

1 Greater cross-viewer similarity of semantic associations for  
2 representational than for abstract artworks

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## 15Abstract

16

17It has been shown previously that liking and valence of associations in response to artworks  
18show greater convergence across viewers for representational than for abstract artwork. The  
19current research explored whether the same applies to the semantic content of the  
20associations. We used data gained with an adapted Unique Corporate Association Valence  
21(UCAV) measure, which invited 24 participants to give short verbal responses to 11 abstract  
22and 11 representational artworks. We paired the responses randomly to responses given to  
23the same artwork, and computed semantic similarity scores using UMBC Ebiquity software.  
24This showed significantly greater semantic similarity scores for representational than  
25abstract art. A control analysis, in which responses were randomly paired with responses  
26from the same category (abstract, representational) showed no significant results, ruling out  
27a baseline effect. For both abstract and representational artworks, randomly paired  
28responses resembled each other less than responses from the same artworks, but the effect  
29was much larger for representational artworks. Our work shows that individuals share  
30semantic associations in response to artworks with other viewers to a greater extent when  
31the artwork is representational than abstract. Our novel method shows potential utility for  
32many areas of psychology that aim to understand the semantic convergence of people's  
33verbal responses, not least aesthetic psychology.

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36KEYWORDS: AESTHETIC PSYCHOLOGY; SEMANTIC ASSOCIATION; SOCIAL  
37PSYCHOLOGY; ART; COMPUTATIONAL LINGUISTICS

### 38Introduction

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40Aesthetic appreciation of visual art involves multiple complex processes, including visual,  
41cognitive, emotional, social and semantic processes (see e.g. Jacobsen, 2010; Leder, Belke,  
42Oeberst, & Augustin, 2004; Leder, 2013; Lindell & Mueller, 2011; Palmer, Schloss, &  
43Sammartino, 2013). While responses to artwork may be subjective, there are some  
44properties of artwork that predictably influence aesthetic appreciation across individuals. The  
45property of interest in this article is the representational content of the art. We contrast  
46representational art, which depicts the physical visual world, usually in a non-distorted way,  
47with abstract art, which does not contain recognizable objects, but instead features shapes,  
48patterns, forms, or color compositions. It has been found by a number of researchers that  
49viewers prefer representational art to abstract art, and it has been proposed that this may be  
50because they find it more difficult to find meaning in abstract than in representational art,  
51especially if they lack art expertise (see e.g. Gordon, 1952; Hekkert & van Wieringen, 1996;  
52Landau, Greenberg, Solomon, Pyszczynski, & Martens, 2006; Leder, Carbon, & Ripsas,  
532006; Martindale, 1984; Mastandrea, Bartoli, & Carrus, 2011; Vartanian & Goel, 2004;  
54Winston & Cupchik, 1992).

55

56In addition to a global preference for representational art, particularly by naïve viewers, there  
57is also evidence that viewers agree more with other viewers in their preferences for  
58representational than abstract images (Vessel & Rubin, 2010). Vessel and Rubin argued that  
59this was because representational images are likely to generate associations that are shared  
60by other viewers, which also have similar emotional connotations (e.g. pleasant,  
61unpleasant), while responses to abstract images may be more idiosyncratic. Schepman,  
62Rodway, Pullen, & Kirkham (2015) provided support for Vessel & Rubin's (2010) claim that  
63the shared liking was due to a greater level of shared valence of semantic associations for  
64representational art by asking participants to generate semantic associations, and to provide  
65valence ratings for these associations. Schepman et al. (2015) found, using this method, that  
66representational artworks generated semantic associations that shared valence (positive,  
67negative) with those of other viewers to a greater extent than was the case for abstract  
68artwork. What Schepman et al. (2015) were not able to probe directly, and what was also not  
69the empirical focus of Vessel and Rubin's (2010) work, was the semantic content of the  
70associations generated by viewers. For Vessel and Rubin's claim to be fully supported, the  
71semantic associations generated by viewers should overlap in meaning to a greater extent  
72when they relate to representational than when they relate to abstract artwork. Testing this  
73hypothesis is the aim of the current study, which follows on from Schepman et al. (2015).

