Top-Down or Bottom-Up?

Disentangling Channels of Attention in Risky Choice

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Motivation

- Attention is an important mechanism for the decision process.
- Economics: Increased interest in attention
  - Rational Inattention (Sims, 2003; Gabaix, 2019; Avoyan and Schotter, 2020)
  - Salience theory (Bordalo et al., 2013)
  - Sequential sampling models (e.g., Krajbich et al., 2010, 2012; Fudenberg et al., 2018, 2020)
  - Game Theory and rationality (Brocas et al., 2014; Polonio et al., 2015, e.g.,)
- Advances in capturing (visual) attention in experimental settings have improved drastically over the years
  - Reduced cost and increased efficiency of eye-trackers
  - MouselabWeb (Willemsen and Johnson, 2011)
  - Webcam ET (still work in progress)

What do we get from attention data?

- Too much...

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- Too much...
- Multiple variables like:
  - Fixation-Times / Total Dwelling-Time (or proportion of time)
  - Saccades
  - First/Last Fixations
  - Time to first fixation
  - Pupil Dilation
- The dimensions of these variables scale up with the amount of stimuli
- These variables give us information about:
  - Stimulus relative importance (dwell-times, first/last fixation)
  - Strategies in the decision process (saccades)
  - Engagement (Time to first fixation)
  - Emotional reaction to stimulus (Pupil dilation)

How can we use attention in our experiments?

- This is the real question

How can we use attention in our experiments?

- This is the real question
- There are multiple frameworks/approaches:
  - attentional Drift-Diffusion model
  - Clustering analysis
  - Rational Inattention
  - Attention-based models (Pachur et al., 2018, e.g.,)
- Attention-based models use the theory from cognitive psychology and neuroscience and connects it with theoretical models.
- The problem is that attention is connected with the decision process in multiple ways.
- How to incorporate attention to a DM model is very important and not trivial.

In this presentation

We will see:

- When and how attention can be useful
- Empirical model that incorporates attention
- Theory and assumptions behind it
- Some results from different studies

Decision Process

- Consider a population of agents J
- They have to make a series of decisions $\{d_{i,t}\}_{t \in T}$ for all $i \in J$
- In order decide, the agents need to collect information $\{x_k\}_{k \in K}$
- We assume agents linearly integrate the information and make their decision based on this.

$$d_{i,t} = \alpha_{i,0} + \sum_{k \in K} \omega_{i,k,t} x_{k,t} + \nu_{i,k,t}$$

- Where $\omega_{i,k,t}$ is the decision weight for attribute k.
- The decision weight can have individual- and trial-specific effects.

Decision weights and attention

The links between attention and the decision weights (Review in Orquin and Mueller Loose, 2013) for example:

- Relevant information is attended for longer
- Processing information is easier if you look at it
- Salient/striking information can influence choice

We model the link between attention and the decision weights as follows:

$$\begin{aligned} a_{i,k,t} &= \eta_{i,k} + \sum_{l} z^{l}_{k,t} + \epsilon^{a}_{i,k,t} \\ \omega_{i,k,t} &= \pi_{k,\eta}\eta_{i,k} + \sum_{l} z^{l}_{k,t}\beta^{l}_{k} + \epsilon^{\omega}_{i,k,t} \end{aligned}$$

- Individual differences $\eta_{i,k}$ in attention (e.g., preferences)
- Contextual factors $z_{k,t}$ affecting attention (e.g., Salience, Available info on trial, within-subject treatments, learning)

Estimating the factors

$$\begin{aligned} a_{i,k,t} &= \eta_{i,k} + \sum_{l} z^{l}_{k,t} + \epsilon^{a}_{i,k,t} \\ \omega_{i,k,t} &= \pi_{k,\eta}\eta_{i,k} + \sum_{l} z^{l}_{k,t}\beta^{l}_{k} + \epsilon^{\omega}_{i,k,t} \end{aligned}$$

- Our goal is to have better estimates of $\omega_{i,k,t}$ based on the attention data $A = \{a_{i,k,t}\}_{t \in T, i \in J, k \in K}$ and any observables O.
- We estimate $E(\eta_{i,k}|A, O)$ and $E(z_{k,t}|A, O)$ on a first stage.
- Then use them to estimate:

$$E(\omega_{i,k,t}|A, O) = \pi_{k,\omega} E(\eta_{i,k}|A, O) + E(z'_{k,t}|A, O)\beta_k$$

