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1 Making sense of tourists' photographs using Canonical Variate Analysis

2

3 **1. The problem**

4 There is a considerable untapped potential for applying visual research methods in tourism
5 (Garrod, 2008). This is despite the significant progress that has been made in recent years in
6 terms of theorising visual tourism research (Scarles, 2011), addressing critics' concerns about
7 the 'subjective' nature of visual research (Crang, 2003; Balomenou & Garrod, 2014), and
8 technological advances in personal photography (Straumann et al., 2014). More specifically,
9 tourists' photographs can serve as rich datasets to help answer pressing questions about
10 tourists' preferences and behaviours. Such images are increasingly available in large volumes,
11 whether they are collected using participant-generated image (PGI) techniques (Sun et al.;
12 2014; Pan et al., 2014; Fung and Jim, 2015; Cutler et al., 2016) or employ images found in the
13 media, notably the burgeoning number of social media sites such as Flickr and Instagram
14 (Michaelidou et al., 2013; Kim & Stepchenkova, 2015; Konijn et al., 2016). As such, they can
15 be thought of as 'big data' and have enormous potential for the application of data-mining
16 techniques, for example to identify the elements of the destination that appeal the most to
17 tourists and can be emphasised in marketing activities.

18 Big photographic datasets can, however, be exceedingly resource-hungry to prepare, analyse
19 and interpret (Pearce et al., 2015; Balomenou & Garrod, 2014). Merely the coding-up can take
20 months of researcher time. Pearce et al. (2015), for example, used a team of two researchers
21 who worked full time for four months coding 10,000 photos into 42 variables. One of the
22 authors of this note, meanwhile, spent two months of full-time work coding 500 photos into
23 33 variables, and a further four months coding 996 photos into 12 variables. These significant
24 resource demands serve to limit the practicality of using visual methods with large numbers
25 of images.

26 This research note sets out a possible response, which is to identify a reduced set of variables
27 that are of greatest relevance to the research questions involved (Darlington et al., 1973),
28 thus making the coding-up and subsequent analytical processes more manageable.

29 Researchers have long proposed that a preliminary interpretation phase could be applied to
30 reduce the number of variables to be coded up (Albrecht, 1980).

31 Principal Component Analysis (PCA) has, to date, been the most widely used technique (Taylor
32 et al., 2002; Schultz et al., 2004; Johnson et al., 2007) for dimensionality reduction. A
33 proposed advantage of PCA is that it does this by introducing new variables that are
34 composites of the original variables. It is important to note, however, that PCA is
35 fundamentally an unsupervised technique (Martens & Neaes, 1989), so it does not allow *a*
36 *priori* hypotheses to be tested. Even where correlations are observed, PCA can provide no
37 measure of the significance of these (Johnson et al., 2007). Moreover, PCA cannot provide
38 clear graphical representations of the interrelationships between the variables, which would
39 be particularly useful in the interpretation of large datasets. Assuming unknown weights for
40 the variables in PCA also risks losing valuable information. This is mainly because of
41 correlation between the number of units analysed and the number of variables (Pérez et al.,
42 2013). Moreover, PCA cannot be used in cases where the data come from multiple samples,
43 nor for a repeated-measures design. This limits the utility of PCA as a means of dimensionality
44 reduction.

