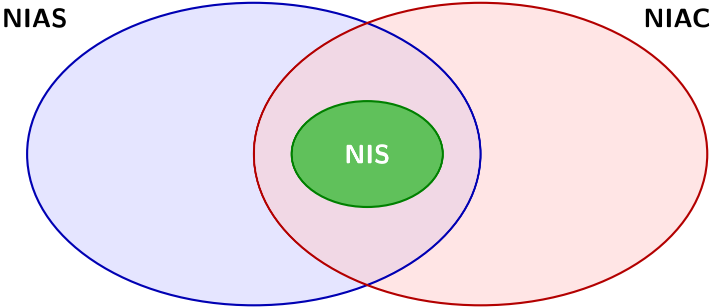
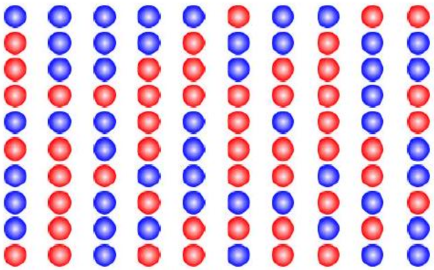


Figure: Relationship between NIS and existing conditions (NIAS and NIAC).

An Experimental Example



- In Dean and Neligh (JPE 2022), subjects presented with 100 balls
- State is determined by the number of red balls
- Prior distribution of red balls is told to subjects

A note on probability points

- In this example and the experiments, payments are done through probability points p (probability of winning a cash amount)
- The decision-maker (assumed) to have a strictly increasing utility function over cash
- Under expected utility assumptions: the u(probability point prize) is linear and increasing in the number of probability points
- WLOG, normalize the utility of receiving the cash to 100 and not receiving the cash to 0 $\implies$ the utility of the probability point prize is point identified: the utility of p probability points is exactly p

An Experimental Example

Decision Problem 1

Payoff/utility

Action	State= **49** red balls	State= **51** red balls
a	10	0
b	0	10

Prior: $\{0.5, 0.5\}$

State-conditional action probabilities

Action	State = **49** red balls	State = **51** red balls
a	$\frac{2}{3}$	$\frac{1}{3}$
b	$\frac{1}{3}$	$\frac{2}{3}$

$$P_1 = \begin{array}{cc} 49 & 51 \\ \left(\begin{array}{cc} \frac{2}{6} & \frac{1}{6} \\ \frac{1}{6} & \frac{2}{6} \end{array}\right) \end{array} \begin{array}{c} \\ a \\ b \end{array}$$

An Experimental Example

Decision Problem 2

Payoff/utility

Action	State= **49** red balls	State= **51** red balls
a	20	0
b	0	20

Prior: $\{0.5, 0.5\}$

State-conditional action probabilities

Action	State = **49** red balls	State = **51** red balls
a	$\frac{3}{4}$	$\frac{1}{4}$
b	$\frac{1}{4}$	$\frac{3}{4}$

$$P_2 = \begin{array}{cc} 49 & 51 \\ \left(\begin{array}{cc} \frac{3}{8} & \frac{1}{8} \\ \frac{1}{8} & \frac{3}{8} \end{array}\right) \end{array} \begin{array}{c} \\ a \\ b \end{array}$$

In our example:

- Check NIAS within DP1

In our example:

- Check NIAS within DP1
- Check NIAS within DP2

In our example:

- Check NIAS within DP1
- Check NIAS within DP2
- The value of info in decision problem 1 is:

$$\underbrace{P_1(a,\omega=49)u_1(a,\omega=49)}_{\frac{2}{6}\times 10}+\underbrace{P_1(a,\omega=51)u_1(a,\omega=51)}_{\frac{1}{6}\times 0}+$$

$$\underbrace{P_1(b,\omega=49)u_1(b,\omega=49)}_{\frac{1}{6}\times 0}+\underbrace{P_1(b,\omega=51)u_1(b,\omega=51)}_{\frac{2}{6}\times 10}$$

$= 6.666$

In our example:

- The value of the learning in decision problem 1 is 6.666
- Switching to the learning in problem 2 while keeping the optimal actions and prizes in problem 1 results in:

$$\underbrace{P_2(a,\omega=49)u_1(a,\omega=49)}_{\frac{3}{8}\times 10}+\underbrace{P_2(a,\omega=51)u_1(a,\omega=51)}_{\frac{1}{8}\times 0}+$$

$$\underbrace{P_2(b,\omega=49)u_1(b,\omega=49)}_{\frac{1}{8}\times 0}+\underbrace{P_2(b,\omega=51)u_1(b,\omega=51)}_{\frac{3}{8}\times 10}$$

$= 7.5$

In our example:

- The value of the learning in decision problem 1 is 6.666
- Switching to the learning in problem 2 while keeping the optimal actions and prizes in problem 1 results in:

$$\underbrace{P_2(a,\omega=49)u_1(a,\omega=49)}_{\frac{3}{8}\times 10}+\underbrace{P_2(a,\omega=51)u_1(a,\omega=51)}_{\frac{1}{8}\times 0}+$$

$$\underbrace{P_2(b,\omega=49)u_1(b,\omega=49)}_{\frac{1}{8}\times 0}+\underbrace{P_2(b,\omega=51)u_1(b,\omega=51)}_{\frac{3}{8}\times 10}$$

$$= 7.5$$

NIS fails (in the direction of increasing incentives)!

Statistical Testing

- NIS is a property of the distribution $P(a|\omega)$, which is not observed
- Instead we observe $\hat{P}(a|\omega)$, the proportion of action a condition on the state ω in data
- $\hat{P}(a|\omega)$ satisfying NIS does not implies $P(a|\omega)$ satisfying NIS, nor vise versa
- $\hat{P}(a|\omega)$ is binomially distributed, with mean $P(a|\omega)$. With large sample it is approximately normal distributed

Statistical Testing

- NIS says

$$\sum_{a \in A_i} \sum_{\omega \in \Omega} P_i(a, \omega) u_i(a, \omega) \geq \sum_{a \in A_j} \max_{\hat{a} \in A_i} \sum_{\omega \in \Omega} P_j(a, \omega) u_i(\hat{a}, \omega)$$

- In our case, it is

$$P_i(a, 1) \cdot z_i + P_i(b, 2) \cdot z_i \geq P_j(a, 1) \cdot z_i + P_j(b, 2) \cdot z_i$$

for all i, j. That is

$$P_i(a|1) + P_i(b|2) - P_j(a|1) - P_j(b|2) = 0$$

for all i, j. This is our null hypothesis

Statistical Testing

- **Defining the Restrictions:** For any two groups A_i and A_j, under the NIS condition we have:

$$\gamma_j \equiv P_1(a|1) + P_1(b|2) - P_j(a|1) - P_j(b|2) = 0,$$

- And then we can write our null hypothesis as

$$\gamma \equiv \begin{pmatrix} \gamma_1 \\ \gamma_2 \\ \dots \\ \gamma_J \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ \dots \\ 0 \end{pmatrix}$$

Statistical Testing — Delta Method

- To test this hypothesis, we need the covariance matrix of the vector $\hat{\gamma}$
- $\hat{\gamma}$ is a function of $\hat{P}_j(a|1)$, $\hat{P}_j(a|2)$, $\hat{P}_j(b|1)$ and $\hat{P}_j(b|2)$. We know the covariance matrix of these estimates because we estimated them directly from the data
- By the Delta Method, the asymptotic covariance matrix of $\hat{\gamma}$ is given by: $\Sigma_{\hat{\gamma}} = G\Sigma_{\hat{P}}G^\top$, where:
    - $\Sigma_{\hat{P}}$ is the covariance matrix of the estimated probabilities $\hat{P}$,
    - G is the Jacobian matrix of γ with respect to $\hat{P}$, defined as

$$G = \frac{\partial \gamma}{\partial \hat{P}}$$

Statistical Testing — Wald Test

- Under the null hypothesis, the test statistic is:

$$T = \hat{\gamma}^{\top} \Sigma_{\hat{\gamma}}^{-1} \hat{\gamma}$$

which asymptotically follows a χ^2_J distribution under the null hypothesis

What can we learn from existing experiments?

