State Pooling and Belief Polarization

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Today's Presentation

- Motivating Example
- Research Question
- Related Literature
- State Pooling Model
- Laboratory Experiment

Motivating Example

Motivating Example

Setting

- Alice and Bob face a choice: go to the Theater or stay Home
  - Theater: uncertainty about the quality of the movie [state s]
  - Home: "safe" choice [status quo]

	Theater	Home	
s	$v_i^T(s)$	$v_A^H(s)$	$v_B^H(s)$
bad	0	0.45	0.55
medium	0.5	0.45	0.55
good	1	0.45	0.55

- Assume uniform prior $p_s = \frac{1}{3}$ and risk neutrality

Motivating Example

Scenario 1

- Alice and Bob have the same beliefs (expected quality)
  - $EV(\text{Theater}) = 0.5$
- Alice and Bob make different choices
  - A chooses Theater as $0.5 = EV(\text{Theater}) > EV(\text{Home}) = 0.45$
  - B chooses Home as $0.5 = EV(\text{Theater}) < EV(\text{Home}) = 0.55$

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Motivating Example

Scenario 2

- Same problem as before, but now A and B can collect "some" information about the movie quality
- Note that we have 2 actions (T/H) and 3 states (b/m/g)
  - For Alice it is *sufficient* to know if the movie is b or (m/g)

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Motivating Example

Scenario 2

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- Note that we have 2 actions (T/H) and 3 states (b/m/g)
  - For Bob it is *sufficient* to know if the movie is (b/m) or g

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Motivating Example

Scenario 2

- If the movie is good (bad) they agree about the action Theater (Home)
- But they do not agree about the expected quality of the movie
  - Good movie: $EV_A(T|g) = 0.75 < EV_B(T|g) = 1$
  - Bad movie: $EV_A(T|b) = 0 < EV_B(T|b) = 0.25$

- If the movie is medium they still disagree about the action
- But they also disagree about the expected quality of the movie
  - Alice chooses Theater: $EV_A(T|m) = 0.75$
  - Bob chooses Home: $EV_B(T|m) = 0.25$

Motivating example 2

Motivating Example

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- But they also disagree about the expected quality of the movie
  - Alice chooses Theater: $EV_A(T|m) = 0.75$
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▸ Motivating example 2

Motivating Example

Summary

- Alice and Bob have the same prior beliefs
- The introduction of **endogenous information collection** created disagreement about expected quality

- **State pooling**: avoid redundant information if the action space is smaller than the state space
- **Belief polarization**: posterior beliefs are more extreme because of the different relevant information

Motivating Example

Summary

- Alice and Bob have the same prior beliefs
- The introduction of **endogenous information collection** created disagreement about expected quality

- **State pooling**: avoid redundant information if the action space is smaller than the state space
- **Belief polarization**: posterior beliefs are more extreme because of the different relevant information

Research Question

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Can endogenous information acquisition provide an explanation for belief polarization?

Broad question that includes prior heterogeneity, update heterogeneity, confirmatory/contradictory strategies, etc.

How do DMs subjectively evaluate information?

Test whether agents:

- Seek information based on the impact on their action
- Ignore information without instrumental value (state pooling)

Jump to the Experimental design

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How do DMs subjectively evaluate information?

Test whether agents:

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Jump to the Experimental design

Related Literature

Related Literature

- Polarization is an ubiquitous phenomenon
- Information and belief polarization: McCarty, Poole and Rosenthal (2006), Boxell, Gentzkow and Shapiro (2017)
- Explanations for polarization based on exogenous information and/or exogenously imposed biases: Rabin, Schrag (1999); Fryer, Harms, Jackson (2017), Wilson (2014), Lord, Ross, Lepper (1979) [confirmation bias], Ortoleva and Snowberg (2015) [overconfidence and correlation neglect], Klayman and Ha (1987), Nickerson (1998) [positive test strategy]
- Confirmation bias and rational inattention: Su (2014), Nimark and Sundaresan (2018), Dixit and Weibull (2007) [prior heterogeneity]