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## 75 **Methods**

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### 77 **Data collection**

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79 We analyzed a previously unanalyzed part of the dataset generated by Schepman et al.  
80 (2015, Experiment 2), briefly summarized here so that the study can be understood  
81 independently of the cited source. Twenty-four adults who were not art experts provided  
82 short verbal responses to 22 artworks (11 representational, 11 abstract). We classed  
83 artworks as representational if they resembled the ordinary shapes and colors of the entities  
84 represented (without major distortions in e.g. color or shape), while abstract artworks  
85 contained no recognizable objects, but could include shapes. A full description of the  
86 artworks is provided in Schepman et al. (2015), with a list appearing in its Supplementary  
87 Information (<http://jov.arvojournals.org/Article.aspx?articleid=2278788>), but, in summary, a  
88 range artworks of a variety of styles, colors and subjects / visual appearances were chosen.  
89 Works by non-famous artists were used to minimize the probability that participants had  
90 seen the work before or had been exposed to others' opinions or interpretations of the  
91 works. Works were presented in a printed booklet (A4), with blocks of abstract /  
92 representational artworks in a random order, with blocks counterbalanced across  
93 participants. Participants also rated the images on rating scales (see Schepman et al.,  
94 2015), but rating data do not feature in this paper, which focuses on verbal responses  
95 elicited by the task. These verbal responses were elicited in writing using an adaptation of  
96 the Unique Corporate Association Valence (UCAV) measure (Spears, Brown, & Dacin;  
97 2006). The instructions (also reported in Schepman et al., 2015) were: "please write a word  
98 or short description in the boxes below of any thoughts that the work of art brought to mind.  
99 Please try to complete a minimum of three boxes and then please circle how positive,  
100 neutral or negative the description is". Participants could complete a maximum of five  
101 response boxes. The "circled" ratings of the descriptions have been reported in Schepman et  
102 al. (2015) as measures of the valence of the associations and will not feature here. Instead,  
103 we concentrate on a semantic similarity analysis of the verbal responses. Participants  
104 generated responses consisting of an average 6.61 words per representational artwork and  
105 5.33 words per abstract artwork. We entered these responses for further semantic similarity  
106 analysis.

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## 110 Analysis method

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112 Building on Vessel and Rubin (2010) and Schepman et al. (2015), our hypothesis was that  
113 verbal responses to representational artworks would show greater semantic similarity across  
114 viewers than verbal responses to abstract artworks. To operationalize the analysis, we  
115 identified semantic similarity analysis software that could accommodate the types of  
116 responses that had been elicited and that could compute a numeric semantic similarity score  
117 for pairs of these responses for further statistical analysis. Based on our constraints, we  
118 chose UMBC Ebiqity (Han, Kashyap, Finin, Mayfield, & Weese, 2013;  
119 <http://swoogle.umbc.edu/SimService/index.html>). This software uses a hybrid approach to  
120 computing semantic similarity, namely distributional similarity and Latent Semantic Analysis,  
121 supplemented with a thesaurus method using WordNet (see Han et al. 2013). Of the three  
122 variants of the software available, we chose Semantic Textual Similarity (STS;  
123 <http://swoogle.umbc.edu/StsService/index.html>), because it was able to cope with the full  
124 range of responses (from words, through short phrases, to sentences). For each pair  
125 presented, this software yields a score between 0 and 1. A score of 0 means no similarity at  
126 all, or it can also indicate that a word is not in its dictionary, while a score of 1 is a perfect  
127 match. To illustrate, the words “ocean” and “sea” yield a score of 1, the phrases “old  
128 acquaintances” and “absent friends” yield a score of 0.369, while the sentences “The farm  
129 was located in a mountainous region.” and “He read five books in two days.” yield a score of  
130 0. Note that these examples were not from our corpus, but have been created by us  
131 specifically to illustrate the output from the semantic similarity software. As described more  
132 fully in Han et al. (2013), the software has multi-layered set of routines to optimize the  
133 accuracy of the semantic similarity scores, and performs well against other, similar software.  
134

135 For each artwork, the 24 participants had been asked to provide a minimum of three and a  
136 maximum of five short verbal responses in so-called description boxes. We randomly paired  
137 these verbal responses with other verbal responses using random numbers generated by  
138 [www.random.org](http://www.random.org) (sequence generator) in one of two ways, experimental and control  
139 pairings, which will be discussed in turn.