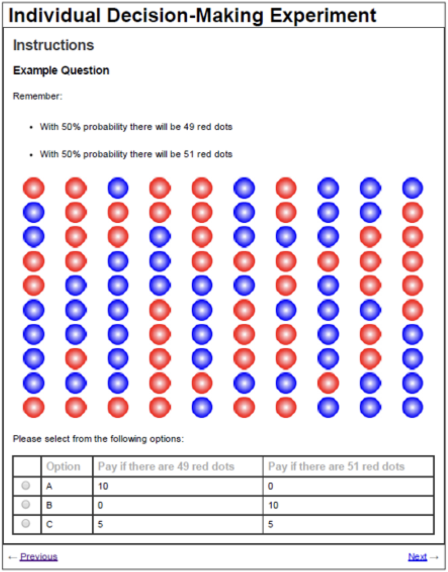
Experiments we looked at:

- Dean and Neligh [2023]: Experiments 1.2 and 2.2
- Caplin et al. [2020]
- Dewan and Neligh [2020]

Dean and Neligh (2023) Experiment 1.2

- Subjects are shown a grid of 100 blue or red balls
- There are 49 or 51 red balls with equal chance
- The task is to identify the correct number of red balls
- Denote the two states $\Omega = \{49, 51\}$
- Denote the actions $A = \{a, b\}$

Dean and Neligh (2023) Experiment 1.2: Interface



Individual Decision-Making Experiment

Instructions

Example Question

Remember:

- With 50% probability there will be 49 red dots
- With 50% probability there will be 51 red dots

Please select from the following options:

	Option	Pay if there are 49 red dots	Pay if there are 51 red dots
○	A	10	0
○	B	0	10
○	C	5	5

Dean and Neligh (2023) Experiment 1.2: Design

DP	Payoffs/utility			
	$u(a, 49)$	$u(a, 51)$	$u(b, 49)$	$u(b, 51)$
1	5	0	0	5
2	40	0	0	40
3	70	0	0	70
4	95	0	0	95

- Binary state set and action set
- a is the correct action in state 49, b is the correct action in state 51
- The four decision problems have increasing stakes

Dean and Neligh (2023) Experiment 1.2: SDSC Data

$$P_1 = \begin{array}{c} \\ \\ \end{array}\begin{array}{cc} \omega = 49 & \omega = 51 \\ \end{array}$$

$$P_1 = \left(\begin{array}{cc} 0.37 & 0.20 \\ 0.13 & 0.30 \end{array}\right)\begin{array}{c} a \\ b \end{array}$$

$$P_2 = \left(\begin{array}{cc} 0.38 & 0.17 \\ 0.12 & 0.33 \end{array}\right)\begin{array}{c} a \\ b \end{array}$$

$$P_3 = \left(\begin{array}{cc} 0.39 & 0.17 \\ 0.11 & 0.33 \end{array}\right)\begin{array}{c} a \\ b \end{array}$$

$$P_4 = \left(\begin{array}{cc} 0.39 & 0.14 \\ 0.11 & 0.36 \end{array}\right)\begin{array}{c} a \\ b \end{array}$$

Dean and Neligh (2023) Experiment 1.2: SDSC Data

$$P_1 = \begin{array}{c} \\ \\ \end{array}\begin{array}{cc} \omega = 49 & \omega = 51 \\ \end{array}$$

$$P_1 = \begin{array}{ccc} \omega = 49 & \omega = 51 & \\ \left(\begin{matrix} 0.37 \\ 0.13 \end{matrix}\right. & \left.\begin{matrix} 0.20 \\ 0.30 \end{matrix}\right) & \begin{matrix} a \\ b \end{matrix} \end{array} \qquad P_2 = \begin{array}{ccc} \omega = 49 & \omega = 51 & \\ \left(\begin{matrix} 0.38 \\ 0.12 \end{matrix}\right. & \left.\begin{matrix} 0.17 \\ 0.33 \end{matrix}\right) & \begin{matrix} a \\ b \end{matrix} \end{array}$$

$$P_3 = \begin{array}{ccc} \omega = 49 & \omega = 51 & \\ \left(\begin{matrix} 0.39 \\ 0.11 \end{matrix}\right. & \left.\begin{matrix} 0.17 \\ 0.33 \end{matrix}\right) & \begin{matrix} a \\ b \end{matrix} \end{array} \qquad P_4 = \begin{array}{ccc} \omega = 49 & \omega = 51 & \\ \left(\begin{matrix} 0.39 \\ 0.11 \end{matrix}\right. & \left.\begin{matrix} 0.14 \\ 0.36 \end{matrix}\right) & \begin{matrix} a \\ b \end{matrix} \end{array}$$

Subjects improve their accuracy in the direction of increasing incentives!