▸ Related Literature

Experimental Literature

1. **Ambuehl and Li (2018)** ▸ Design
   - Systematic analysis of belief updating and demand for information
   - Compression effect: subjective valuation of useful information underreacts to increased informativeness
   - Biases mainly due to non-standard belief updating rather than risk preferences
2. **Charness, Oprea, Yuksel (2018)** ▸ Design
   - Study how people choose between biased information sources
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3. Vast experimental literature
   - Heterogeneity in belief updating: El-Gamal and Grether 1995, Fehr-Duda and Epper 2012, Augenblick and Rabin 2015, Buser et al 2016, Antoniou et al 2017.
   - Biases in demand for information: Eli and Rao 2011, Mobius et al 2011, Bursks et al 2013, Oster et al 2013, Sicherman et al 2015

State Pooling Model

Model

- Simplified RI model (Matveenko and Novak)
- Stage 1: collect information, stage 2: make a choice

- $N > 2$ possible states of the world $s \in \{1, ..., N\}$
- DM facing discrete binary choice problem $i \in \{1, 2\}$
- Binary actions - risky ("reform") and safe ("status quo")

- Risky option
  - value v_s, where $s \in 1, \ldots, n$
  - $v_i < v_j$ for $i < j$
- Safe option
  - value R
  - $v_k \leq R \leq v_{k+1}$ for some $k \in 1, \ldots, n-1$
  - Assumption: $v_1 < R < v_n$

Model

- p_s - prior belief state s realized, $\sum_{s=1}^{n} p_s = 1$
- **Stage 1: collect information**
  - Choose one "advisor" $(\pi_e, c_e) \in \{(\pi_e, c_e)\}_e$ [experiment-cost]
  - Pay the cost c_e to observe the experiment π_e
- **Observe signal realization and update beliefs**
- **Stage 2: make a choice**
  - Choose one action $a \in \{1, 2\}$
  - Safe action (return R) and risky action (return v_s)

Model

- The experiment π_e can generate only two signals $\sigma \in \{1, 2\}$ and is defined by the triplet $\pi(\sigma = 1|s)$
- The instrumental value of a signal structure π_e is

$$U(\pi_e) = \underbrace{\sum_{\sigma} v^*(p(s|\sigma))\pi(\sigma)}_{\text{EV with } \pi_e} - \underbrace{v^*(p(s))}_{\text{EV w/o } \pi_e}$$

where v^* is the expected value of the optimal action (conditional on available information)

- **Stage 1: collect information**
  - A rational agent chooses the signal structure

$$e^* = \text{argmax}_e U(\pi_e) - c_e$$

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- We can simplify further the calculation of the value
- Irrelevant experiments have $a^*(\varnothing) = a^*(\sigma = 1) = a^*(\sigma = 2)$

$$U(\pi_e) = 0$$

- Relevant experiments have wlog $a^*(\varnothing) = a^*(\sigma = 1) \neq a^*(\sigma = 2)$

$$U(\pi_e) = Pr(\sigma = 2) \cdot \Delta E[v^*|\sigma = 2]$$

Full Model (Matveenko and Novak)

- DM is rationally inattentive (Sims, 2003, 2006)
  - Information costly - Shannon cost
  - λ - marginal cost of information
  - $\kappa(P, G)$ - **expected reduction in entropy**
  - $G(v)$ prior distribution
  - $P(i|v)$ probability of choosing action i conditional on v

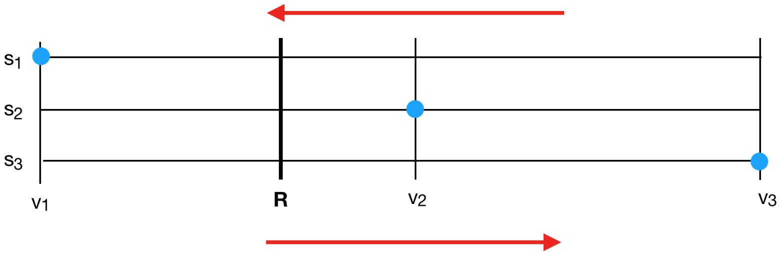
- Main result: possible "wrong direction" updating of beliefs dependent on respective position of prior beliefs and safe option. It leads to polarization (more extreme posterior beliefs).

