

1 Title: Prefrontal cortex activation reflects efficient exploitation of higher-order statistical structure

2 Abbreviated title: Exploitation of 1st- and 2nd-order information

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4 Authors: Christiane Ahlheim^{1,2}, Anne-Marike Schiffer^{3,4}, Ricarda I. Schubotz^{1,2}

5 ¹Institute of Psychology, Westfälische Wilhelms-Universität, 48149 Münster, Germany

6 ²Max Planck Institute for Neurological Research, 50931 Cologne, Germany

7 ³Department of Experimental Psychology, University of Oxford, OX1 3UD Oxford, United Kingdom

8 ⁴Department of Life Sciences, Brunel University, Uxbridge, Middlesex UB8 3PH, UK

9

10 Corresponding author:

11 Christiane Ahlheim

12 Fliegerstr. 21,

13 48149 Münster

14 c.ahlheim@ucl.ac.uk

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20 Abstract

21 Since everyday actions are statistically structured, knowing which action a person has just completed allows
22 predicting the most likely next action step. Taking even more than the preceding action into account improves
23 this predictability, but also causes higher processing costs. Using fMRI, we investigated whether observers
24 exploit 2nd-order statistical regularities preferentially if information on possible upcoming actions provided by
25 1st-order regularities is insufficient. We hypothesized that anterior prefrontal cortex balances whether or not 2nd-
26 order information should be exploited. Participants watched videos of actions that were structured by 1st- and
27 2nd-order conditional probabilities. Information provided by the 1st and by the 2nd order was manipulated
28 independently. BOLD activity in the action observation network was more attenuated the more information on
29 upcoming actions was provided by 1st- order structure, reflecting expectation suppression for more predictable
30 actions. Activation in posterior parietal sites decreased further with 2nd-order information, but increased in
31 temporal areas. As expected, 2nd-order information was integrated more when less 1st-order information was
32 provided, and this interaction was mediated by anterior prefrontal cortex (BA 10). Observers spontaneously
33 used both the present and the preceding action to predict the upcoming action, and integration of the preceding
34 action was enhanced when the present action was uninformative.

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36 Keywords: action observation, anterior prefrontal cortex, BA 10, information theory, statistical learning

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38 1. Introduction

39 Humans use knowledge about structural regularities to shape their expectations about upcoming events
40 (Bubic, von Cramon, & Schubotz, 2010; Friston & Kiebel, 2009; Kok, Brouwer, van Gerven, & de Lange,
41 2013; Summerfield, Trittschuh, Monti, Mesulam, & Egner, 2008; Turk-Browne, Scholl, Johnson, & Chun,
42 2010). A good example of this ability is action observation: actions provide a conditional structure of sequential
43 action steps, so that knowing about a preceding action step improves predictability of the upcoming action
44 (Zacks, Kurby, Eisenberg, & Haroutunian, 2011). Therefore, it appears that the more preceding action steps an
45 observer takes into account, the more accurate the prediction will be. For instance, we do expect that a person
46 will put a tea bag into a mug after switching on a kettle, but we do not if we observed that person putting a
47 descaler into the kettle right before. Here, the 1st-order conditional probability of “putting a tea bag in a mug”
48 after observing “switching on a kettle” is modulated by taking one additional previous action step into account,
49 which constitutes a 2nd-order conditional probability. However, retrieving this 2nd-order information comes with
50 processing costs, and may thus not always be worth the investment. This leads to the question: do observers
51 always consider as many preceding action steps as possible to optimize their predictions, or do they only do so if
52 their expectation is hardly informed by the directly preceding action? We know that humans do not take into
53 account all available sources of information to make optimal decisions, but often jump to conclusions, taking
54 heuristic shortcuts (Gigerenzer & Goldstein, 1996). A basic question in human cognition concerns this cost-
55 benefit ratio: How much information processing is invested (as a cost) to optimize expectations and behavior (as
56 a benefit)?

57 Behavioral and functional MRI (fMRI) findings strongly suggest predictive mechanisms are engaged
58 during action observation. Humans are particularly fast and accurate at recognizing actions, even if visual
59 information is sparse (Blake & Shiffrar, 2007) or parts of the action are occluded (Stadler, Schubotz, & von
60 Cramon, 2011; Zacks et al., 2011). The so-called action observation network (AON), including premotor cortex,
61 inferior parietal lobule, and posterior temporo-occipital regions (Caspers, Zilles, Laird, & Eickhoff, 2010) shows
62 reduced activation for expected compared to unexpected actions (expectation suppression, see Summerfield &
63 de Lange 2014; Summerfield et al. 2008). For instance, AON activation is attenuated by previous encounters of
64 an action (Schiffer, Ahlheim, Ulrichs, & Schubotz, 2013), successful inference of action goals (Wurm, Hrkać,
65 Morikawa, & Schubotz, 2014), or predictive regularities between action steps (Ahlheim, Stadler, & Schubotz,
66 2014; Schubotz, Wurm, Wittmann, & von Cramon, 2014). This shows that the human brain exploits previous
67 action steps to prepare for upcoming action steps. However, it is so far unknown how many previous action

68 steps are considered to improve predictability, and whether this occurs as a function of the uncertainty regarding
69 the next action step.

70 In general, the predictability of an upcoming event depends on the degree of structure that underlies the
71 event sequence, and knowledge of this structure allows for more accurate predictions. Using various paradigms
72 and stimuli, it has been shown that humans spontaneously learn about 1st-order structures defined by conditional
73 probabilities between successive items, which can be accessed directly through pairwise associations. Humans
74 use knowledge of those probabilities to prepare for upcoming stimuli, both in abstract stimulus sequences as
75 well as actions (Ahlheim et al., 2014; Baldwin, Andersson, Saffran, & Meyer, 2008; Fiser & Aslin, 2002;
76 Swallow & Zacks, 2008; Turk-Browne, Scholl, Chun, & Johnson, 2009). However, most everyday actions are
77 not guided by simple 1st-order conditional probabilities, but involve higher-order (e.g., 2nd-order structures).
78 Contrary to 1st-order information, 2nd-order information cannot be assessed directly, but requires retrieving
79 information about the event $t-2$ from memory, and integrating it with the 1st-order information. This integration
80 is necessary, as the event $t-2$ alone does not constitute the 2nd order, but only in combination with the event $t-1$.
81 While the beneficial effects of 1st-order regularities on neural processing and behavior are uncontroversial, it
82 remains unclear whether and how 2nd-order regularities influence behavior and prediction of upcoming events,
83 and how this depends on concurrently available 1st-order information. Findings are mixed, as some studies do
84 not show an effect of higher-order structures (Gureckis & Love, 2010), while others show that learning of
85 higher-order structures is slower (Remillard, 2008), or not different from 1st-order learning (Domenech &
86 Dreher, 2010). Research in amnesic patients revealed a specific deficit in the learning of higher-order
87 conditional structures, whereas learning of 1st-order associations remained intact (Curran, 1989). This suggests
88 that the hippocampal formation, which is frequently damaged in amnesia, specifically contributes to learning of
89 higher-order compared to lower-order structures, additionally to its critical role in episodic memory and
90 associative knowledge (Fortin, Agster, & Eichenbaum, 2002; Kumaran & Maguire, 2009; Strange & Dolan,
91 2001).

92 In order to account for the mixed findings on learning of higher-order structures, it has been suggested
93 that humans are biased towards attending to lower-order structures, and only attend to higher-order structures if
94 the information provided by the lower-order structure is insufficient to reliably predict the upcoming event
95 (Gureckis & Love, 2010). It is so far unclear whether the same principle holds for action observation, and which
96 neural structures could underpin this process of integration of predictive information. Recent findings indicate
97 that the search and use of further information is orchestrated by the lateral BA 10 (Badre, Doll, Long, & Frank,
98 2012; Daw, O'Doherty, Dayan, Seymour, & Dolan, 2006). Badre et al. (2012) showed that activation in the BA

99 10 increases with relative uncertainty about a potential action outcome, but only in participants that showed a
100 so-called explorative behavior, i.e. participants that were searching for additional information from unknown
101 choices. This links the BA 10 to explorative choice. In a similar vein, Daw et al. (2006) showed that activation
102 in the lateral BA 10 is higher for explorative, or information-gathering, choices. Exploration can be understood
103 as search for information, and higher activation in the BA 10 is also frequently observed during episodic or
104 source memory retrieval tasks (Ramnani & Owen, 2004), that is, when information needs to be gathered from
105 memory. Furthermore, the BA 10 has been associated with the integration of different sources of information
106 (Nee, Jahn, & Brown, 2013).