Dean and Neligh (2023) Experiment 1.2: Results

Incentive level					
Lower	Higher	NIS LHS	NIS RHS	NIS inequality fails?	p-value
5	40	3.34	3.56	Yes	0.03
5	70	3.34	3.61	Yes	0.02
5	95	3.34	3.77	Yes	< 0.01
40	70	28.46	28.84	Yes	0.33
40	95	28.46	30.12	Yes	0.05
70	95	50.47	52.72	Yes	0.11

LHS $=$ expected utility with the subject's learning in the current DP
RHS $=$ best expected utility that can be achieved with the learning in the other DP

Dean and Neligh (2023) Experiment 2.2: Design

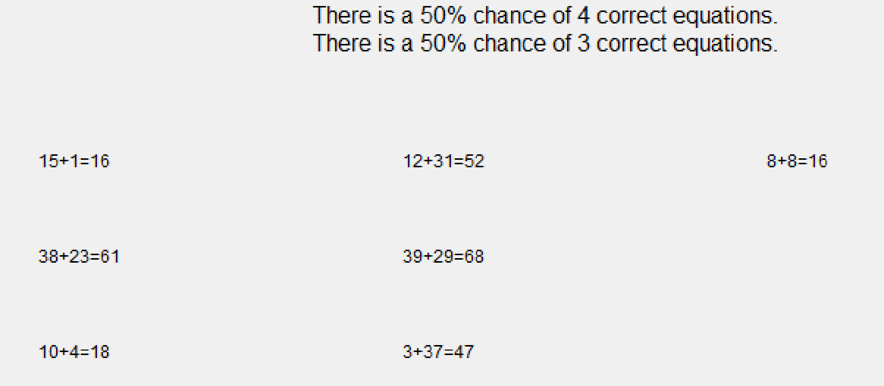
- Similar design
- 7 equations instead of dots
- 2 states: either 3 or 4 of the 7 equations correct ($\omega \in \{3, 4\}$)
- 5 or 95 probability points (depending on the decision problem)

Payoff/utility

Action	$\omega = 3$	$\omega = 4$
a	5	0
b	0	5

Action	$\omega = 3$	$\omega = 4$
a	95	0
b	0	95

Dean and Neligh (2023) Experiment 2.2: Interface



There is a 50% chance of 4 correct equations.
There is a 50% chance of 3 correct equations.

15+1=16	12+31=52	8+8=16
38+23=61	39+29=68	
10+4=18	3+37=47	

Dean and Neligh Experiment 2.2 : Subjects' Choices

$$P_5 = \begin{array}{cc} \omega = 3 & \omega = 4 \\ \end{array}$$

$$\begin{array}{rccl} & \omega = 3 & \omega = 4 & \\ P_5 = & \left(\begin{matrix} 0.412 \\ 0.088 \end{matrix}\right. & \left.\begin{matrix} 0.086 \\ 0.414 \end{matrix}\right) & \begin{matrix} a \\ b \end{matrix} \end{array} \qquad \begin{array}{rccl} & \omega = 3 & \omega = 4 & \\ P_{95} = & \left(\begin{matrix} 0.411 \\ 0.089 \end{matrix}\right. & \left.\begin{matrix} 0.069 \\ 0.431 \end{matrix}\right) & \begin{matrix} a \\ b \end{matrix} \end{array}$$

where P_5 is data from a decision problem with 5 probability points payoff and P_{95} is from a decision problem with 95 probability points payoff