Main Results

Theorem

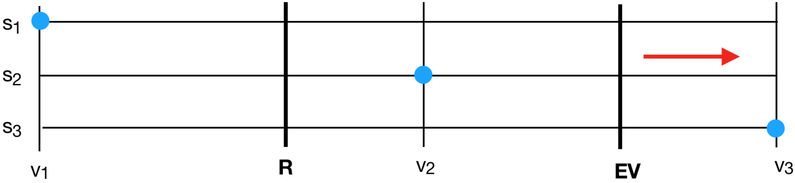
The sign of $(v_{s^*} - R)$ ***is the same as the sign of***
$\Delta_{EV} = E[EV_{post}] - EV_{prior}$

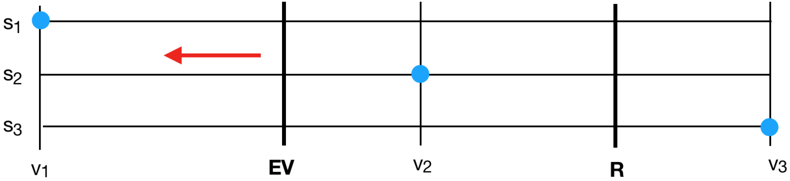
- Agent cannot be biased (cannot update against the true state)
  - when the realized state is $s^* = 1$ or $s^* = 3$



Updating in the Wrong Direction

- Agent is biased when $s^* = 2$ in the following cases
  - when $v_2 < R$ and at the same time $\mathbb{E}v < v_2$
  - when $v_2 > R$ and at the same time $\mathbb{E}v > v_2$





- And unbiased otherwise.

Simplified Model

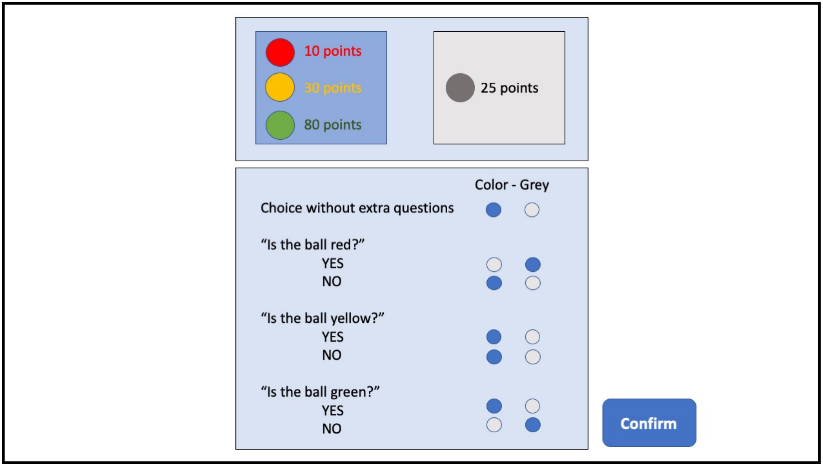
- Consider only pairs of advisors $\{(\pi_1, c_1), (\pi_2, c_2)\}$
- Two special cases of signal structure choice:
- $c_1 = c_2 = 0$ both signal structures are free
  - **The DM selects the most informative advisor**
- $c_1 > c_2 = 0$ only one signal structure is costly,
  but $\pi_2(\sigma = 1|s) = 1$, i.e. the free signal is not informative
  - **The DM selects the informative advisor only if $U(\pi_1) \geq c_1$**