107 In the present fMRI study, we tested the hypothesis that observers' exploitation of 2nd-order statistical
108 information in action sequences depends on how much information was already provided by the 1st order. We
109 used fMRI to test whether information from an observed action's 2nd-order statistical structure is used the more
110 the less informative the action's 1st-order statistical structure is and whether this cost-efficient integration of
111 information would be signified by BA 10 activity.

112 We presented observers with videos of action sequences structured by 1st- and 2nd-order conditional
113 probabilities. That is, the probability of a given action step t was to a quantifiable amount determined by the
114 preceding action step $t-1$ (1st-order statistical structure) and to another amount by the combination of the
115 preceding ($t-1$) and the last but one preceding action step $t-2$ (2nd-order statistical structure). Importantly, the
116 amount of information provided by 1st- and by 2nd-order structure was varied independently. This enabled us to
117 estimate both effects independently and also their interaction. We modeled the BOLD effect at the beginning of
118 action t as a function of the amount of information provided by the action $t-1$ alone and by the combination of
119 action $t-1$ and $t-2$. We expected three effects:

120 1) First, we expected to replicate findings from our previous studies (Ahlheim et al., 2014; Wurm et al.,
121 2014), showing that facilitating the prediction of the upcoming action step leads to attenuation of activity in the
122 AON. The more informative action $t-1$, the better the prediction of the upcoming action t . Accordingly, we
123 expected the BOLD response in the action observation network to decrease with the amount of information
124 provided by action $t-1$.

125 2) At the same point in time, integrating information from action $t-2$ with information from action $t-1$
126 can effectively modulate expectations based on the relation between the actions $t-1$ and t , and thereby increase
127 predictability of action t . Unlike 1st-order information, 2nd-order information cannot be accessed through direct
128 associations between stimuli, but requires action $t-2$ to be retrieved from working memory and integrated with
129 action $t-1$. Moreover, previous encounters of a particular combination of preceding action steps need to be

130 retrieved from long-term memory in order to derive information on upcoming actions from the combination. We
131 expected the retrieval and integration of 2nd-order information to be reflected in the hippocampal formation, due
132 to its role in learning of higher-order sequences (Curran, 1989; Fortin et al., 2002; Kumaran & Maguire, 2009;
133 Strange & Dolan, 2001). Activation of the hippocampus has furthermore been found to correlate positively with
134 amount of information provided on an upcoming event (Harrison, Duggins, & Friston, 2006). We assumed that
135 this effect generalizes to higher-order structures and hypothesized that activation in the hippocampal formation
136 will correlate positively with the amount of information provided by the 2nd order. Furthermore, we expected
137 use of 2nd-order information to draw on the AON. Here, we considered two potential scenarios. First, given that
138 the exploitation of 2nd-order information improves predictability of the upcoming action, it can be expected to
139 result in a further attenuation of the AON, paralleling the effect of 1st-order information, and pointing towards
140 an interpretation of AON activity as reflecting a gain in predictability. Alternatively, activation in the AON
141 could also be expected to increase with the amount of 2nd-order information. This is because the more
142 information is provided by the 2nd-order structure, the more the predictions based on the 1st-order change and
143 thus, integrating 2nd-order information is more demanding. This pattern would point towards sensitivity of the
144 AON to the integration costs of 2nd-order information with the previously provided 1st-order information.

145 3) Lastly, we were particularly interested in the question as to how exploitation of 2nd-order
146 information depends on the amount of information already provided by the 1st-order – that is, which brain areas
147 show a stronger modulation by 2nd-order information when 1st-order is low compared to when it is high. We
148 hypothesized that integration of 2nd-order information should be especially enhanced when action $t-1$ alone was
149 less informative about the upcoming action t and the need for further information is high. Thus, we expected a
150 stronger modulation of the BOLD-signal by the 2nd-order information for trials with low compared to high 1st-
151 order information. We expected Brodmann Area 10 at the frontal pole to show this interaction effect, as it has
152 not only be reported to be activated by integration of information (Nee et al., 2013) but also to orchestrate
153 uncertainty-driven search for information (Badre et al., 2012; Daw et al., 2006).

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155

156 2. Methods

157 2.1 Participants

158 Twenty-two healthy, right-handed participants volunteered for the study and were paid 80 € for their
159 participation. The local ethics committee of the University of Münster approved the experimental protocol and
160 written informed consent was obtained from each participant. Three participants had to be excluded after
161 completing the experiment, one because of poor performance in the control task (score below two SD from
162 mean), and two because of self-reported inattentiveness and sleep during the fMRI session. All following
163 analyses are based on the data of the remaining 19 participants (mean age 25.35 ± 2.13 years, 14 females).

164

165 2.2 Stimuli and Task

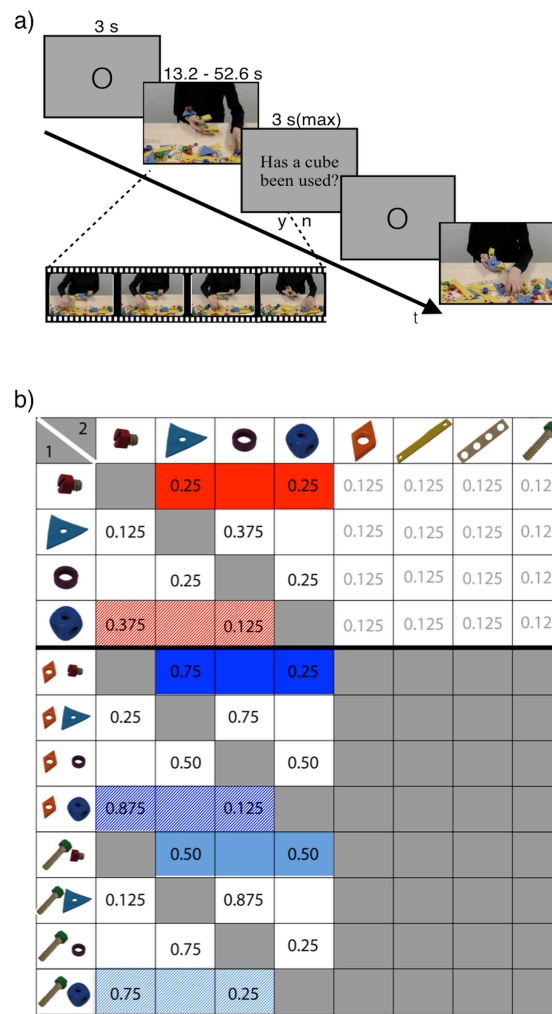
166 We employed a paradigm that required constant monitoring of sequences of action steps that were
167 structured by 1st- and 2nd-order conditional probabilities. To construct sequential actions devoid of semantic
168 expectations, we used eight objects from the constructional toy Baufix® and defined the grasping and
169 manipulation of an object as one action step. Overall, we created a total of 140 action sequences, ranging from
170 four to nine action steps. Base-rate probability of occurrence was nearly identical for all action steps, ranging
171 from 12% to 14%. Therefore, predictions of upcoming action steps could not reliably be based on frequency.

172 To prevent participants from episodically remembering entire video clips as a basis for prediction we
173 shot every sequence in seven versions, each with different starting scaffolds, which consisted of various
174 different mounted objects (see Figure 1a for an illustration of the video clips).

175 Action videos were displayed on a grey background in the middle of a computer screen. A fixation
176 circle with a duration of 3 s, or adjusted length after question trials, preceded all videos. Within the videos, onset
177 asynchronies of the single action steps ranged from 1.28 s to 12.24 s (mean 4.39 s).