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141 For the experimental pairings, for each artwork, we paired the responses given by the 24  
142 participants in one description box randomly with one of the responses from that set. We did  
143 this by description box, to avoid the possibility that the response from a participant in one  
144 description box would be paired with his or her own response in a different description box,  
145 as that could inflate the similarity scores. For the first three description boxes, which yielded  
146 full datasets (bar very rare missing data), we did not constrain for the probability that the

147response would be randomly matched with itself, as this probability was deemed stable  
148across the two conditions (abstract, representational). As participants had been asked to  
149provide 3 – 5 responses, this process was repeated for all boxes and all artworks separately.  
150Boxes 4 and 5 (which were optional) had fewer responses per artwork, but the same  
151process was used, except in cases with very few responses, when any matches to the  
152response itself were re-randomized, and any single responses by only one person to a  
153particular artwork were deleted from the analysis. This process yielded 1729 pairs, of which  
154842 were responses to abstract artwork, and 887 to representational artwork.

155

156In addition to running the within-artwork and within-description box pairings, control pairings  
157were created for a key control analysis. This was partly because it had been observed that  
158more words were produced in response to representational than abstract artworks. It was felt  
159that this may introduce inflation of similarity scores in the representational artworks. In  
160addition, there may be other general aspects of the text that may have led to higher similarity  
161scores for representational artwork than for abstract artwork without these necessarily being  
162attributable to the specific artworks. Thus, pairings were created in which all the responses  
163within a category (abstract, representational) were randomly paired with other responses  
164from across all artworks and description boxes of that category. These pairings were not  
165subject to any constraints. It was hypothesized that, if this analysis revealed a significant  
166difference in similarity scores between abstract and representational artworks, then any  
167significant difference in the experimental analysis would be likely to be a baseline effect. On  
168the other hand, a non-significant result in the control comparison could be argued to rule out  
169this baseline effect.

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171Custom-written Javascript code sent all experimental and control word pairs through the  
172UMBC Ebiquity STS service and stored the resulting output in an Excel spreadsheet. The  
173semantic similarity scores yielded by this process were used to test the experimental  
174hypothesis and the control hypotheses.

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## 177**Results**

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### 179**Sample pairings and output**

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181To illustrate the data, we report a sample of experimental response pairs and their similarity  
182scores. A sample abstract artwork featuring white protruding forms with black and blue line  
183shapes on beige / grey background (Pol Ledent: Abstract 882140

184[http://c300221.r21.cf1.rackcdn.com/abstract-882140-1335238270\\_b.jpg](http://c300221.r21.cf1.rackcdn.com/abstract-882140-1335238270_b.jpg)), gave rise to  
185experimental response pairs including “earthy tones” paired with “puzzled” (semantic  
186similarity score: 0); “dark” with “mystery” (0.13); “messy and random” with “complicated”  
187(0.31); “hidden meaning” with “abstract” (0.15); “ship in storm” with “cold flames” (0.13);  
188“nature” with “anger” (0); “paranoid” with “cotton wool” (0); “snow” with “interesting colours”  
189(0). A sample representational artwork featuring a woman standing by a wall laughing (Jean  
190Smith: Laugher #4