Dean and Neligh (2023) Experiment 2.2: Results

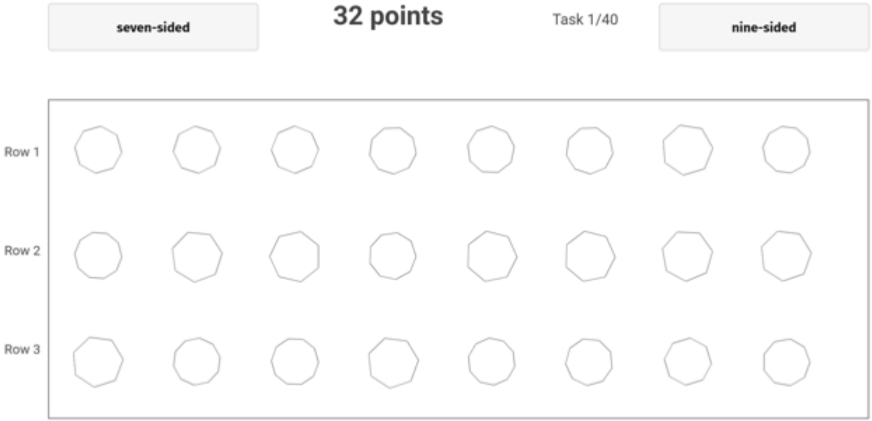
DP1	DP2	LHS	RHS	NIS inequality fails?	p-value
5	95	4.13	4.21	Yes	0.19

Table: NIS inequalities in direction of increasing incentives (aggregate data from experiment 2.2)

Caplin, Csaba, Leahy and Nov (2020): Design

- Shown 24 geometric objects at once
- Objects: polygons with either 7, 8, 9 or 10 sides
- States: more 7-sided polygons or more 9-sided polygons ($\omega \in \{7, 9\}$)
- Actions: more 7-sided (action a) or more 9-sided (action b)
- Vary difficulty level: difference between number of 7-sided and 9-sided polygons was 1, 2, 3, or 6
- Probability of winning \$10: 0, 1, 2, 4, 8, 16, or 32 probability points

Caplin, Csaba, Leahy and Nov (2020): Interface



Caplin, Csaba, Leahy and Nov (2020): SDSC Data

$$P_0 = \begin{array}{cc} \omega = 7 & \omega = 9 \\ \end{array}$$

$$P_0 = \begin{array}{c} \\ \\ \end{array}\left(\begin{array}{cc} 0.30 & 0.20 \\ 0.22 & 0.28 \end{array}\right)\begin{array}{c} a \\ b \end{array}$$

Caplin, Csaba, Leahy and Nov (2020): Results

DP1	DP2	LHS	RHS	NIS inequality fail?	p-value
1	2	0.63	0.66	Yes	< 0.01
1	4	0.63	0.66	Yes	< 0.01
1	8	0.63	0.66	Yes	< 0.01
1	16	0.63	0.69	Yes	< 0.01
1	32	0.63	0.68	Yes	< 0.01
2	4	1.31	1.32	Yes	0.33
2	8	1.31	1.32	Yes	0.37
2	16	1.31	1.38	Yes	< 0.01
2	32	1.31	1.36	Yes	0.03
4	8	2.64	2.64	No	0.48
4	16	2.64	2.76	Yes	< 0.01
4	32	2.64	2.72	Yes	0.06
8	16	5.27	5.52	Yes	< 0.01
8	32	5.27	5.44	Yes	0.05
16	32	11.05	10.87	No	0.21

Dewan and Neligh (2020): Dots Design

- Shown dots on the screen
- States (equally likely): 38, 39, 40, 41, or 42 dots
- Actions: 38 (action a), 39 (action b), 40 (action c), 41 (action d), or 42 (action e)
- Payment is a randomly selected option out of $\{1, 2, \dots 100\}$ probability points (one observation at each payment level)
  - Use quartiles of probability points (1-25,...)

Dewan and Neligh (2020): Dots Interface

This is task number 2 out of 200.

A correct answer to this question is worth **61** points.

How many dots are in the picture?

Dewan and Neligh (2020): Dots SDSC Data

$$P_1 = \begin{array}{cc} \begin{array}{ccccc} \omega = 38 & \omega = 39 & \omega = 40 & \omega = 41 & \omega = 42 \end{array} & \\ \begin{pmatrix} 0.1022 & 0.0352 & 0.0212 & 0.0182 & 0.0218 \\ 0.0340 & 0.0946 & 0.0292 & 0.0236 & 0.0198 \\ 0.0334 & 0.0392 & 0.1022 & 0.0480 & 0.0406 \\ 0.0214 & 0.0188 & 0.0340 & 0.0908 & 0.0318 \\ 0.0090 & 0.0122 & 0.0132 & 0.0196 & 0.0860 \end{pmatrix} & \begin{array}{l} \text{action a} \\ \text{action b} \\ \text{action c} \\ \text{action d} \\ \text{action e} \end{array} \end{array}$$