Estimating the factors

$$
\begin{aligned}
a_{i,k,t} &= \eta_{i,k} + \sum_{l} z^{l}_{k,t} + \epsilon^{a}_{i,k,t} \\
\omega_{i,k,t} &= \pi_{k,\eta}\eta_{i,k} + \sum_{l} z^{l}_{k,t}\beta^{l}_{k} + \epsilon^{\omega}_{i,k,t}
\end{aligned}
$$

- Consider the Fixed-Effects regression:

$$
a_{i,k,t} = \mu_{i,k} + O_t\delta_k + \varepsilon_{i,k,t}
$$

- Assume every observable is linked to one specific contextual factor $z^{l}_{k,t} \in z_{k,t}$.
- $O^{l}_{t} \subseteq O_t$ are the observables associated to $z^{l}_{k,t}$

Estimating the factors

$$a_{i,k,t} = \eta_{i,k} + \sum_l z^l_{k,t} + \epsilon^a_{i,k,t}$$

$$\omega_{i,k,t} = \pi_{k,\eta}\eta_{i,k} + \sum_l z^l_{k,t}\beta^l_k + \epsilon^\omega_{i,k,t}$$

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- Assume every observable is linked to one specific contextual factor $z^l_{k,t} \in z_{k,t}$.
- $O^l_t \subseteq O_t$ are the observables associated to $z^l_{k,t}$

$$E(\eta_{i,k}|A,O) = \hat{\mu}_{i,k}$$

$$E(z^l_{k,t}|A,O) = O^l_t\hat{\delta}_k$$

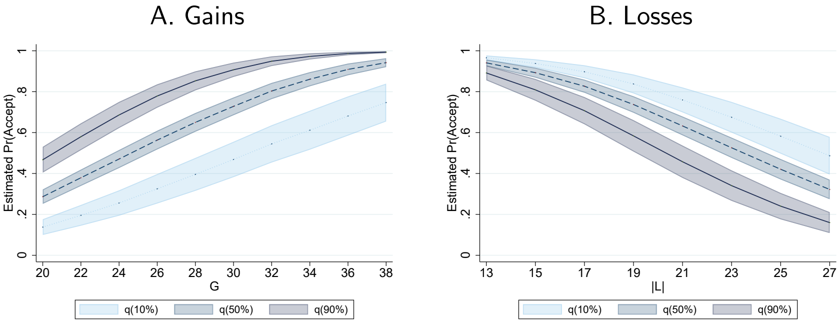
$$E(\omega_{i,k,t}|A,O) = \pi_{k,\eta}\hat{\mu}_{i,k} + \sum_l \hat{z}^l_{k,t}\beta^l_k$$

Expected Individual factors

$$E(\omega_{i,k,t}|A,O) = \pi_{k,\eta}\hat{\mu}_{i,k} + \sum_{l} \hat{z}^{l}_{k,t}\beta^{l}_{k}$$

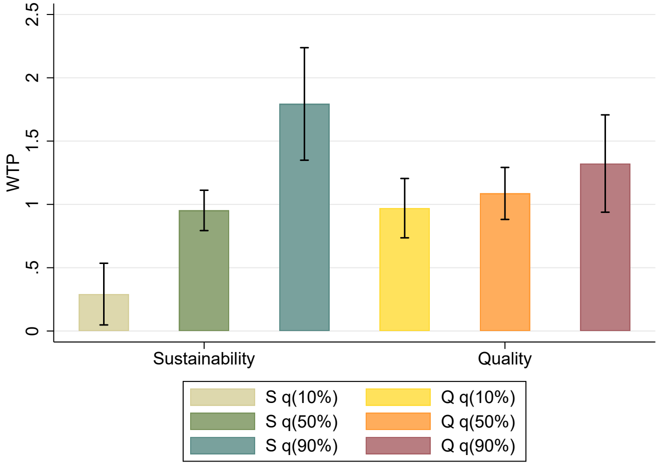
- Preferences: More relevant information is attended for longer and more times
- Strategies: Information that is needed more, is visited more often.
- Then: $\pi_{k,\eta} > 0$

Example 1: Gains vs. Losses



Source: Engelmann, Hirmas & van der Weele (2021) [WP]

