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Impulsive Decision Making

Findings from the modeling of 3 versions of the Iowa Gambling Task

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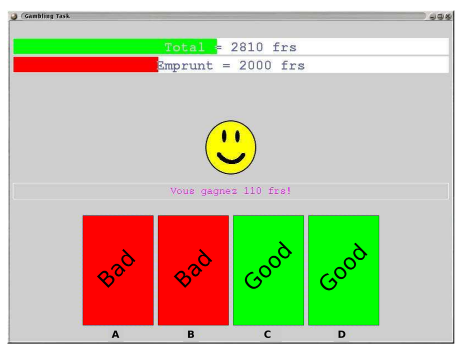
The Iowa Gambling Task (IGT)

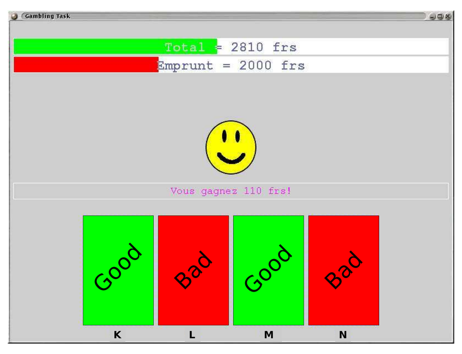
- The ABCD version of the IGT (Bechara et al., 1994) is frequently used in neuropsychology and psychopathology to assess decision-making;
- Participants have to select among 4 decks of cards, each selection is followed by a reward or a punishment (gain or loss of fictive money). Selections are repeated 100 times;
- Bad decks are disadvantageous (loss in the long run), good decks are advantageous (gain in the long run).

New versions of the IGT

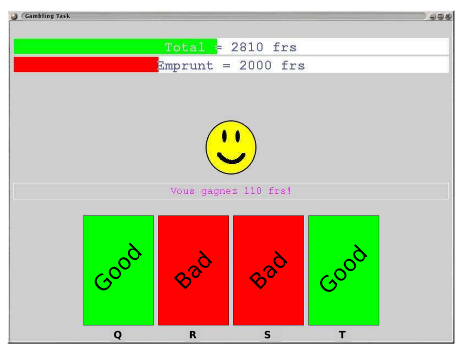
- Version KLMN and QRST were recently created to allow repeated assessments of decision making;
- Position of the good decks changes from one version to the other;
- Difficulty increases from one version to the other.



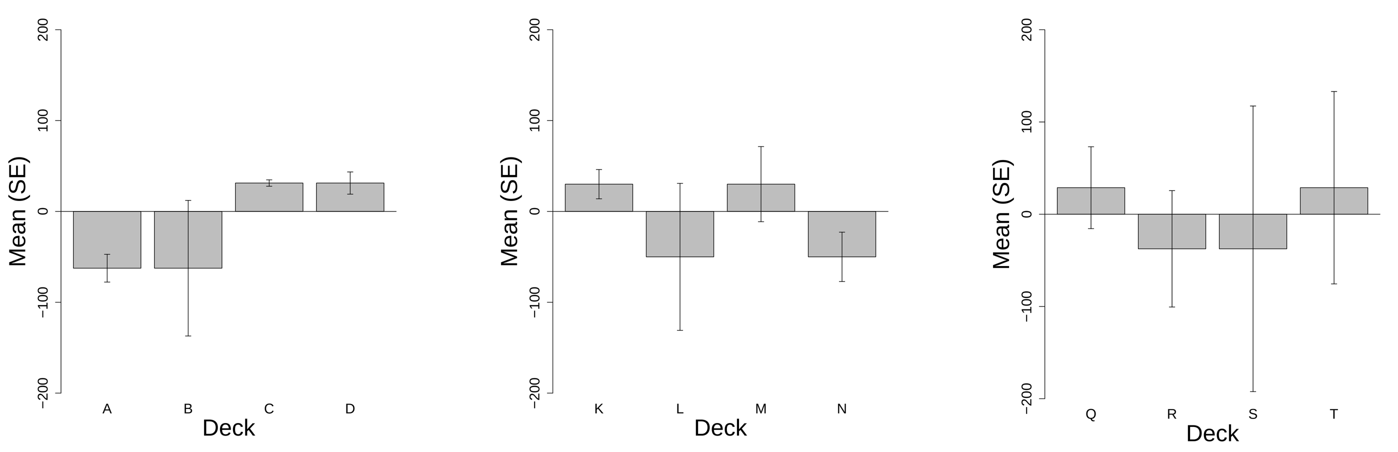
Version ABCD.



Version KLMN.



Version QRST.



Expected gain.

Modeling decision-making

- Decision-making in the IGT depends on several psychological processes;
- Authors (Busemeyer & Stout, 2002) have used a reinforcement learning model with 3 parameters to explain performance in the IGT:
  1. An updating rate ($0 < \beta < 1$);
  2. A sensitivity to reward ($0 < \sigma < 1$);
  3. An exploration tendency ($0 < \tau$).