$$P_2 = \begin{array}{cc} \begin{array}{ccccc} \omega = 38 & \omega = 39 & \omega = 40 & \omega = 41 & \omega = 42 \end{array} & \\ \begin{pmatrix} 0.1208 & 0.0332 & 0.0180 & 0.0122 & 0.0148 \\ 0.0310 & 0.0992 & 0.0234 & 0.0272 & 0.0152 \\ 0.0238 & 0.0376 & 0.1206 & 0.0414 & 0.0358 \\ 0.0178 & 0.0190 & 0.0240 & 0.1002 & 0.0324 \\ 0.0066 & 0.0108 & 0.0140 & 0.0190 & 0.1016 \end{pmatrix} & \begin{array}{l} \text{action a} \\ \text{action b} \\ \text{action c} \\ \text{action d} \\ \text{action e} \end{array} \end{array}$$

Dewan and Neligh (2020): Dots SDSC Data

$$P_2 = \begin{array}{cl} \begin{array}{ccccc} \omega = 38 & \omega = 39 & \omega = 40 & \omega = 41 & \omega = 42 \end{array} & \\ \begin{pmatrix} 0.1208 & 0.0332 & 0.0180 & 0.0122 & 0.0148 \\ 0.0310 & 0.0992 & 0.0234 & 0.0272 & 0.0152 \\ 0.0238 & 0.0376 & 0.1206 & 0.0414 & 0.0358 \\ 0.0178 & 0.0190 & 0.0240 & 0.1002 & 0.0324 \\ 0.0066 & 0.0108 & 0.0140 & 0.0190 & 0.1016 \end{pmatrix} & \begin{array}{l} \text{action a} \\ \text{action b} \\ \text{action c} \\ \text{action d} \\ \text{action e} \end{array} \end{array}$$

$$P_3 = \begin{array}{cl} \begin{array}{ccccc} \omega = 38 & \omega = 39 & \omega = 40 & \omega = 41 & \omega = 42 \end{array} & \\ \begin{pmatrix} 0.1424 & 0.0274 & 0.0152 & 0.0110 & 0.0092 \\ 0.0270 & 0.1246 & 0.0246 & 0.0130 & 0.0110 \\ 0.0170 & 0.0238 & 0.1256 & 0.0324 & 0.0206 \\ 0.0096 & 0.0186 & 0.0246 & 0.1208 & 0.0370 \\ 0.0042 & 0.0056 & 0.0100 & 0.0228 & 0.1224 \end{pmatrix} & \begin{array}{l} \text{action a} \\ \text{action b} \\ \text{action c} \\ \text{action d} \\ \text{action e} \end{array} \end{array}$$

Dewan and Neligh (2020): Dots SDSC Data

$$P_3 = \begin{array}{cccccc} \omega = 38 & \omega = 39 & \omega = 40 & \omega = 41 & \omega = 42 & \\ 0.1424 & 0.0274 & 0.0152 & 0.0110 & 0.0092 & \text{action a} \\ 0.0270 & 0.1246 & 0.0246 & 0.0130 & 0.0110 & \text{action b} \\ 0.0170 & 0.0238 & 0.1256 & 0.0324 & 0.0206 & \text{action c} \\ 0.0096 & 0.0186 & 0.0246 & 0.1208 & 0.0370 & \text{action d} \\ 0.0042 & 0.0056 & 0.0100 & 0.0228 & 0.1224 & \text{action e} \end{array}$$

$$P_4 = \begin{array}{cccccc} \omega = 38 & \omega = 39 & \omega = 40 & \omega = 41 & \omega = 42 & \\ 0.1560 & 0.0198 & 0.0100 & 0.0056 & 0.0076 & \text{action a} \\ 0.0246 & 0.1420 & 0.0196 & 0.0128 & 0.0060 & \text{action b} \\ 0.0070 & 0.0208 & 0.1366 & 0.0298 & 0.0102 & \text{action c} \\ 0.0084 & 0.0108 & 0.0232 & 0.1288 & 0.0280 & \text{action d} \\ 0.0042 & 0.0068 & 0.0106 & 0.0226 & 0.1484 & \text{action e} \end{array}$$