178 Approximately half of the video clips (64 of 140 during the training, 32 of 70 during the fMRI session)
179 were followed by questions trials. Here, participants were required to answer questions concerning the previous
180 video, e.g., “Has a long screw been used?”. Responses were given via computer mouse with the right button
181 (i.e., middle finger of the right hand) corresponding to the answer “no” and the left button (i.e., right index
182 finger) corresponding to “yes”. Half of the questions required a positive answer and all participants responded
183 according to the same response contingencies. Questions were presented for 3 s or until the first response, and
184 had to be answered within 3 s (see Figure 1a). The duration of the fixation circle following responses was
185 adapted to compensate for different response times and could range from 2 to 5 s. Questions were followed by a
186 feedback of 2 s indicating correct (“+”), incorrect (“-“), or delayed (“/”) responses.

Figure 1



a) Illustration of the trial course. A fixation circle preceded each video and 46% of the videos were followed by a two-alternative forced choice question. Feedback on correctness of responses was only given during the training sessions. b) Excerpt of the employed transition matrix. Rows 1-4 show 1st-order conditional probabilities between action steps, rows 5-12 show 2nd-order conditional probabilities. Objects in rows depict the preceding objects of the transition. Red marked are two examples for possible 1st-order transitions with high or low information. Transitions with high information provided by the 1st-order structure are marked with criss-cross lines (red for 1st-order conditional probabilities, light or dark blue for 2nd-order conditional probabilities). Light blue fields show exemplary transitions with low, dark blue fields with high modulatory influence of the 2nd-order structure.

187 2.2.1 Markov Matrix

188 The succession of action steps within the sequences followed pre-defined 1st- and 2nd-order conditional
 189 probabilities (see Figure 1b for an excerpt of the transition matrix). First-order conditional probability refers to
 190 the probability of each action step based on the immediately preceding action, ranging from 12.5% to 37.5%
 191 (rows 1-4 in the transition matrix, Figure 1b). The larger the difference between probabilities of the possible
 192 upcoming actions, the more information about the upcoming action was provided by the 1st-order structure. For
 193 instance, the blue cube provided more 1st-order information than the short screw, as it allowed for a better
 194 prediction of the upcoming action. Paralleling the 1st-order, the 2nd-order conditional probability refers to the
 195 probability of each action step based on the combination of the two preceding actions, ranging from 12.5% to
 196 87.5% (rows 5-12 in the transition matrix, Figure 1b). Here, the larger the difference between probabilities of
 197 the possible upcoming actions, i.e., between all actions within one row of the matrix, the more information was
 198 provided by the 2nd-order structure. For instance, if a screw nut preceded the short screw, it provided much
 199 information on the upcoming action: the previously balanced probabilities on the 1st-order structure would

200 become biased, and putting the triangle would become the most likely action step. Contrary to that, a long screw
201 preceding the short screw provided little information, as the probability ratio between the next possible actions
202 stays the same. As can be seen from the matrix, the amount of information provided by the 2nd-order structure
203 varied independently of the information provided by the 1st-order structure. This feature of the statistical
204 structure is important as it allowed us to test if the amount of information provided by the 1st order affects
205 exploitation of the 2nd order as an additional source of information.

206

207

208 2.3 Experimental Procedure

209 Prior to the fMRI scan, each participant completed three 90-minute training sessions on three
210 successive days to acquire implicit knowledge of the statistical structure. Since we wanted to test if human
211 observers spontaneously attend to different levels of statistical structure, participants did not receive explicit
212 learning instructions at any point either in training or during the fMRI session, and were not told that there was a
213 certain systematic concerning the structure of the action sequences. Participants were familiarized with the eight
214 different objects as well as with the type of question they would be asked before they started the training
215 sessions.

216 The course of the fMRI session was identical to the training session, but no feedback was provided
217 after question trials. To account for the limits in maximal duration of fMRI sessions, only 70 out of the 140
218 action sequences were presented, resulting in approximately 45 minutes of fMRI scan. The selected 70
219 sequences were a representative sample of the total set of sequences, while ensuring that rare action
220 combinations (i.e. with low 1st- or 2nd-order conditional probabilities) occurred with sufficient frequency.

221 To test our prediction that participants would be capable of learning both 1st- and 2nd-order conditional
222 probabilities, we implemented two post-scanner tests to assess participants' knowledge of the action syntax.

223 The first computer-based post-test was a serial reaction time task (SRTT, Nissen & Bullemer 1987)
224 wherein pictures of the eight Baufix objects occurred at different locations on the screen. Unknown to the
225 participants, the succession of the objects was defined by the same statistical structure as in the main
226 experiment. Participants had to press a button, specifically assigned to each of the objects on an eight-button
227 response pad as fast as possible. Wrong answers were followed by a negative feedback. This test was designed
228 to test whether reaction times (RTs) would be modulated by both 1st- and 2nd-order conditional probability of the
229 occurring object.

230 The second post-test was a paper-pencil test. Eight video clips were presented in randomized order.
231 Videos ended after the actor had used one object and reached for another. The participants' task was to mark
232 those objects out of the set of eight that they expected to be used next and to weight them according to their
233 respective probability. They made this judgment in the form of eight crosses, which they could assign among the
234 eight objects. For instance, if participants saw a clip in which the long screw had been used and they expected
235 the board and the screw nut afterwards with equal probabilities, they assigned four crosses to each of them. The
236 number of eight crosses allowed participants to select up to all eight possible objects and to weigh them
237 accurately (each cross corresponded to $p = .125$).

238

239 2.4 Data Acquisition

240 A 3T Siemens Magnetom Trio (Siemens, Erlangen, Germany) system equipped with a standard
241 birdcage head coil was used in the functional imaging session. Participants lay supine in the scanner and their
242 right hand was placed on a four-button response-box. Index and middle finger were placed on the response
243 buttons and response contingencies were the same as in the training sessions. Participants' heads and arms were
244 stabilized using form-fitting cushions, and earplugs were provided to attenuate scanner noise. The experiment
245 was presented via a mirror that was built into the head coil and adjusted individually to provide a good view of
246 the entire screen.

247 During the functional imaging, 28 axial slices (128.8 mm field of view, 4 mm thickness, 0.6 mm
248 spacing; in-plane resolution of 3x3 mm) parallel to the bi-commissural line (AC-PC) were collected using a
249 single-shot gradient echo-planar (EPI) sequence (2000 ms repetition time; echo time 30 ms, flip angle 90°, serial
250 recording, 1260 repetitions) blood-oxygenation level-dependent (BOLD) contrast. After the functional imaging,
251 28 slices of anatomical T1-weighted MDEFT images (4 mm thickness, 0.6 mm spacing) were acquired.

252 High-resolution 3D T1-weighted whole brain MDEFT sequences (128 sagittal slices, 1 mm thickness)
253 were recorded for each participant in a separate session for improved localization of activation foci. Functional
254 data were offline motion-corrected using the Siemens motion protocol PACE (Siemens, Erlangen, Germany).
255 Further processing was conducted with the LIPSIA software package, version 2.1 (Lohmann et al., 2001). To
256 correct for temporal offsets between the slices acquired in one scan, a cubic-spline interpolation was used. To
257 remove low-frequency signal changes and baseline drifts from the BOLD signal, we applied a high-pass filter of
258 $1/89 - 1/70$ Hz, defined by an algorithm implemented in the Lipsia software package. Functional data slices
259 were aligned with a 3D stereotactic coordinate system. The matching parameters (six degrees of freedom, three
260 rotational, three translational) of the T1-weighted 2D-MDEFT data onto the individual 3D-MDEFT reference

261 set were calculated. These parameters were used in a transformation matrix for a rigid spatial registration,
262 normalized to a standardized Talairach brain size ($x = 135, y = 175, z = 120$ mm; Talairach & Tournoux, 1988)
263 by linear scaling. Thereafter the normalized transformation matrices were applied to the functional slices in
264 order to transform them using trilinear interpolation and align them with the 3D-reference set in the stereotactic
265 coordinate system. The spatial resolution of the resulting functional data was $3 \text{ mm} * 3 \text{ mm} * 3 \text{ mm}$ (27 mm^3).
266 A spatial Gaussian filter of 8 mm full width at half maximum (FWHM) was applied to the data.