Rational and aims

- The ABCD version has been used to model decision-making;
- This is problematic because it has been shown that model parameters are unreliable when estimated on only 100 trials (d'Acremont et al., 2006);
- Based on this limitation, our aims were twofolds:
  1. See if the model parameters are more reliable when estimated on the 3 versions of the IGT offering 300 trials (simulation);
  2. Estimate the model parameters on data collected with the 3 versions of the IGT and explore their relationships with impulsivity (application on real data).

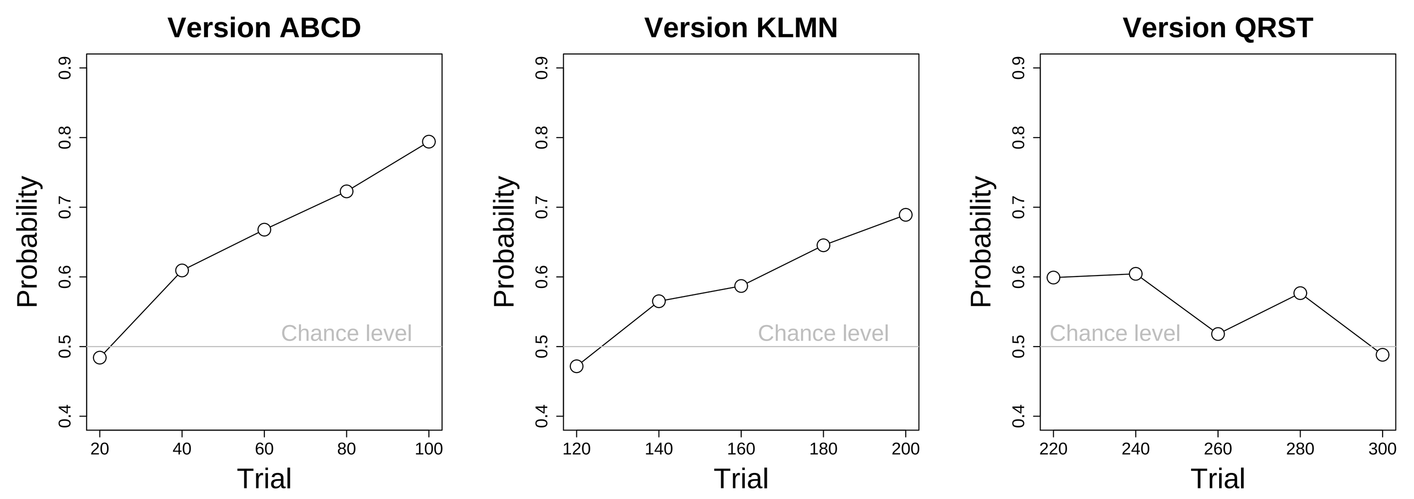
Simulated decisions

Reinforcement learning algorithm:

Initialize action probability $p_i = 0.25, \quad i = 1, \ldots, 4$
Initialize action value $\texttt{ActVal}_i = 0, \quad i = 1, \ldots, 4$
for $k = 1 : n$ **do**
  Select deck i according to p
  $\texttt{RewVal} = (\sigma\,\texttt{Reward}_i + (1-\sigma)\,\texttt{Punish}_i)$
  $\texttt{PredErr} = \texttt{RewVal} - \texttt{ActVal}_i$
  $\texttt{ActVal}_i = \texttt{ActVal}_i + \beta\,\texttt{PredErr}$
  $x_i = \exp(\texttt{ActVal}_i/\tau), \quad i = 1, \ldots, 4$
  Update action probability $p_i = x_i / \sum_{j=1}^{4} x_j$
end for

Simulation on version ABCD, KLMN, and QRST:

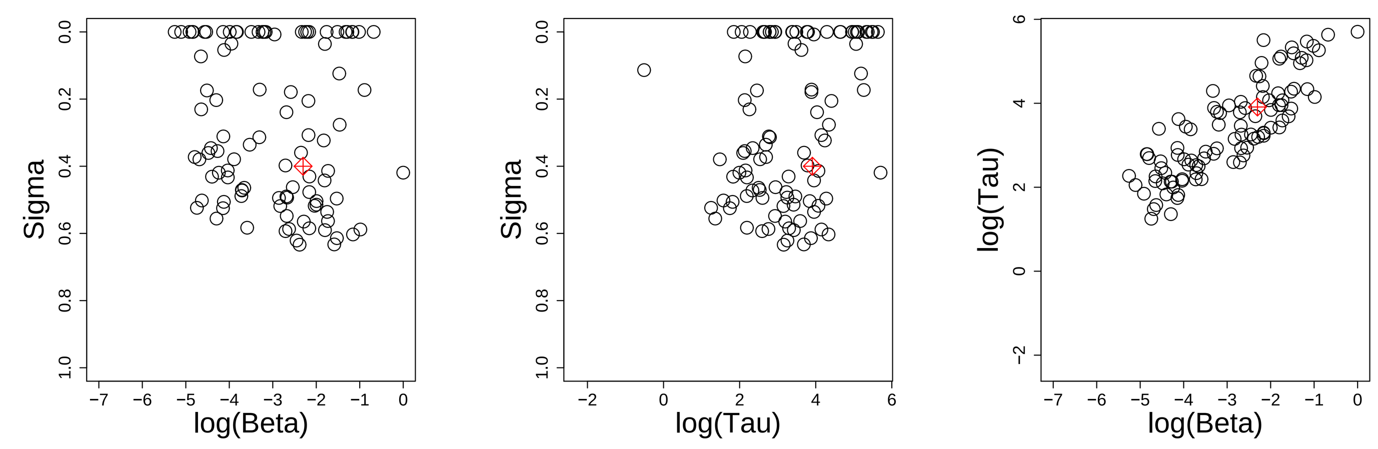
- Parameters in the learning algorithm are fixed to: a moderate updating rate ($\beta = .10$), a low sensitivity to reward ($\sigma = .40$), and a tendency to explore the environment ($\tau = 50$);
- The learning algorithm is used to simulate the decision of one "subject";
- Results indicate that the probability to select the good decks increases with trials in the ABCD and KLMN version ⇒ the algorithm learns to take advantageous decisions;
- There is no learning in the QRST version ⇒ this result reflects the difficulty of version QRST.



Probability to select the good decks.

Estimation on version ABCD:

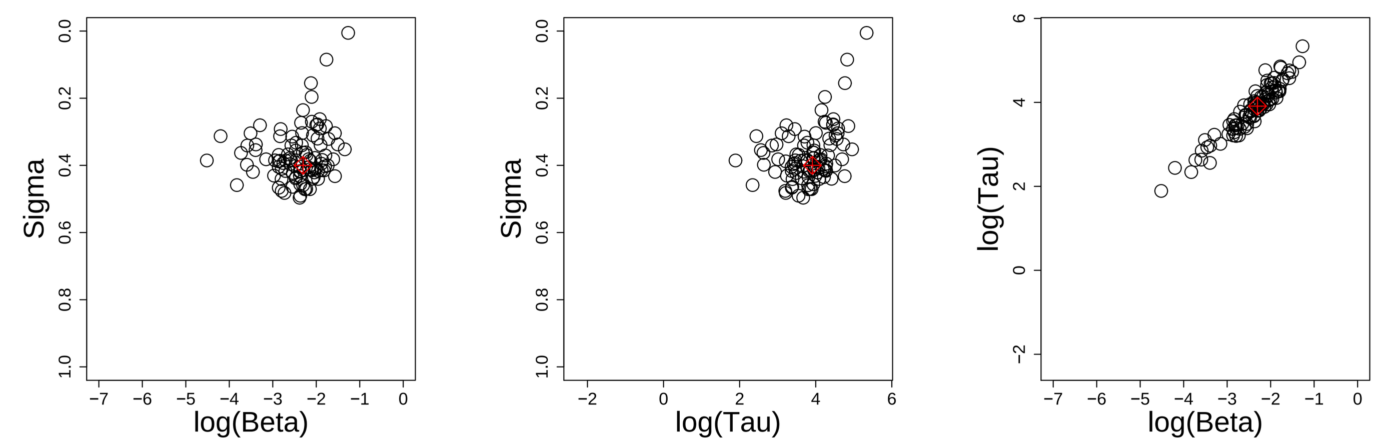
- Parameters in the learning algorithm are fixed to the same values: ($\beta = .10$, $\sigma = .40$, $\tau = 50$);
- Decisions for 100 "subjects" are simulated with the learning algorithm on version ABCD;
- For each "subject", the models parameters are estimated by mean of maximum likelihood;
- Results show a high variability of the estimated parameters around the fixed parameters.



The red point = fixed parameters. Small points = estimated parameters for 100 "subjects".

Estimation on version ABCD, KLMN, and QRST:

- The same strategy is used, but decisions for the 100 "subjects" are simulated on the 3 versions;
- Results show a reduced variability of the estimated parameters around the fixed parameters ⇒ the reliability of the estimated parameters increased with the use of the 3 versions;



The red point = fixed parameters. Small points = estimated parameters for 100 "subjects".

Parameter estimation from real data

- 61 adults completed successively the 3 versions of IGT and the UPPS Impulsive Behavior Scale (Whiteside & Lynam, 2001);
- The model parameters (β, σ, τ) were estimated for each subject on the 300 trials;
- A significant correlation was found between lack of Premeditation (one aspect of impulsivity) and sensitivity to reward, r = .34*, 95% CI = (.09, .55);
- This results corroborate the hypothesis of a higher sensitivity to reward in impulsive subjects (Corr et al., 1995);

Conclusions

- Simulation revealed that the use of 3 versions of the IGT gives a more accurate estimation of the parameters;
- An application on real data showed a meaningfull relationship between one aspect of impulsivity and decision-making.

References

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