Laboratory Experiment

Laboratory Experiment

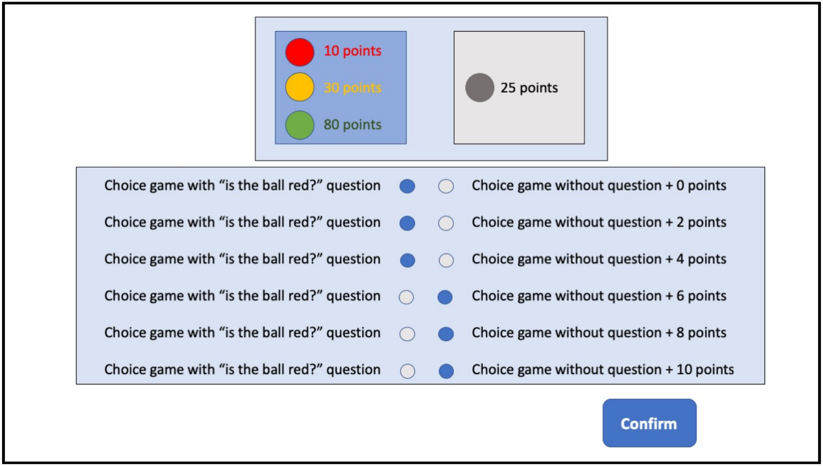
- **How do agents evaluate information?**
- Stage 1: choose or “hire” an advisor
- Observe signal realization
- Stage 2: choose an action [risky/safe]
- We want to collect separately
  - Action (conditional on posterior beliefs)
  - WTP for advisor / preferences over advisors
  - Posterior beliefs [guessing task]
- Deviations from optimality can enhance or reduce the predictions of the model
- A controlled lab setting allows to analyze individually all the components of the decision process

Part 1 - State Pooling and Signal Structure Valuation



Signal realization contingent choices - Collect actions $a_i(\sigma)$.

Part 1 - State Pooling and Signal Structure Valuation



Signal structure value elicitation - Collect subjective $U_i(\pi)$.

Part 1 - State Pooling and Signal Structure Valuation

We can test:

1. whether agents choose optimally in the binary choice stage, conditional on the available information
2. how they evaluate the additional information represented by the signal
3. whether the status quo affects choice and signal valuation (if subjects' reaction is qualitatively and quantitatively coherent with the optimal one)

Theoretical predictions:

- choose the lottery with the highest expected value
- the maximum v to pay in order to receive the signal is $U(\pi_e)$ (instrumental value)

Part 2 - Advisor Choice and Control Tasks

Are the results robust to noisy signal structures?

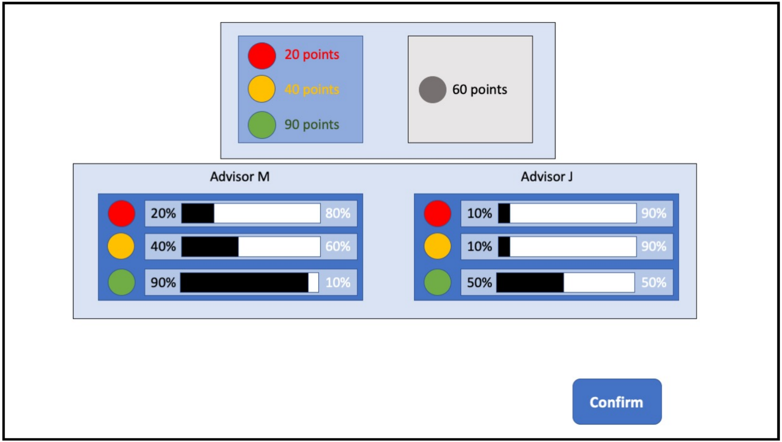
We can test:

1. if agents choose signal structures that are more informative in instrumental way
2. if agents correctly update own beliefs
3. if agents correctly estimate the probability of each realization

$$EV_e = E[v(\sigma)|\sigma = 0] \cdot P(\sigma = 0) + E[v(\sigma)|\sigma = 1] \cdot P(\sigma = 1)$$