267

268 2.5 Data Analyses

269 2.5.1 Information Theoretical Modeling

270 To operationalize the amount of information provided by the 1st and 2nd order, respectively, we used
271 measures derived from information theory and an *ideal observer model* to estimate conditional probabilities of
272 action steps (cf. Ahlheim et al. 2014; Bornstein & Daw 2012; Harrison et al. 2006; Strange, Duggins, Penny,
273 Dolan, & Friston, 2005). Therefore, simulated probabilities were calculated across the training session, and
274 continued through the scanning session. The base probabilities (p) of single items were calculated as the number
275 of occurrences n of item x_i divided by the sum of all items x_i that have appeared so far (see equation 1).
276 Conditional probabilities were calculated by dividing the probability of co-occurrence of two items by the
277 preceding item's base probability (see equation 1b); this formula was extended for the case of 2nd-order
278 conditional probabilities.

279

$$280 \quad p(x_i) = \frac{n(x_i) + 1}{\sum_i x_i + 1}$$

281 Equation 1a. Calculation of base probabilities.

$$282 \quad p(x_i | x_{i-1}) = \frac{p(x_i \cap x_{i-1})}{p(x_{i-1})}$$

283 Equation 1. Calculation of 1st-order conditional probabilities.

284

285 The amount of information provided by an event can be quantified as the degree to which uncertainty
286 about an upcoming event is reduced. Uncertainty can be represented as entropy (H) (Equation 2), which is
287 higher when unexpected events are probable (Cover & Thomas, 1991; Shannon, 1948). Entropy is therefore also
288 referred to as expected surprise. The surprise of an event is defined as the negative logarithm of its probability,
289 i.e. the surprise of an event is higher if the event was less likely. Formally, entropy is maximal if all possible

290 events are equally likely to occur, so that $p_{\text{event}} = 1/n_{\text{events}}$. On the 1st order, the entropy about possible upcoming
 291 events (members of X) after occurrence of one other event (member x_{t-1} of all X) can be quantified as forward
 292 entropy (Ahlheim et al. 2014; Bornstein & Daw 2012, see Equation 3). If the forward entropy $H(X|x_{t-1})$ is
 293 smaller than the general entropy $H(X)$, occurrence of x_{t-1} provided information about the occurrence of X. This
 294 information I_1 can be quantified as the difference between the general entropy $H(X)$ and the forward entropy
 295 (taking the preceding event into account, i.e., $H(X|x_{t-1})$). The same logic applies to information provided by the
 296 2nd order I_2 , which can be quantified as the difference between the 1st-order forward entropy $H(X|x_{t-1})$ and the
 297 2nd-order forward entropy $H(X|x_{t-1}, x_{t-2})$ (Equation 4). To ensure that differences between 1st- and 2nd-order
 298 forward entropy were not driven by different 1st-order conditional probabilities, we normalized the forward
 299 entropy by the 1st-order probability of co-occurrence.

$$301 \quad H(X) = \sum_i p(x_i) * -\log p(x_i)$$

302 Equation 2. Calculation of the general entropy.

$$304 \quad H(X|x_{t-1}) = p(x_{t-1}) \sum_i p(x_i | x_{t-1}) * -\log p(x_i | x_{t-1})$$

305 Equation 3. Calculation of the 1st-order forward entropy.

$$307 \quad H(X|x_{t-1}, x_{t-2}) = p(x_{t-1}, x_{t-2}) \sum_i p(x_i | x_{t-1}, x_{t-2}) * -\log p(x_i | x_{t-1}, x_{t-2})$$

308 Equation 4. Calculation of the 2nd-order forward entropy.

310 2.5.2 Behavioral Analysis of post-fMRI Tests

311 The behavioral analysis was conducted with the statistic software package R, version 3.1 (R
 312 Foundation for Statistical Computing, Vienna, Austria) and SPSS statistics version 22 (SPSS Inc. Chicago,
 313 Illinois, USA). If not indicated otherwise, all inferential decisions were based on an alpha level of .05.

315 3) SRTT Analysis

316 The first post-fMRI test, the SRTT, was designed to measure whether RTs were modulated by 1st- and
 317 2nd-order conditional probability. This would provide evidence for implicit learning of the respective orders. To

318 test for this, we conducted a multiple regression analysis separately for each participant, which included the
319 predictors of 1st-order conditional probability and 2nd-order conditional probability (see Equation 1) as well as
320 the trial number to control for general learning effects. Using multiple regressions enables us to identify how
321 much each predictor contributes to the observed data in the context of the simultaneously available predictors.
322 Only correct trials with an RT between 100 ms and 2000 ms were included in the analysis. On average, 7 % (45
323 of 651 trials) were excluded per participant. One participant had to be excluded due to excessively prolonged
324 RTs ($z > 2$), resulting in 18 participants in the final analysis of the SRTT. To account for the non-normal
325 distribution of the RT data, all RTs were logarithmized prior to analysis. For each participant, we obtained one
326 standardized regression coefficient that reflected how strongly their RTs were modulated by the 1st-order
327 conditional probabilities, and one that reflected how strongly RTs were modulated by 2nd-order conditional
328 probabilities, while controlling for effects of the respective other predictor. Those standardized regression
329 coefficients were tested for significant deviation from zero, using separate one-sample *t*-tests (cf. Bornstein &
330 Daw, 2012 for a similar approach).

331

332 2) Paper-Pencil Analysis

333 The second post-fMRI test was a paper-pencil test where we assessed participants' explicit knowledge
334 of the 1st-order structure. One participant failed to complete the post-test and was thus excluded from the
335 analysis. We aggregated the number of crosses for the underlying true probability level (0, 12.5, 25, 37.5), for
336 instance, how many crosses a participant distributed on average for a 0.25 conditional probability between
337 action steps. This data was entered into a univariate ANOVA with the factor PROBABILITY (0, 0.125, 0.25,
338 0.375) to test for significant differences between the levels. To test for the expected increase of probability
339 ratings with implemented probabilities, planned paired *t*-tests between the successive probability levels were
340 conducted.

341

342 2.5.3 fMRI Data analysis

343 For the statistical evaluation of the BOLD signal, a design matrix was generated modeling events with
344 a delta (stick) function, convolved with the hemodynamic response function (gamma function; Glover 1999).
345 All modeled actions had a minimal inter-stimulus-interval of 2 seconds. The first two actions of each sequence
346 were discarded, as 2nd-order information was not available for those. The general linear model included five
347 regressors, which were modeled time-locked to the onset of the action steps and with a duration of 1 s. Onset of

348 action steps was defined as the moment the hand started to reach towards the next object. The first regressor
349 served as a baseline and was modeled with an amplitude of 1.

350 To model information provided by the 1st order, we included a parametric regressor in which entries in
351 the amplitude vector corresponded to the amount of information provided by the 1st order (I_1). Paralleling this
352 account, we included another parametric regressor in which entries in the amplitude vector corresponded to the
353 amount of information provided by the 2nd order (I_2). To assess whether exploitation of the 2nd-order information
354 depended on whether the 1st-order structure provided more or less information, we constructed an additional
355 parametric regressor which modeled only those events for which the amount of information provided by the 1st
356 order fell within the 1st or 4th quartile of the distribution of information provided by the 1st order (lowest and
357 highest 25%). The amplitude entries on this regressor corresponded to the interaction term of 1st- and 2nd-order
358 information, calculated as their mean-centered product (see Figure 2a for an illustration for the course of the
359 parametric regressors during an excerpt of the experiment).

360 In addition to the parameters modeling amount of provided information, we included the 1st-order
361 conditional surprise, i.e., the negative logarithm of each action step's conditional probability, as a nuisance
362 regressor. Amplitudes of all parametric regressors were separately z-scored for each participant.

363 To account for question trials and general effects of observing actions, we included question trials with
364 a duration of 3 s and video clips with a duration according to the duration of the video, both with an amplitude
365 of 1.

