# 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). Using neurodesign (Durnez et al., 2018; edited 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 implicit 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. 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 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 at the 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 3 euros penalty (I am not sure about the penalty; the maximum to win is 25,60€, but they would probably get a around 21-22€, so 3 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 havinf only one category of stimulus (scene or object) and having three out of ten unique stmuli repeated once. The stimulus were 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

* Which rewarded
* Response side
* Reward reverse

## 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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