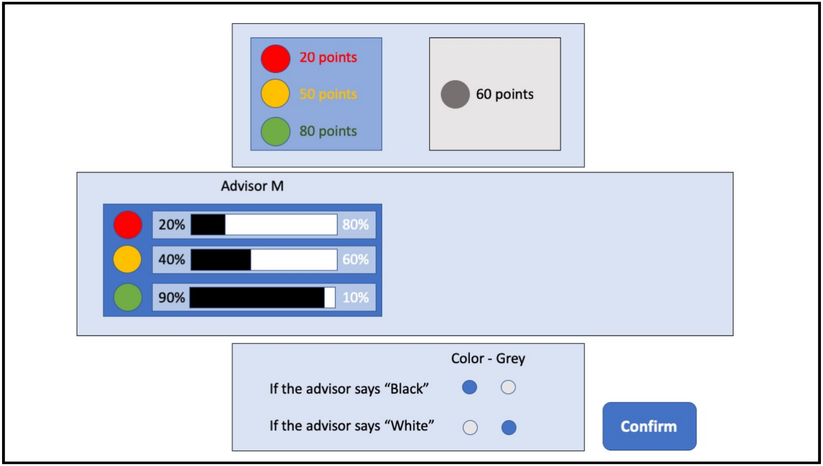
The EV given a signal structure e is a function of the strategy $v(\sigma)$ conditional signal realization σ. We record separately subjective estimates of $P(s|\sigma)$ and $P(\sigma = 0)$

Part 2 - Task A - Collect preferences over advisors



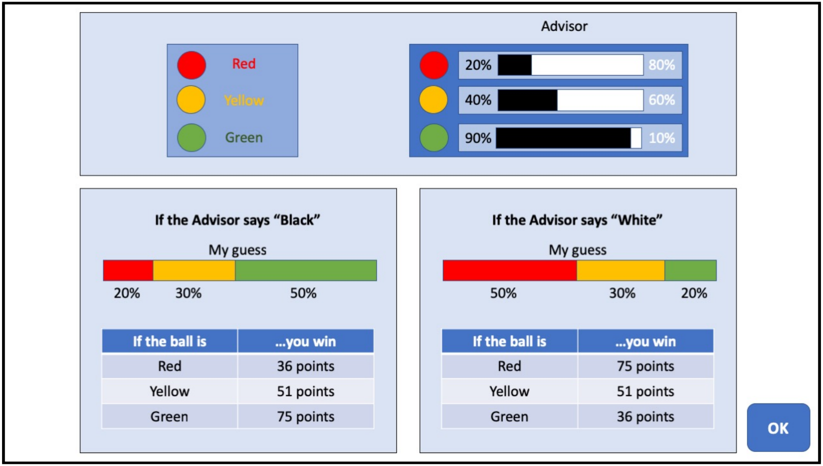
Binary advisor choice - Collect preference over π_e ($c = 0$).

Part 2 - Task A - Collect actions



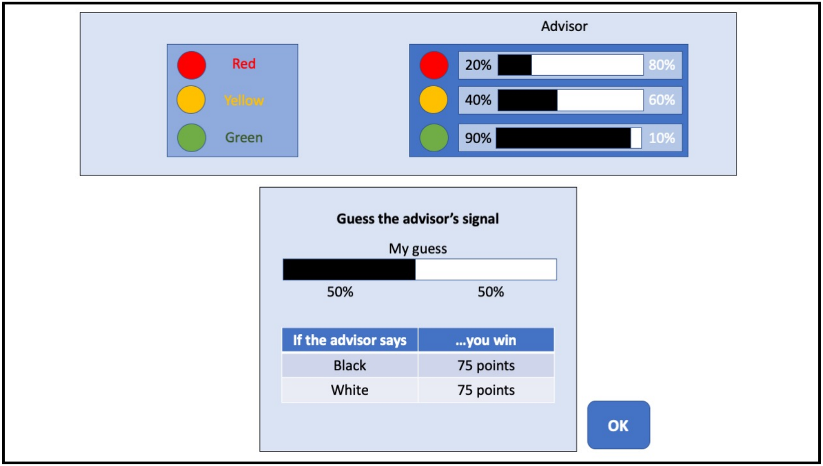
Signal realization contingent choice - Collect actions $a_i(\sigma)$.