366 We corrected for multiple comparisons by applying a two-step correction approach, resulting in a
367 correction at $p < .05$ at the cluster level. In the first step, an initial z -threshold of 2.57 ($p < .01$, two-tailed) was
368 defined. All voxels showing activation above this threshold entered the second step of the correction. Here, a
369 Monte Carlo simulation was used to define thresholds for cluster-size and cluster-value at a significance level of
370 $p < .05$. The combination of cluster size and cluster value decreases the risk of neglecting true activations in
371 small structures. Thus, all reported activations were significant at $p < .05$, corrected for multiple comparisons at
372 the cluster level.

373

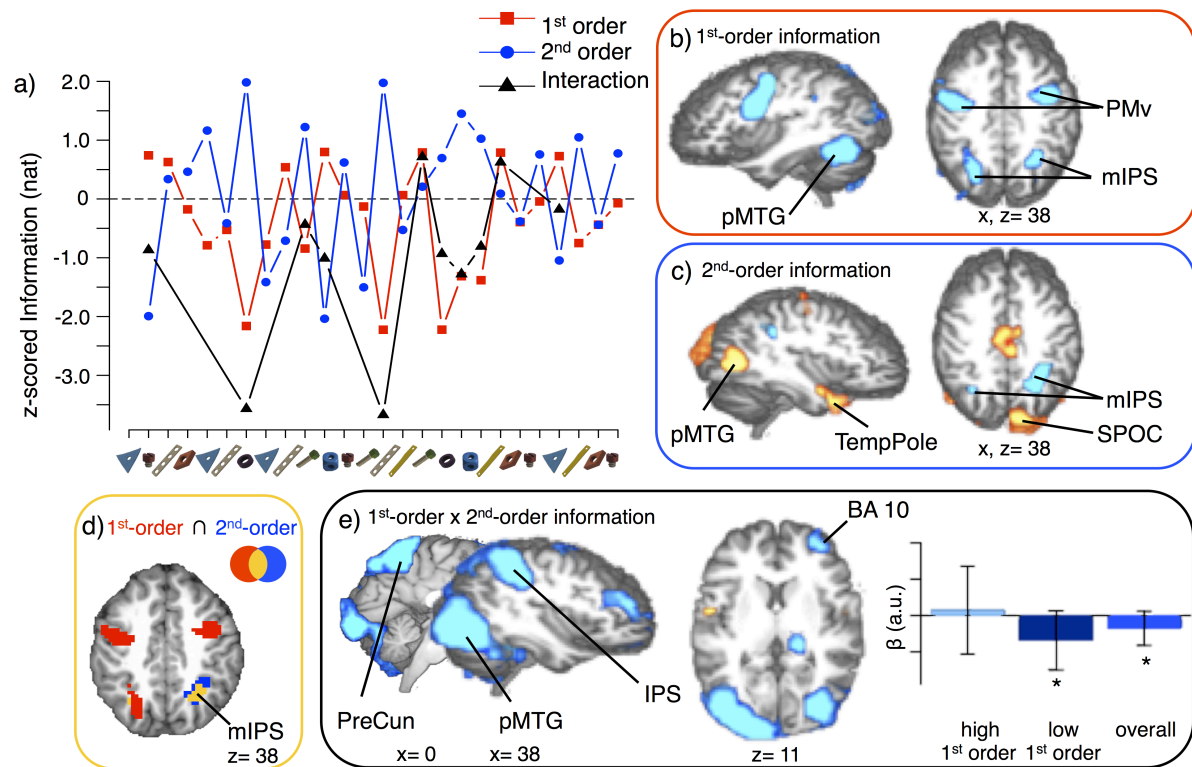
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Figure 2



a) Example course of the parametric regressors for 1st-order information (red), 2nd-order information (blue), and their interaction term (black) during an excerpt of the experiment. b) Parametric effects of the amount of information provided by the 1st-order statistical structure. PMv: ventral premotor cortex, mIPS: midposterior intraparietal sulcus, pMTG: posterior middle temporal gyrus. c) Parametric effects of the amount of information provided by the 2nd-order statistical structure. mIPS: midposterior intraparietal sulcus, pMTG: posterior middle temporal gyrus, SPOC: superior parieto-occipital cortex, TempPole: temporal pole. d) Overlay of the parametric effects of the 1st- and 2nd-order statistical structure in observed action videos. Effects of 1st-order information are displayed in red, 2nd-order in blue. Effects of both parameters overlapped in the midposterior intraparietal sulcus (yellow) and comprised 1188mm³ (59.46% of the activation cluster revealed in the 1st-order contrast) in the right and 432mm³ (5.05%) in the left hemisphere. e) Interaction of parametric effects of the amount of information provided by the 2nd-order statistical structure and the amount of information provided by the 1st-order structure. The bar chart depicts beta-values in the BA 10 when the interaction term modeled only events with high 1st-order information (light blue, $t(18) = -0.18, p = .855$), low 1st-order information (dark blue, $t(18) = -3.12, p = .006$), and the interaction effect when events with high or low 1st-order information were modeled (middle blue, $t(18) = -3.41, p = .003$). Error bars depict ± 1 standard deviation. pMTG: posterior middle temporal gyrus, IPS: intraparietal sulcus, preCun: precuneus.

378

379

380 3. Results

381 Participants answered on average 26.4 out of 32 question trials correctly ($SD = 3.27$), indicating a high
382 attentiveness during the fMRI session.

383

384 3.1 Behavioral Results

385 3.1.1 Results of the post-fMRI SRTT

386 The multiple regression testing for effects of the 1st-order and 2nd-order conditional probabilities on the
387 logarithmized RTs revealed a significant negative relationship between 1st-order conditional probability and
388 RTs, showing that higher 1st-order probabilities led to faster RTs ($t(17) = -6.92, p < .001$, two-tailed, $M = -0.12$,
389 $SD = 0.07$ of the standardized coefficients). This effect was consistent across all participants. The effect of the
390 2nd-order conditional probability was also significant ($t(17) = 2.37, p = .030$, two-tailed, $M = 0.03, SD = 0.06$),
391 indicating slower RTs with higher 2nd-order probabilities (see Figure 3). Thirteen out of the 18 tested
392 participants showed a positive correlation between 2nd-order conditional probabilities and RTs. As we conducted
393 multiple regressions, those results show that RTs were slower for higher 2nd-order conditional probabilities
394 whilst controlling for an effect of 1st-order conditional probabilities.

395 We furthermore wanted to test whether the effect of 2nd-order conditional probabilities depended on the
396 degree to which expectations based on 1st-order conditional probabilities had been modulated by these 2nd-order
397 conditional probabilities. To that end, we conducted a median split of the data for each participant, dividing
398 trials by whether the 2nd order modulated the 1st order to a greater or lesser extent. We performed two multiple
399 regressions parallel to the multiple regression described above, with 1st-order and 2nd-order conditional
400 probability, as well as trial number, as predictors. The resulting standardized coefficients for the 2nd-order
401 conditional probability depending on how strongly the 2nd order changed the expectations based on the 1st-order
402 conditional probabilities were tested against each other using a paired t -test. A marginally significant difference
403 was revealed ($t(17) = 2.04, p = .057$, two-sided). Thus, RTs showed a trend for being more strongly modulated by
404 2nd-order probabilities if those modulated the expectations based on 1st-order probabilities strongly ($M = 0.11$,
405 $SD = 0.15$) compared to if the modulation was weak ($M = 0.03, SD = 0.11$; see Figure 3).

