# Methods

## Experimental design

The experiment was controlled using Opensesame (Mathôt et al., 2012) with PsychoPy (Peirce, 2007) as backend. The experiment consisted of four phases in the scanner: Preconditioning, Conditioning, Distractor/Localizer, Inference; in addition to a quick memory test outside the scanner at the end. In all the phases except the distractor/Localizer phase, the stimulus duration was always 1.5s.

The Preconditioning phase consisted of six runs in which each of the stimuli pairs (16 Scene-Object pairs and 4 Scene-Scene distractor pairs) was presented once (120 trials total). Eight of those pairs were semantically linked, and eight were not. Using neurodesign (Durnez et al., 2018; adapted for python3 by Peer Herholtz on github.com/amazinger13), the order and the ITIs were optimized within blocks for better signal deconvolution. The ITIs (showing a fixation cross) between trials (i.e. between pairs) were taken from a truncated exponential distribution (between 1.5 and 10s) of mean 2.5s. The relatively high lower range of the ITI distribution (1.5s) was chosen to facilitate learning, with a ITI close to two ISIs (Delgado et al., 2011; Walther, 2002; Wimmer & Shohamy, 2012). The ISIs (showing a blank screen) between the two stimuli of the pair were randomly jittered across 3 values (.8s, 1s, 1.2s) so that each pair experienced each ISI value twice. The participants were instructed to press the left or right button (balanced across participants) when the second image of a pair was a repeated scene, in order to keep them attentive.

The conditioning phase consisted of four runs in which each pair (16 Object-Outcome pairs) was presented three times (192 trials total). This high number of repetition (12 per pair) allows for a real dopaminergic system response to be put in place, although the associations were learned in 2 to 5 repetitions. Out of the 8 rewarded Objects, 4 were previously paired with a semantically linked Scenes, and 4 were paired with non-semantically linked Scenes. The same was also true for the non-rewarded Objects. As in the Preconditioning phase, order and ITIs were optimized using neurodesign, and the ITIs were taken from a truncated exponential distribution (between .5s and 10s) of mean 2s, as in Wimmer & Shohamy, 2012. The ISIs (between object and outcome) were randomly jittered across 3 values (.8s, 1s, 1.2s) so that each pair experienced each ISI value once in each block. The participants were instructed to predict whether the Object image was going to be rewarded (the outcome was an image of a 20 euro-cents coin) by pressing the left button, or not rewarded (the outcome was an image of a grey circle in place of the coin) by pressing the right button (balanced across participants). In case of an incorrect prediction of a reward, the grey circle was slightly redder; and in the case of an incorrect prediction of no reward the coin was replaced by a scrambled coin. The participants were told that the gains were real in the case of correct prediction of a reward. However, to avoid the strategy of always predicting a reward, they were informed that more than 16 erroneous predictions of a reward when there was none would result in a 5 euros penalty (I am not sure about the penalty; the maximum to win is 32€, but they would probably get around 25€, so 5 seems fair?). The rewarded and non-rewarded objects were balanced across participants.

The Distractor/Localizer phase consisted of 8 blocks of 13 stimulus, with each block having only one category of stimulus (scene or object) and having three out of ten unique stimuli repeated once. The stimulus was presented for 2s and separated by a .3s fixation cross. The participants were instructed to press right or left (same as in the Preconditioning phase) when they saw an image repeating.

The Inference phase consisted of two runs of each scene (16) presented twice in each run, followed by two runs of each object (16) presented twice in each run (128 trials total). During this phase, the outcome is not shown. As for the Preconditioning and Conditioning phases, the order and ITIs were optimized for better signal. The ITIs (fixation cross) were taken from a truncated exponential distribution (between .5s and 10s) of mean 2s, and an additional 1s blank screen was presented just after each stimulus. The participants were instructed that they should transfer the value they had learn about objects to the associated scenes, and that they should predict the rewarded state of the stimuli as in the Conditioning phase, but without feedback this time. They were also instructed that the gains would be 20cts per correctly predicted reward as before.

In the Memory phase, both a scene and an object were presented on the screen, so that each stimulus was presented once with its previously associated stimulus, and once with a new one; for a total of 16 previous pairings and 16 new ones. The order was pseudo-randomized with a custom python script so that the same stimulus was not shown two trials in a row. The participants were instructed to press the left button if the pairing was old and the right if it was new (balanced across participants)

Finally, two different sets of optimized order and ITIs were used, so that half of participants were confronted to one set, and the other half the other set.

Overall, five factors were balanced across participants: the responses to repetitions in Preconditioning and Distractor/Localizer phase (left or right); the button to predict reward in Conditioning and Inference phases (left or right); the response to old versus new pairings in the Memory phase (left or right); the optimized order and ITIs (set 1 or set 2); and the pairs rewarded and neutral (reversed).

## Stimuli

The stimuli used in the main experiment were 16 scene-object pairs, with half of the pairs comporting a semantic link between the scene and objects. The semantic links are taken from previous experiment on contextual value of objects (Bar & Aminoff, 2003) and on consistency between scene and object (Lauer et al., 2018). Thus, the objects chosen were strongly associated to a specific context (e.g. the umbrella to the beach), contrary to objects with low contextual values (e.g. keys, rubber band…).

The stimuli used were all rescaled (from higher or equal resolutions) to size 600\*600px, and shown at a scale of 0.35 against a white background.

The stimulus used in the distractor/localizer task are from previous experiments from the group (REF unknown)

The rest of the stimuli are mainly from two databases. The objects are from the BOSS database (Brodeur et al., 2014), and the scenes from the SUN09 database (Choi et al., 2010), except from the 4 distractor stimuli shown in the first phase (preconditioning) which were obtained from freely available online resources labeled with a Creative Commons License.

The object images were double-balanced across reward and semantic link condition, regarding to naming accuracy, familiarity and outside/inside associated context, with the data from the Boss database. Thus the 8 semantically linked and the 8 not semantically linked pairs had non-significantly different averages in those three categories; and similarly, the 8 rewarded and the 8 non-rewarded pairs had non-significantly different averages in those 3 categories.

## References

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