Part 2 - Task B - Collect posterior beliefs



Posterior beliefs elicitation (exogenous signal structure) - Collect $\hat{p}_i(s|\sigma)$.

Part 2 - Task C - Collect signal realization beliefs



Signal probability elicitation (exogenous signal structure) - Collect $\hat{p}_i(\sigma)$.

Part 2 - Advisor Choice and Control Tasks

We are mostly interested in Task A (advisor choice), but we need B and C (guess tasks) for robustness.

Choose pairs of signal structures $\{\pi_1, \pi_2\}$ such that:

1. they have the same information about the states (Shannon entropy reduction)
2. π_1 should be chosen if $R < \overline{R}$
3. π_2 should be chosen if $R > \overline{R}$

The same pairs appears in two separate trials, with different status quo R.

Summary

Motivation: Empirical evidence of belief polarization

Information valuation

$\Downarrow$

Endogenous information acquisition

$\Downarrow$

Belief polarization

- RI model with N>2 states and binary choice
- State pooling depends on status quo (safe action)
- **Prediction** about optimal information acquisition
- Lab experiment to test separately the **assumptions**

State Pooling and Belief Polarization

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Part 3 - Sequential Information Collection

Are the results robust to a more complex environment?

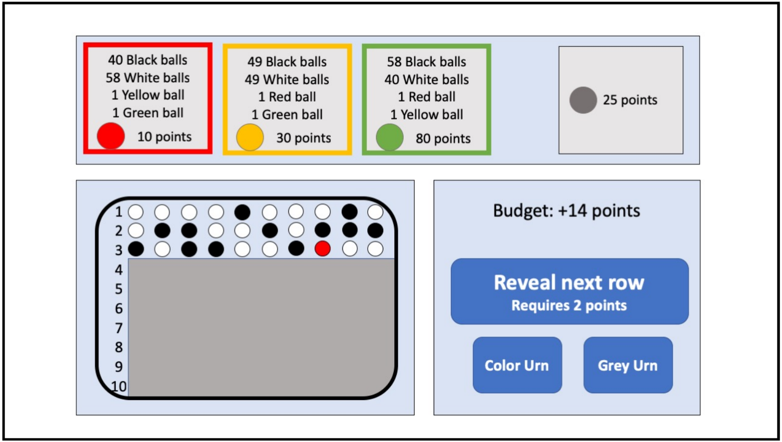
We can test:

1. whether agents adapt their strategy to the environment
2. whether "sampling" and actions follow the theoretical predictions (including state pooling)

Task with a *rational inattention* flavor:

- the true state can be exactly revealed
- cheaper signals are less informative

Part 3



Sequential information collection - Gradual resolution of uncertainty.

Appendix - The Model

Agent's problem

Denote: $\mathbf{v} = (v_1, \ldots, v_n)$, $G(\mathbf{v})$ - prior joint distribution
Find an information strategy maximizing:

$$\max_{P(i|v)} \left\{ \sum_{i=1}^{2} \int_{\mathbf{v}} v_i P(i|\mathbf{v}) G(d\mathbf{v}) - \lambda\kappa(P, G) \right\},$$

where

$$\kappa(P, G) = -\sum_{i=1}^{2} P_i^0 \ln P_i^0 + \int_{\mathbf{v}} \left(\sum_{i=1}^{2} P(i|\mathbf{v}) \ln P(i|\mathbf{v}) \right) G(d\mathbf{v}).$$

$P(i|v)$ is the conditional on the realized value of v, the probability of choosing option i and

$$P_i^0 = \int_{\mathbf{v}} P(i|\mathbf{v}) G(d\mathbf{v}), \;\; i = 1, 2$$

where P_i^0 is the unconditional probability of option i to be chosen.