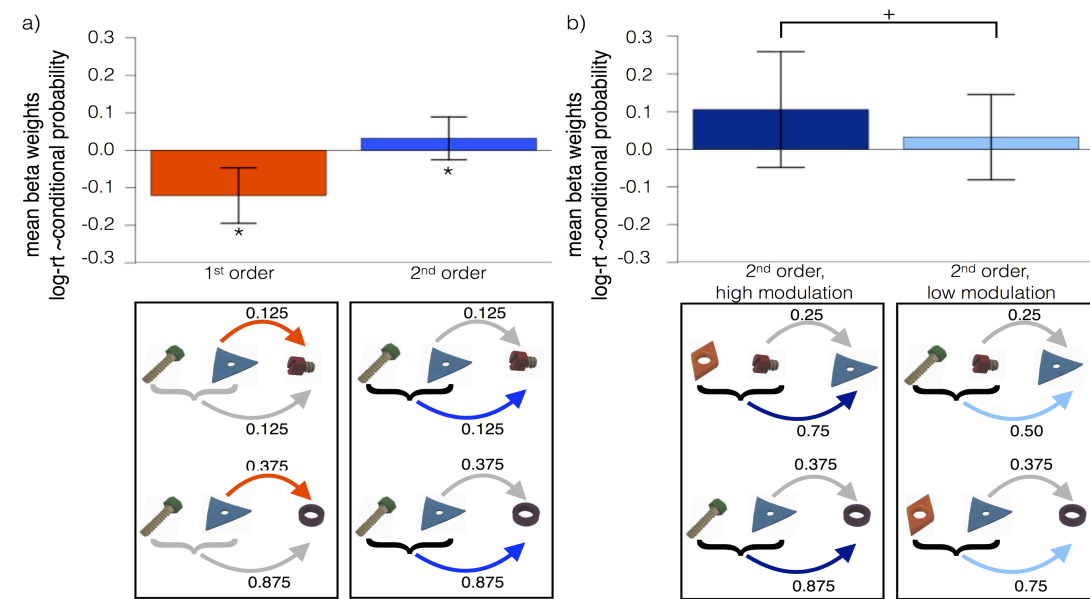
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Figure 3



Results of the serial reaction time post-test. a) Mean beta weights expressing the relationship between 1st- and 2nd-order conditional probabilities and reaction times. Reaction times decreased with increasing 1st-order conditional probabilities and increased with increasing 2nd-order conditional probabilities b) Comparison between effects of 2nd-order conditional probabilities on reaction times in dependence on the degree to which 1st-order conditional probabilities were modulated by the 2nd order. Reaction times showed a trend towards a stronger modulation by 2nd-order conditional if 1st-order conditional probabilities were modulated to a larger extent. Error bars depict ± 1 standard deviation. * $p < .05$, + $p < .06$.

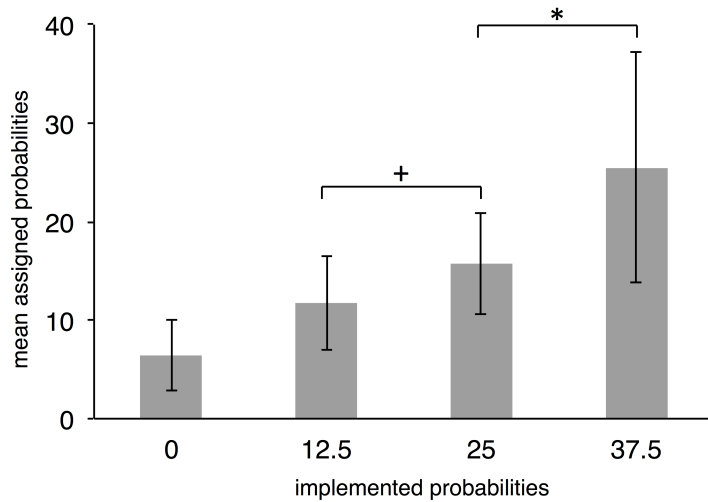
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411 3.1.2 Results of the post-fMRI paper-pencil test

412 The results of the paper-pencil post-test, which assessed knowledge of the 1st-order structure, further
 413 corroborated the significant effect of 1st-order conditional probabilities on RTs. The repeated-measures ANOVA
 414 testing for an overall effect of the factor PROBABILITY on the assigned weight turned out significant ($F(3,$
 415 $51) = 18.17, p < .001$, partial $\eta = .52$). As we expected rated probabilities to reflect actually implemented
 416 probabilities, planned paired t -tests were conducted between the single successive levels. We found no
 417 difference between probabilities of 0 and 0.125 ($t(17) = 1.61, p = .063$, one-tailed, $d = 0.38$), a marginally
 418 significant difference between probabilities of 0.125 and 0.25 ($t(17) = 2.09, p = .026$, one-tailed, $d = 0.49$) and a
 419 significant difference between 0.25 and 0.375 ($t(17) = 3.48, p = .002$, one-tailed, $d = 0.82$), with an alpha-level of
 420 $.017$, adjusted for the three comparisons (see Figure 4; note that the mean assigned values were scaled by the
 421 factor 12.5 to match the scaling of the implemented probabilities). This indicates that participants formed
 422 predictions based on the 1st-order conditional probabilities, and that their representation of 1st-order conditional
 423 probabilities was more precise for higher probability values. None of the participants claimed conscious
 424 knowledge of the structure when interviewed after the experiment.

425

Figure 4



Results of the paper-pencil post-test, showing that assigned probabilities increased as implemented probabilities increased. Number of assigned crosses was multiplied by 12.5 to achieve same scaling as underlying probabilities. Error bars depict ± 1 standard deviation. * $p < .017$, + $p < .03$.

426

427 3.2 fMRI Results

428 Manipulating the amount of information provided by the 1st and 2nd order of the statistical structure
429 independently of each other allowed us to assess functional correlates of the exploitation of each of the levels
430 independently. Furthermore, it enabled us to investigate how the amount of information provided by the 1st
431 order affects exploitation of further information provided by the 2nd order.

432 1) Effects of 1st-order information

433 The contrast testing for a modulation of the BOLD response by the amount of information provided by
434 the 1st-order structure yielded an attenuation of activation in the predicted network of ventral premotor cortex
435 (PMv), the midposterior part of the intraparietal sulcus (mIPS), and the fusiform gyrus and posterior middle
436 temporal gyrus (pMTG), which is classically reported for action observation (see Table 1 for a list of all
437 activations, Figure 2b). Since information provided by the 1st-order structure and information provided by the
438 2nd order were modeled simultaneously, this finding shows that increased predictability based on information
439 provided by the 1st-order structure can reduce activation even when information from the 2nd-order structure is
440 also available.

441

442

443

444 Table 1: MNI coordinates and maximal z-scores of significantly activated clusters following correction for
 445 multiple comparison for the parametric contrast of information provided by the 1st-order structure

Localization	MNI coordinates			z-values, local maxima	Cluster size (mm ³)
	x	y	z		
ventral premotor cortex	-41	1	33	-4.39	11691
	37	4	33	-4.22	9855
midposterior intraparietal sulcus	-17	-62	48	-3.99	8559
	25	-53	42	-3.38	1998
midposterior intraparietal sulcus/ Precuneus (BA 19)	13	-65	54	-2.87	567
	28	-71	22	-2.97	810
Fusiform gyrus / posterior middle temporal gyrus	-50	-59	0	-3.96	6939
	40	-50	-21	-3.06	1107

446

447 2) Effects of 2nd-order information

448 We expected 2nd-order information to draw onto activation in the AON as well, though we considered either a
 449 positive or a negative correlation as possible.

450 Higher 2nd-order information was associated with a decrease of activation in mIPS, which overlapped
 451 with the cluster observed in the 1st-order contrast (1188 mm³ in the left, 432 mm³ in the right hemisphere; see
 452 Figure 2d for a conjunction of the two contrasts). The mIPS was the only area for which an overlap was
 453 revealed. We found an increase in activation with higher 2nd-order information in pMTG and superior parieto-
 454 occipital cortex (SPOC). An unhypothesized positive correlation between BOLD activation and 2nd-order
 455 information was furthermore revealed in the right temporal pole (see Table 2 for a list of all activations, Figure
 456 2c). Those findings show that 2nd-order information is spontaneously integrated, independent of 1st-order
 457 information. To additionally test which areas are more sensitive towards 1st- than towards 2nd-order information,
 458 we calculated the direct contrast between the two parametric regressors. This contrast revealed significantly
 459 higher activation for the 2nd-order in the premotor cortex and the pMTG, showing that activation there was more
 460 strongly attenuated by 1st-order information (see supplementary Table 1 and supplementary Figure 1).