191<http://jeansmithartist.com/wp-content/gallery/laughter-project/laughter4.jpg> gave rise to  
192experimental response pairs including “positive and happy” paired with “fun” (0.20);  
193“shadow” with “happy” (0); “I want to meet this lady, she looks fun” with “yellow” (0);  
194“Amusing” with “I would love to know why she is laughing” (0.45); “colourful” with “I love the  
195contrast between the background and the woman” (0.16); “good colour choice” with  
196“embarrassment” (0); “funny” with “snapshot” (0); “good times” with “happy” (0.15). As can  
197be seen from the sample response pairs, responses were quite varied for both types of art,  
198but, in this small illustrative sample, it seems that the semantic content of the responses to  
199the representational artwork may overlap to a greater extent, and the responses to the  
200abstract art may be more varied. Our statistical analyses, set out in the next subsections,  
201aim to put this notion to the test.

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203

#### 204**Experimental pairings**

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206Normality tests and distribution plots (see top panels of Figure 1) showed a non-normal  
207distribution for both categories, and therefore statistical analysis was carried out using the  
208non-parametric Mann-Whitney test for two independent samples, which tested for  
209differences in ranks. The mean semantic similarity score for abstract artworks was .1141  
210( $SD = .257$ ), while for representational artworks it was higher, at .1298 ( $SD = .251$ ), and the  
211similarity scores differed significantly when comparing the two types of artwork,  $Z = -3.622$ ,  $p$   
212 $< .001$ . The abstract set contained 504 zero scores (59.9%) and 53 scores of one (6.3%).  
213The representational set contained 455 zero scores (51.3%) and 44 scores of one (5.0%).

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215-----Please insert Figure 1 about here; for caption, see immediately below -----

216

217Figure 1: Dot plots of the distributions of semantic similarity scores for the representational  
218and abstract artworks in the experimental and control pairings.

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220





## 222Control pairings

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224This control analysis yielded a mean of .0681 ( $SD = .159$ ) for representational artworks and  
225a slightly higher mean of .0726 ( $SD = .178$ ) for abstract artworks. The difference between  
226conditions was not significant,  $Z = -1.166$ ,  $p = .244$ . The abstract set contained 543 (64.5%)  
227zeros and 18 (2.1%) scores of one, while the representational set contained 541 (61.0%)  
228zeros and 13 (1.5%) scores of one. The distribution of scores for these two datasets can be  
229seen in the lower panels of Figure 1.

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## 232Experimental vs. random pairings

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234Given the patterns reported above, we felt it would be useful to run a third analysis, which  
235explored whether, for both abstract and representational artworks, the cross-viewer similarity  
236of the responses given by participants to specific artworks significantly exceeded the  
237similarity scores observed in the random control pairings. The main focal points in the  
238analysis were to examine whether abstract artwork showed some convergence compared to  
239a random baseline, and, if so, on what order of magnitude the effect size may be different  
240from the equivalent comparison in the representational artworks. This analysis was done  
241using a pairwise non-parametric test, namely Wilcoxon's signed rank test. This showed that  
242for representational artworks, semantic similarity of the experimental pairs exceeded that of  
243the random control pairings significantly,  $Z = -7.010$ ,  $p < .0001$ . Crucially, this also applied to  
244the abstract artworks, but with a smaller effect size,  $Z = -3.928$ ,  $p < .001$ .

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## 247Discussion

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249Our current work shows, for the first time, that there is a greater overlap in the semantic  
250associations elicited by representational artwork than by abstract artwork. This finding  
251directly supports Vessel and Rubin's (2010) associationist explanation of the greater  
252consistency in preferences for representational versus abstract artworks. Although it is  
253somewhat difficult to translate the software's semantic similarity value into real-world  
254semantic overlap, within its possible range of 0 to 1, the semantic similarity scores for both  
255types of artworks in the experimental pairings were relatively low within that range, which  
256suggests that a large proportion of the responses were individual. Nevertheless, to the  
257extent that responses are shared between viewers, those generated by representational  
258artwork showed a greater similarity across viewers than the responses generated by

259abstract artwork. It could be argued that this is to be expected, because representational art  
260features obvious semantic referents in the physical entities depicted, while abstract art does  
261not, and thus representational art may generate some description-based associations that  
262are not available for abstract artworks. On the other hand, the quantitative data and the  
263sample response pairs show that representational artworks generate considerably varied  
264responses. Thus, the finding that these responses overlap is not likely to be solely due to  
265basic object naming, but seems more likely to be associated with higher level interpretative  
266processes.