Lemma 1 (Matějka, McKay, 2015)

Conditional on the realized state of the world s^* probability of choosing risky option is

$$P(\text{picking risky}|\text{state is } s^*) = \frac{P_1^0 e^{\frac{v_s^*}{\lambda}}}{P_1^0 e^{\frac{v_s^*}{\lambda}} + (1 - P_1^0) e^{\frac{R}{\lambda}}}$$

of choosing safe option is:

$$P(\text{picking safe}|\text{state is } s^*) = \frac{(1 - P_1^0) e^{\frac{R}{\lambda}}}{P_1^0 e^{\frac{v_s^*}{\lambda}} + (1 - P_1^0) e^{\frac{R}{\lambda}}}$$

here P_1^0 is unconditional probability of choosing risky option.

Beliefs

- Agent's prior expected value of the risky option is:

$$\mathbb{E}v = \sum_{s=1}^{n} v_s g_s$$

we **fix the state** of the nature: it is s^*

- Observer sees agent's updated belief about the average of v:

$$\mathbb{E}_i[\mathbb{E}(v|i)|s^*] = P(i = 1|s^*)\mathbb{E}(v|\text{picking option 1})+ \\ + (1 - P(i = 1|s^*))\mathbb{E}(v|\text{picking option 2})$$

where for option $i \in \{1, 2\}$

$$\mathbb{E}(v|\text{picking option i}) = \sum_{j=1}^{n} v_i P(\text{state is j}|\text{picking option i})$$

Beliefs

Theorem

Expected posterior value of the risky option for a rationally inattentive decision maker is

$$\mathbb{E}_i[\mathbb{E}(v|i)|s^*] = \sum_{i=1}^{n} v_i g_i \frac{\alpha_{s^*} e^{\frac{v_i}{\lambda}} + (1-\alpha_{s^*})e^{\frac{R}{\lambda}}}{P_1^0 e^{\frac{v_i}{\lambda}} + (1-P_1^0)e^{\frac{R}{\lambda}}} \tag{1}$$

where

$$\alpha_{s^*} = \frac{P_1^0 e^{\frac{v_{s^*}}{\lambda}}}{P_1^0 e^{\frac{v_{s^*}}{\lambda}} + (1-P_1^0)e^{\frac{R}{\lambda}}}$$

Updating of beliefs

We are interested in

$$\Delta = \mathbb{E}_i[\mathbb{E}(v|i)|s^*] - \mathbb{E}v$$

Theorem

The sign of Δ is the same as the sign of $(v_{s^*} - R)$.

Proof.

Straightforward and we use:

Lemma 2

Relations $\alpha_{s^*} \gtrless P_1^0$ under $P_1^0 > 0$ are equivalent to $v_{s^*} \gtrless R$

$\square$

Example 3 states, 2 actions

- 3 possible states of the world - indexed by s
- 2 options/actions - indexed by a
  - Option 1 - Risky with values: $v_1 < v_2 < v_3$
  - Option 2 - Safe option with value R in all states
- Prior belief about the states: g_1, g_2, g_3
- Marginal cost of information: λ

Assumption 1: to rule out uninteresting cases

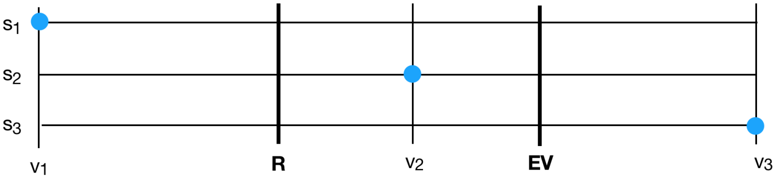
$$v_1 < R < v_3$$

Updating in "wrong" direction

We are interested when the conditional expectation moves in the **"wrong" direction**