461 To test for the hypothesized correlation between 2nd-order information and activation in the
 462 hippocampal formation reflecting effects for retrieval of 2nd-order information, we additionally conducted an
 463 ROI analysis in the anterior hippocampus. ROI coordinates were taken from a previous publication of our group

464 (Ahlheim et al., 2014) and were based on reported effects of sensitivity of the hippocampus to entropy
 465 (Bornstein & Daw, 2012; Harrison et al., 2006; Strange et al., 2005). The center of the ROI in the left
 466 hippocampus was at $x = -25$, $y = -16$, $z = -18$, and the center of the ROI in the right anterior hippocampus was
 467 at $x = 31$, $y = -17$, $z = -19$. Both ROIs had a sphere with a radius of two adjacent voxels (6 mm). Unexpectedly,
 468 neither ROI showed a significant modulation by 2nd-order information (all $p > .09$, Bonferroni-corrected alpha-
 469 level of .025; see Table 3 for inferential statistics).

470

471 Table 2: MNI coordinates and maximal z-scores of significantly activated clusters following correction for
 472 multiple comparison for the parametric contrast of information provided by the 2nd-order structure.

Localization	MNI coordinates			z-values, local maxima	Cluster size (mm ³)
	x	y	z		
dorsal premotor cortex	28	-11	54	3.82	4725
local maximum in pCC	7	-12	39	3.58	
midposterior intraparietal sulcus	-29	-59	30	-2.91	594
	25	-50	36	-3.31	3294
posterior middle temporal gyrus	-50	-68	18	3.11	405
	37	-62	9	4.23	4455
superior parieto-occipital cortex (BA 18)	-20	-89	15	3.00	648
	16	-92	21	4.56	13851
Temporal pole	52	4	-30	3.50	4401

473

474 Table 3: Inferential statistics of hippocampal ROI analyses.

		<i>t</i> (18)	<i>p</i>
Parametric effect of 1 st -order	left hippocampus	1.75	.097
information	right hippocampus	0.42	.683
Parametric effect of 2 nd -order	left hippocampus	1.29	.212
information	right hippocampus	1.75	.096
Parametric effect of interaction	left hippocampus	-0.25	.806
term	right hippocampus	-0.07	.943

475

476 3) 1st-order dependent exploitation of 2nd-order information

477 We hypothesized that exploitation of the 2nd-order information depends on the amount of information
478 provided by the 1st-order structure. To test this, we included an interaction term modeling only those events for
479 which the 1st-order structure provided least information (lowest 25% of the distribution) or the most information
480 (uppermost 25% of the distribution). The interaction therefore reveals areas that were significantly more
481 strongly modulated by information provided by the 2nd-order structure if the 1st-order structure provided only
482 little information about the upcoming event. We found that activation in the PMd, the IPS, the precuneus, and
483 the occipito-temporal lobe were more strongly modulated by information provided by the 2nd order of the
484 statistical structure when less information was provided by the 1st-order structure.

485 Additionally, the interaction contrast yielded the predicted modulation of activity in lateral BA 10. BA
486 10 did not show a significant modulation by 2nd-order information or 1st-order information alone, which
487 indicates that it is more strongly modulated by information provided by the 2nd order if integration of this
488 information was actually beneficial, i.e. when the 1st-order provided less information (see Table 4 for a list of all
489 activations, Figure 2e). As can be seen from the bar chart in Figure 2e, this interaction effect was indeed driven
490 by the cases in which 1st-order information was low.

491 Notably, the pattern of this revealed interaction effect also held when modeling all instead of only the
492 most (un-) informative 25% of trials (data not shown).

493

494 Table 4: MNI coordinates and maximal z-scores of significantly activated clusters following correction for
 495 multiple comparison for the interaction contrast of information provided by the 2nd-order structure, depending
 496 on the amount of information provided by the 1st-order structure.

Localization		MNI coordinates			z-values, local maxima	Cluster size (mm ³)
		x	y	z		
anterior prefrontal cortex:	BA 10	32	52	9	-3.23	5481
	BA 11	14	50	-15	-3.82	
dorsal premotor cortex		-23	-8	60	-4.27	5076
		22	-2	57	-3.72	4428
Parietal and occipital lobe	intraparietal sulcus	-29	-44	57	-5.49	201285
		33	-40	56	-4.68	
	Precuneus	-9	-62	68	-4.90	
		13	-65	46	-4.56	
	superior parieto-occipital cortex	-15	-101	-6	-5.20	
	posterior middle temporal gyrus	-38	-87	-13	-5.13	
Thalamus		39	-70	-17	-4.47	
Thalamus		16	-26	12	-4.00	1080
Cerebellum		10	-71	-33	-3.03	621
Temporal pole		52	4	-30	3.50	4401

497

498

499 4. Discussion

500 While it is well established that humans use predictive information in their environment to prepare for
501 upcoming events, it is still unclear to what extent and under which conditions they do so. It is one of the
502 currently most urgent questions how the brain selects the sources of information to generate predictions
503 (Blokpoel, Kwisthout, & van Rooij, 2012; Phillips, 2013). The present study investigated whether information
504 from an action's 2nd-order statistical structure is exploited in dependence on the information provided on the 1st
505 level; in other words, whether the brain predicts upcoming actions in a cost-benefit sensitive manner.

506 Our results show that the brain exploits 1st- as well as 2nd-order statistical information, and that it does
507 so in a cost-benefit effective manner. Our findings are threefold: first, the information derived from the action at
508 $t-1$ saves processing costs of the upcoming action. Second, at the same point in time, information from the $t-2$
509 action is additionally exploited and facilitates the observer's predictions further. And finally, information
510 derived from the $t-2$ action is exploited more when the last action alone is less useful in shaping expectations.

511

512 Attenuation in the action observation network based on 1st-order statistical information

513 The first aim to the present study was to replicate and expand previous findings concerning the neural
514 correlates of an increase in predictability by the 1st-order structure in action sequences (Ahlheim et al., 2014).
515 We established in our behavioral post-tests that human observers learned 1st-order conditional probabilities and
516 were particularly good at discriminating between action pairs of high conditional probability, even though no
517 participant reported noticing those regularities in a post-experimental survey.

518 Previous studies reported that valid prediction of upcoming events leads to decreased activity levels in
519 brain areas that code for these events, and that predictive information facilitates perception (Bar, 2004; den
520 Ouden, Kok, & de Lange, 2012; Kok, Jehee, & de Lange, 2012; Summerfield et al., 2008). We extended these
521 findings to the case of action observation and found that an increase in the amount of 1st-order information led to
522 the predicted attenuation of activity in the action observation network, composed of PMv, mIPS, and posterior
523 temporal cortex (Caspers et al., 2010; Jeannerod, 2001). This shows that prediction of the upcoming action step
524 was facilitated by information provided by the 1st-order structure. The established attenuation in this network
525 adds to previous findings, showing that prediction-facilitating effects of 1st-order structure also occur in the
526 presence of a 2nd-order structure.

527

528 Integration of 2nd-order statistical information

529 To test whether human observers are capable of processing the 2nd-order conditional probabilities in
530 our paradigm, we modeled the amount of information provided by the 2nd-order structure. We found that
531 activation of the mIPS decreased with the additional information provided by the 2nd order, on top of the
532 decrease that mIPS showed as a function of 1st-order information. The mIPS was the only component of the
533 AON that showed this pattern. The mIPS has been found to be a central focus of execution as well as
534 observation of reaching movements (Vingerhoets, 2014). It is particularly interesting here that the mIPS area
535 that we found is suggested to underlie the coupling of reaching and eye movements that is needed when we
536 pursue visual hand input during reaching (Vesia & Crawford, 2012). Using temporally occluded targets during
537 smooth pursuit eye movements, Lencer and co-workers (2004) found that this area bridges target occlusion,
538 pointing to a role in anticipatory saccade tuning. In our paradigm, using 2nd-order information increases the
539 predictability of the upcoming action step further, which allows for a more precise prediction of which object is
540 going to be grasped next, and where this object can be found in the scene. This interpretation is in line with a
541 recent finding showing that separable subregions of the intraparietal sulcus are modulated by processing
542 unexpected events as well as events that require an adaptation of a currently valid predictive model (O'Reilly et
543 al., 2013). The further attenuation of mIPS activation with 2nd-order information here reflects the further
544 reduced processing costs of the upcoming reaching of the object, as target and direction of the reaching can be
545 better predicted.