Example 2: Sustainability vs. Quality



Source: Hirmas & Engelmann (2022) [WP]

Contextual factors

$$E(\omega_{i,k,t}|A, O) \quad = \quad \pi_{k,\eta}\hat{\mu}_{i,k} + \sum_{l} \hat{z}^{l}_{k,t}\beta^{l}_{\omega,k}$$

We consider three potential contextual factors:

- Consideration Sets / Structural Changes:
  Easier contexts, faster processing $\beta^{CS}_{k} \leq 0$
- Visual salience: $\beta^{VS}_{k} > 0$
- Learning: decisions are more efficient and faster $\beta^{CS}_{k} \gtrless 0$

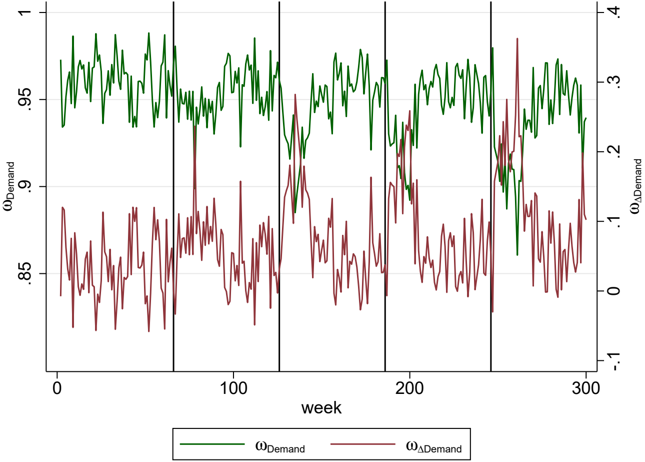
Contextual factors

$$E(\omega_{i,k,t}|A,O) \;=\; \pi_{k,\eta}\hat{\mu}_{i,k} + \sum_{l} \hat{z}^{l}_{k,t}\beta^{l}_{\omega,k}$$

We consider three potential contextual factors:

- Consideration Sets / Structural Changes:
  Easier contexts, faster processing $\beta_k^{CS} \leq 0$
- Visual salience: $\beta_k^{VS} > 0$
- Learning: decisions are more efficient and faster $\beta_k^{CS} \gtrless 0$
- When to expect which?
  - Pseudo-randomization in trials / great variance in stimuli: Consideration Sets
  - Visual / Position changes in stimuli: Visual Salience
  - Many trials: Learning

Example 2: Structural changes



Source: Torres et al. (2022) [WP]

Summary

- Using visual attention in experiments is getting easier
- Using attention data in estimations is not straightforward
- We propose a simple method to separate different mechanisms linking attention and decision process
- Factors:
  - Individual factors
  - Consideration Sets / Structural changes
  - Visual Salience
  - Learning

More information in my Website

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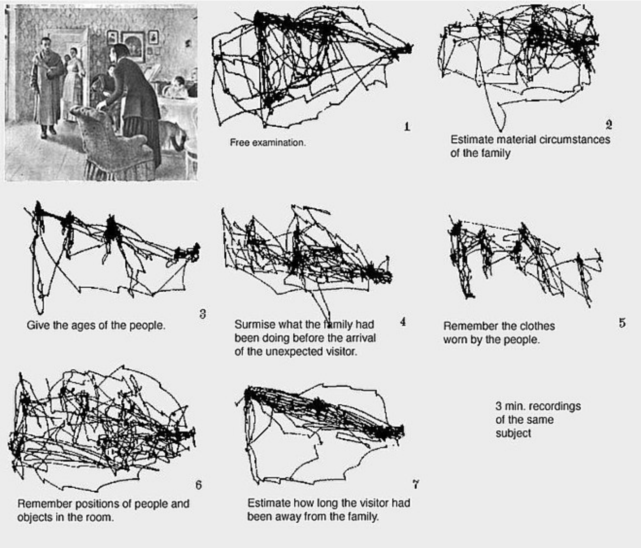
Yarbus (1967)


1
Free examination.
2
Estimate material circumstances of the family
3
Give the ages of the people.
4
Surmise what the family had been doing before the arrival of the unexpected visitor.
5
Remember the clothes worn by the people.
6
Remember positions of people and objects in the room.
7
Estimate how long the visitor had been away from the family.
3 min. recordings of the same subject