267

268Our control analysis shows that our findings cannot be attributed to baseline aspects of the  
269text. One may have expected, for example, that simply producing a higher number of words  
270may lead to higher similarity scores, or one might expect that there may be a higher level of  
271specificity in the responses to representational art than to abstract art giving rise to higher  
272similarity scores without this being connected to the specific artwork. However, the control  
273analysis, which used a different randomization from the experimental analysis, showed that  
274this was not the case. In fact, numerically, the scores for abstract artworks were somewhat  
275higher than representational artworks in this analysis, although not significantly so.

276

277Our other key comparison showed that for both abstract and representational artworks, the  
278semantic similarity of randomly paired responses is exceeded amply and significantly by  
279those of the experimental pairings, though the effect size for this observation was much  
280larger in representational than in abstract artworks. This suggests that, even in abstract  
281artworks, there is some overlap between viewers' responses, and their responses are not  
282purely idiosyncratic. The overlap is stronger in representational artworks, but, based on our  
283data, the difference is one of degree and not in kind. This leaves interesting research  
284possibilities for future research, which could aim to examine the overlap in abstract artworks,  
285which could serve to understand the communication between artist and viewer of abstract  
286entities.

287

288Our work substantially extends Vessel and Rubin's (2010) and Schepman et al.'s (2015)  
289empirical support for the idea that representational artworks generate internal states in  
290viewers that resemble those of other viewers to a greater extent than abstract artworks,  
291because the entities depicted in representational art create associations that show greater  
292semantic similarity with those of other viewers. This takes this evidence beyond that  
293provided by Vessel and Rubin (2010), who provided evidence of similarity in preference, and  
294inferred that internal states were responsible. It also takes the evidence beyond Schepman  
295et al. (2015), who found that the valence of the semantic associations overlapped across

296viewers to a greater extent in response to representational than abstract art, but who were  
297not able to show actual semantic overlap.

298

299In addition to providing evidence on this specific point, we feel that, more generally, using  
300this method opens the door to many other interesting studies that could examine how  
301viewers process the meaning of art and a multitude of other objects. It is particularly useful to  
302extend the methods by which this can be studied, because it is traditionally relatively difficult  
303to study meaning empirically, particularly using quantitative statistical methods. This is  
304especially important because meaning has been deemed a key factor in the appreciation of  
305art (see e.g. Martindale, 1984). While the process of generating meaning may be a crucial  
306process in art viewers, this may be the case more strongly in expert than in naïve viewers.  
307Thus, it would be interesting, in future, to carry out the same experiment with art experts,  
308who may show interesting differences from the non-expert viewers who took part in our  
309study.

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311

## 312**Conclusions**

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314Our data show that responses to representational art show a greater semantic overlap  
315across viewers than responses to abstract art. This bolsters the theoretical view that shared  
316liking is associated with shared semantic representations of art. It also provides novel and  
317original evidence that suggests that meaning plays an important role in the complex  
318processes that lead to aesthetic appreciation.

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## 321**Acknowledgements**

322

323Research Assistant Lindsay Burgess helped with data entry. Her time was funded by a  
324University of Chester internal grant. Note that author Sarah Pullen collected the data as part  
325of a dissertation submitted to the University of Chester, with Paul Rodway as her primary  
326supervisor, and with input from Astrid Schepman and Julie Kirkham. Brian Rodway,  
327[brian@affinitystudios.co.uk](mailto:brian@affinitystudios.co.uk) of Affinity Studios <http://www.affinitystudios.co.uk/index.html> ,  
328UK, wrote the Javascript software that called the semantic similarity service and stored the  
329scores. We denote Astrid Schepman and Paul Rodway as equal primary authors.

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