546 Contrary to 1st-order information, 2nd-order information could not be accessed directly through a
547 pairwise association between action $t-2$ and t . Instead, it was necessary to retrieve information about the action
548 step $t-2$ from memory and furthermore integrate this information with the information provided by the action $t-1$
549 on the 1st order, as the action step at $t-2$ alone was not informative of t . Potentially, these additional processing
550 costs could further account for the unpredicted finding of increased RTs with 2nd-order conditional probabilities
551 in our post-fMRI SRTT: here, RTs increased with higher 2nd-order conditional probabilities whilst controlling
552 for an effect of 1st-order conditional probabilities. Further, a trend-level effect ($p = .057$) tentatively suggests that
553 these processing costs, reflected in RT increase, is higher when 2nd-order information changed expectations
554 based on the 1st-order conditional probabilities to a larger extent. Studies on learning of 2nd-order statistical
555 regularities using a SRTT reported a decrease of RTs as reflection of statistical learning (Curran, 1989;
556 Remillard, 2008). Speculating on possible reasons for the diverging results, it should be noted that our SRTT
557 differed in a critical point from a standard SRTT: Statistical regularities among the action steps were already
558 established at the beginning of the testing, whereas the association between observed object and button press

559 was not. How and when the processing costs of higher-order information begin to turn into a behavioral benefit
560 thus needs to be explored further.

561 On the neural level, we expected that the retrieval of information about the action step $t-2$, which is
562 necessary to assess 2nd-order information, would be reflected in an increased hippocampal activation with more
563 2nd-order information. Yet, using an ROI analysis, we did not find evidence for an increase of activation ($p > .09$)
564 with increasing information provided by the 2nd-order structure in the hippocampus. We found, however, an
565 unhypothesized increase of activation in the right temporal pole, the more information was provided by the 2nd-
566 order, as well as in the pMTG and the SPOC. The temporal pole is considered as “semantic hub” where
567 semantic information about entities is processed, irrespective of their modality (Patterson, Nestor, & Rogers,
568 2007). In particular, it decodes conceptual object properties that go beyond the object’s properties, as for
569 instance the associated manipulation or the usual location of the object (Peelen & Caramazza, 2012).
570 Furthermore, the temporal pole has been found to show a higher activation for initially biased perceptual
571 decisions, and to pass this perceptual bias to visual areas (Summerfield & Koechlin, 2008). In the present study,
572 higher 2nd-order information led to an increase in predictability of the upcoming action step and its associated
573 object – in other words, the expectation of the upcoming action became more biased. This allows for a retrieval
574 of semantic knowledge about the object – for instance, its shape or how it will be grasped and manipulated. We
575 suggest that this retrieval of conceptual knowledge also drove the activation in the temporal pole in our study.
576 Conceptual information is then passed to visual areas, i.e. the SPOC and pMTG. Area SPOC, at the mesial
577 boundary between IPS and occipital lobe, is proposed to store internal representations of reach-to-grasp goals
578 (Vesia & Crawford, 2012). We propose that here enhanced activation in SPOC reflects the maintenance of
579 likely reach targets and their locations, which informs monitoring of the reaching movement in more parietal
580 sites. Processing of this target, which is an object, is additionally enhanced in pMTG, which is a key-site of the
581 processing man-made tools (Beauchamp & Martin, 2007). It should be noted though that we did not distinguish
582 between different aspects of an action, that is the involved object and its manipulation. However, the amount of
583 information provided by a certain object or action step varied depending on its position in the sequence,
584 ensuring that the identity of the object itself could not be the cause of the effects revealed here.

585

586 Evidence for information-state dependent use of 2nd-order information

587 To test the hypothesis that exploitation of the 2nd-order statistical structure depends on the amount of
588 information provided by the 1st order, we conducted a parametric analysis for those events on which the 1st order
589 was of very high or low informative value and tested for an interaction effect of 1st- and 2nd-order information.

590 We found that activation in the PMd, the IPS, the pMTG, and the SPOC was more strongly modulated by the
591 interaction term. Those areas, which have been described as the core areas of the AON (Caspers et al., 2010),
592 were thus modulated more strongly by 2nd-order information when 1st-order information was low. This provides
593 evidence for our hypothesis that higher-order information is preferentially used if 1st-order information is
594 insufficient to generate precise predictions. Exploitation of 2nd-order information causes higher processing costs,
595 as a retrieval of the action at $t-2$ is necessary and 2nd-order information needs to be integrated with 1st-order
596 information. Thus, we hypothesized exploitation of 2nd-order information to depend on a cost-benefit criterion:
597 we expected 2nd-information to be used the more, the less information was provided by the 1st order. Areas
598 implementing this cost-benefit criterion should show a correlation with the interaction term of 1st- and 2nd-order
599 information, rather than with either main effect. We hypothesized that BA 10 implements this cost-benefit trade-
600 off by bolstering search for additional information from the action at $t-2$ if action $t-1$ was of only little
601 informative value. With the current paradigm and methods, some uncertainty remains as to whether BA 10
602 activation reflects the cost-benefit optimized exploitation of 2nd-order information or the increased search for
603 additional information from preceding actions.

604 In line with our hypothesis, we found that activity in the lateral BA 10 was correlated with the
605 interaction term. This correlation resulted from a stronger correlation of activity in the BA 10 with 2nd-order
606 information if the 1st order provided only little information, i.e. if the action step $t-1$ did not allow for a
607 sufficiently precise prediction of action t . Notably, significant activation of the BA 10 was only revealed in the
608 interaction contrast. This corroborates our hypothesis that BA 10 recruitment increases under low 1st-order
609 predictability and enhances the exploitation of 2nd-order information. Across a variety of different paradigms,
610 BA 10 has been reported to be activated when several relations among tasks or rules have to be integrated or
611 organized (Golde, Cramon, & Schubotz, 2010; Koechlin & Hyafil, 2007; Nee et al., 2013; Ramnani & Owen,
612 2004; Schubotz, 2011). Here, and in line with findings from Golde et al. (2010), we showed that the BA 10 is
613 also engaged when information derived from actions needs to be integrated. A particularly interesting parallel to
614 our paradigm is the engagement of BA 10 in uncertainty-driven search for information, when available cues
615 provide insufficient information (Badre et al., 2012). Whereas information in the study by Badre and co-workers
616 (2012) could be gained by searching the environment, in the present study information was gained through
617 retrieval of the action at $t-2$. Our results suggest that BA 10 may particularly contribute to a strategic retrieval of
618 associations if these associations provide a clear gain in information. In other words, BA 10 may implement an
619 efficiency criterion for the exploitation of higher-order information, presumably both in actions as well as in
620 abstract stimuli.

621

622 Conclusion

623 The present findings provide several novel insights about the neurofunctional mechanisms underlying
624 the prediction of observed action sequences. It shows that human observers spontaneously use both 1st- and 2nd-
625 order statistical structure to predict upcoming actions, especially when little information is provided by the 1st
626 order. In particular, 1st-order statistical information in action sequences is automatically exploited and results in
627 a faster and more efficient processing of the upcoming action step, manifesting in smaller RTs and a significant
628 attenuation in the action observation network, respectively. Furthermore, information provided by the 2nd-order
629 structure is retrieved and integrated to sharpen expectations, as indicated by activation increase in the temporal
630 pole, and by attenuation in the IPS. Findings suggest that frontolateral BA 10 moderates the retrieval and
631 integration of 2nd-order information, in line with the emerging understanding of this brain area as a hub for
632 strategic integration of information from various sources.

633

634 Notes

635 Supplemental material for this article is available at <https://dx.doi.org/10.6084/m9.figshare.3443633.v3>.

636

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639

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644

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