Example for $s^* = 1$ the expectation "should" go down, so the agent is biased when

$$\mathbb{E}_a[\mathbb{E}(v|a)|s^*] > \mathbb{E}v > 0$$



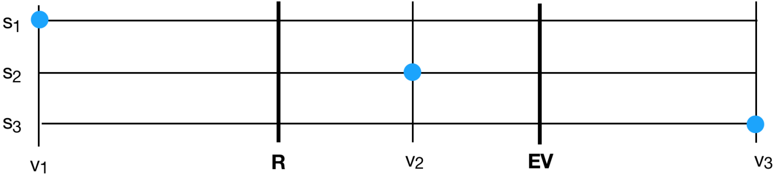
Updating in "wrong" direction

Let's denote $\Delta = \mathbb{E}_a[\mathbb{E}(v|a)|s^*] - \mathbb{E}v.$

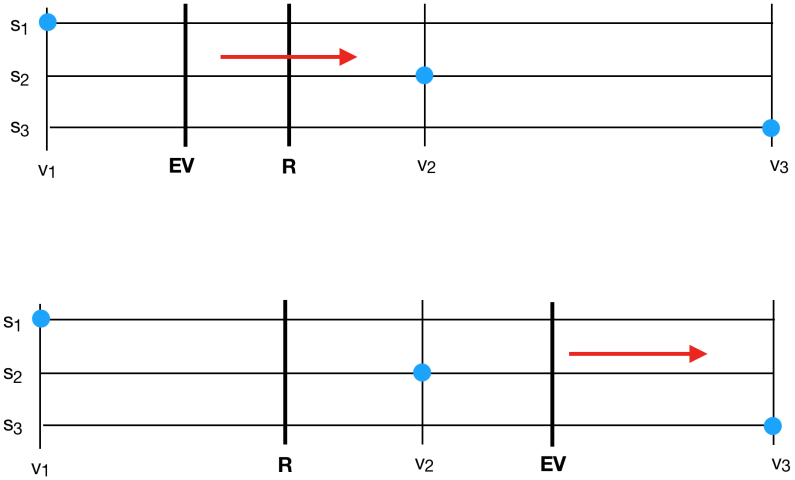
If

$$(\mathbb{E}v - v_{s^*}) \cdot \Delta > 0$$

then the agent is updating belief in the wrong direction



Result



Related Literature

Information and Belief Polarization

- Polarization is an ubiquitous phenomenon
- Mixed evidence of how information contributes to polarization
  - Politicians and voters more polarized despite increased availability of information
    McCarty, Poole and Rosenthal (2006)
  - Greater Internet use is not associated with faster growth in political polarization among US demographic groups
    Boxell, Gentzkow and Shapiro (2017)

Multiple Explanations for Polarization

1. **Confirmation bias**
   - Misreading ambiguous signals: Rabin, Schrag (1999); Fryer, Harms, Jackson (2017)
   - Limited memory: Wilson (2014)
   - Experiments: Lord, Ross, Lepper (1979)
2. **Overconfidence and correlation neglect**
   - Ortoleva and Snowberg (2015)
3. **Positive test strategy**
   - Klayman and Ha (1987), Nickerson (1998)

Results mostly based on exogeneous information and/or exogeneously imposed biases.

Confirmation Bias and Rational Inattention

1. **Su (2014)**
   - Gaussian signal + quadratic loss function
   - Attention proportional to observation window
   - Results: conformism in learning

2. **Nimark and Sundaresan (2018)**
   - Mainly focus on polarization persistence
   - Agent pays more attention to the states which are more likely

3. **Dixit and Weibull (2007)** - not RI
   - Learning about policy in place (signal bimodal)
   - Agents agree on loss function, disagree on probabilities of states
   - Status quo vs. new reform - Divergence of opinions

Experimental Literature

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