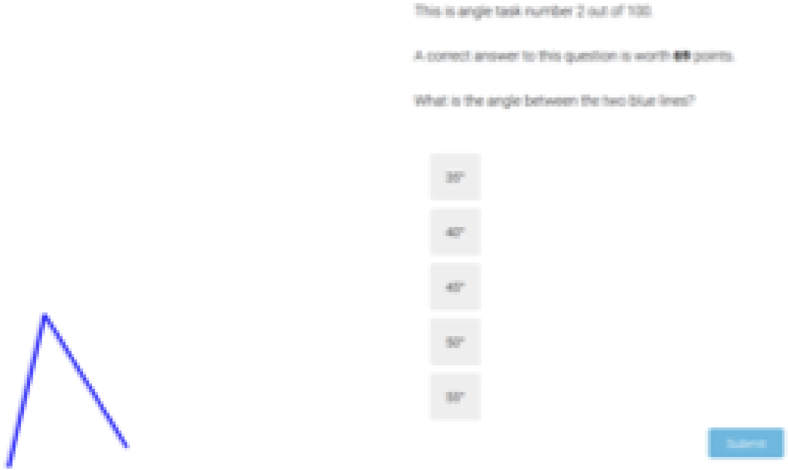
Dewan and Neligh (2020): Dots Results

DP 1	DP 2	LHS	RHS	NIS inequality fail?	p-value
1st	2nd	6.18	7.05	Yes	< 0.01
1st	3rd	6.18	8.27	Yes	< 0.01
1st	4th	6.18	9.25	Yes	< 0.01
2nd	3rd	20.62	24.16	Yes	< 0.01
2nd	4th	20.62	27.05	Yes	< 0.01
3rd	4th	40.05	44.84	Yes	< 0.01

Table: NIS inequalities in direction of increasing incentives (aggregate data pooled across prize sizes from the Dots task)

Dewan and Neligh (2020): Angles Design

- Same structure but angles of 35, 40, 45, 50, and 55 degrees



This is angle task number 2 out of 100.

A correct answer to this question is worth [illegible] points.

What is the angle between the two blue lines?

Dewan and Neligh (2020): Angles SDSC Data

$$P_1 = \begin{array}{cl} \begin{array}{ccccc} \omega = 35 & \omega = 40 & \omega = 45 & \omega = 50 & \omega = 55 \end{array} & \\ \begin{pmatrix} 0.0992 & 0.0416 & 0.0096 & 0.0010 & 0.0010 \\ 0.0734 & 0.0874 & 0.0422 & 0.0166 & 0.0088 \\ 0.0234 & 0.0560 & 0.0950 & 0.0592 & 0.0300 \\ 0.0038 & 0.0134 & 0.0440 & 0.0882 & 0.0808 \\ 0.0000 & 0.0016 & 0.0090 & 0.0350 & 0.0794 \end{pmatrix} & \begin{array}{l} \text{action a} \\ \text{action b} \\ \text{action c} \\ \text{action d} \\ \text{action e} \end{array} \end{array}$$

$$P_2 = \begin{array}{cl} \begin{array}{ccccc} \omega = 35 & \omega = 40 & \omega = 45 & \omega = 50 & \omega = 55 \end{array} & \\ \begin{pmatrix} 0.0982 & 0.0324 & 0.0112 & 0.0024 & 0.0004 \\ 0.0732 & 0.0814 & 0.0470 & 0.0150 & 0.0048 \\ 0.0238 & 0.0608 & 0.0878 & 0.0688 & 0.0268 \\ 0.0046 & 0.0236 & 0.0474 & 0.0806 & 0.0782 \\ 0.0000 & 0.0020 & 0.0066 & 0.0332 & 0.0894 \end{pmatrix} & \begin{array}{l} \text{action a} \\ \text{action b} \\ \text{action c} \\ \text{action d} \\ \text{action e} \end{array} \end{array}$$

