Supplementary references

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Supplementary information is available for this paper.

Supplementary Information

Monkey	A					B					C					D				
Session	1	2	3	4	5	1	2	3	4	5	3	4	5	6	7	1	2	3	4	5
Planned trials	156	234	234	234	234	156	156	156	156	156	234	234	234	234	234	156	234	234	234	234
Completed trials	156	244	288	246	256	153	155	157	158	155	252	275	230	199	276	156	265	338	438	303
Trials in rep.sup. analysis	/	/	222	229	220	/	/	148	148	148	/	/	152	129	158	/	/	237	290	252
Trials in grid code analysis	119	185	175	185	178	119	121	122	122	121	136	160	127	108	122	116	150	182	209	203

Supplementary Table 1. Number of planned and completed trials in each session of experiment 2. Variations are due to the repetition of both pairs for any missed trial. The table also shows the number of trials analysed in the repetition suppression and in the grid code analyses (see Methods).

Supplementary discussion

During a decision process, neural activity implements a competition between two or more representations that culminates in one prevailing over the other. The two most widely used classes of models employed to formalise this process are drift-diffusion models and neural attractor models. Both classes of models can readily explain positive as well as negative effects of value difference on BOLD activity depending on whether it is assumed that the neural activity is immediately reset after the decision threshold is reached, or that activity continues until the motor response. Both models predict that the total neural activity will ramp up until the action selection time. This activity increase will be faster when the evidence is stronger, and slower when the evidence is weaker. When the model reaches a threshold (or an attractor state), activity may immediately be reset to baseline, or it can be maintained at a high level until the motor response is triggered, or even until the reward is delivered. The models themselves do not make strong predictions about when this 'reset' event is meant to happen, so it is plausible that subtle differences in neural function lead the network to be immediately reset in macaques and to maintain the end state for longer in humans. The figure shows that if activity falls immediately after the threshold is reached (thick lines in the top panel and bright colours in the bottom panel), the BOLD response will be negatively correlated with value difference, as in macaques; but if the activity is maintained for longer (dotted lines in the top panel and shaded colours in the bottom panel), the BOLD response will be positively correlated with value difference, as in humans. Other computational hypotheses may also explain this fact, such as different baseline levels of neural activity.