Dewan and Neligh (2020): Angles SDSC Data

$$P_2 = \begin{array}{cccccc}
\omega = 35 & \omega = 40 & \omega = 45 & \omega = 50 & \omega = 55 & \\
0.0982 & 0.0324 & 0.0112 & 0.0024 & 0.0004 & \text{action a} \\
0.0732 & 0.0814 & 0.0470 & 0.0150 & 0.0048 & \text{action b} \\
0.0238 & 0.0608 & 0.0878 & 0.0688 & 0.0268 & \text{action c} \\
0.0046 & 0.0236 & 0.0474 & 0.0806 & 0.0782 & \text{action d} \\
0.0000 & 0.0020 & 0.0066 & 0.0332 & 0.0894 & \text{action e}
\end{array}$$

$$P_3 = \begin{array}{cccccc}
\omega = 35 & \omega = 40 & \omega = 45 & \omega = 50 & \omega = 55 & \\
0.1012 & 0.0346 & 0.0088 & 0.0010 & 0.0004 & \text{action a} \\
0.0722 & 0.0822 & 0.0436 & 0.0130 & 0.0060 & \text{action b} \\
0.0212 & 0.0662 & 0.0936 & 0.0608 & 0.0280 & \text{action c} \\
0.0044 & 0.0142 & 0.0416 & 0.0922 & 0.0778 & \text{action d} \\
0.0010 & 0.0028 & 0.0122 & 0.0330 & 0.0878 & \text{action e}
\end{array}$$

Dewan and Neligh (2020): Angles SDSC Data

$$P_3 = \begin{array}{c} \\ \\ \\ \\ \\ \end{array}\begin{array}{ccccc|c} \omega = 35 & \omega = 40 & \omega = 45 & \omega = 50 & \omega = 55 & \\ 0.1012 & 0.0346 & 0.0088 & 0.0010 & 0.0004 & \text{action a} \\ 0.0722 & 0.0822 & 0.0436 & 0.0130 & 0.0060 & \text{action b} \\ 0.0212 & 0.0662 & 0.0936 & 0.0608 & 0.0280 & \text{action c} \\ 0.0044 & 0.0142 & 0.0416 & 0.0922 & 0.0778 & \text{action d} \\ 0.0010 & 0.0028 & 0.0122 & 0.0330 & 0.0878 & \text{action e} \end{array}$$

$$P_4 = \begin{array}{c} \\ \\ \\ \\ \\ \end{array}\begin{array}{ccccc|c} \omega = 35 & \omega = 40 & \omega = 45 & \omega = 50 & \omega = 55 & \\ 0.0972 & 0.0368 & 0.0062 & 0.0030 & 0.0000 & \text{action a} \\ 0.0786 & 0.0756 & 0.0468 & 0.0186 & 0.0046 & \text{action b} \\ 0.0222 & 0.0730 & 0.0902 & 0.0648 & 0.0222 & \text{action c} \\ 0.0020 & 0.0124 & 0.0516 & 0.0818 & 0.0762 & \text{action d} \\ 0.0000 & 0.0022 & 0.0052 & 0.0318 & 0.0970 & \text{action e} \end{array}$$

Dewan and Neligh (2020): Angles Results

DP 1	DP 2	LHS	RHS	NIS inequality fail?	p-value
1st	2nd	5.84	5.69	No	0.22
1st	3rd	5.84	5.94	Yes	0.29
1st	4th	5.84	5.74	No	0.32
2nd	3rd	16.62	17.37	Yes	0.08
2nd	4th	16.62	16.79	Yes	0.36
3rd	4th	28.80	27.83	No	0.16

Table: NIS inequalities in direction of increasing incentives (aggregate data pooled across prize sizes from the Angles task)

Summary

Experiment	# of incentive levels	NIAS	NIAC	NIS rejected	NIS joint
		point estimate		$(\alpha = 0.05)$	p-value
DN23 1.2	4	Pass	Pass	Yes	< 0.01
DN23 2.2	2	Pass	Pass	No	0.38
CCLN	6	Pass	Fail	Yes	< 0.01
CCLN Difficulty 1	6	Pass	Fail	Yes	< 0.01
CCLN Difficulty 2	6	Pass	Fail	Yes	< 0.01
CCLN Difficulty 3	6	Pass	Fail	Yes	< 0.01
CCLN Difficulty 6	6	Pass	Fail	Yes	< 0.01
DN20 Dots	4	Pass	Pass	Yes	< 0.01
DN20 Angles	4	Pass	Fail	No	0.54

Table: Summary of results for aggregate data from all experiments

Conclusion

- Choice data are consistent with capacity-constrained learning if and only if they satisfy a *No Improving (Action or Attention) Switches (NIS)* condition
- Based on existing experiments: strong evidence that participants fail NIS
- Not true for all existing perceptual tasks in the literature

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