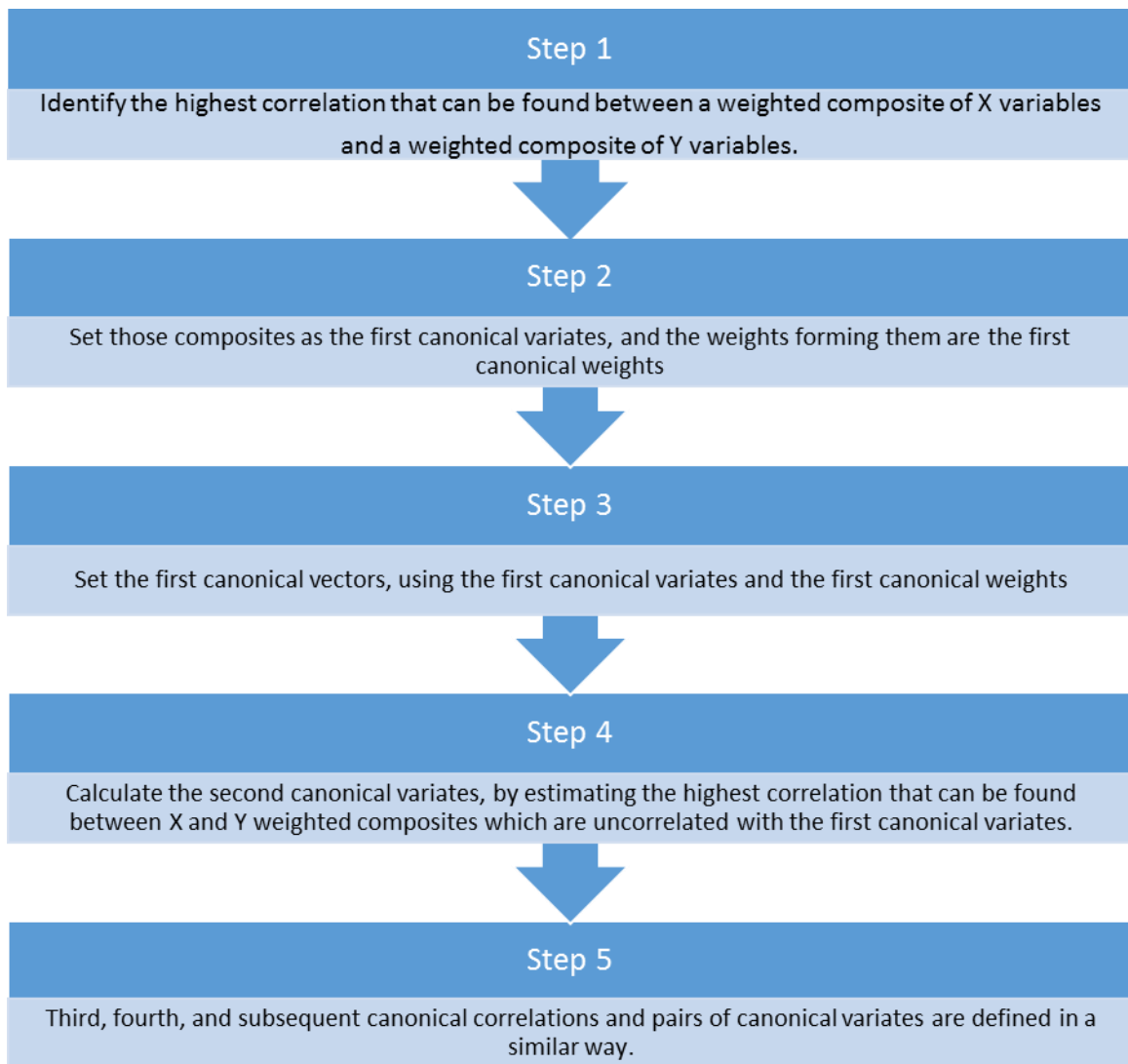
45 An alternative technique that is sometimes used for dimensionality reduction is Factor
46 Analysis. Dwyer et al. (2004), for example, use it to suggest various indicators that can be used
47 to estimate the competitiveness of tourism destinations. However, as with PCA, there are no
48 established criteria against which to assess the findings.

49 This paper proposes that Canonical Variate Analysis (CVA) has strong potential as a
50 dimensionality-reduction technique. It can be said to be superior to similar techniques in
51 several important respects. CVA can measure the comparative contribution of each variable
52 in the canonical (composite) relationships that are calculated, hence allowing the
53 relationships between various sets of the independent and dependent variables to be
54 assessed. As Larimore (1997) explains, CVA is a maximum likelihood statistical technique that
55 can be used to classify the relationships between variables. As such, CVA allows for the testing
56 of hypothesis using a measure of prediction accuracy. The following section presents a brief
57 outline of CVA.

58 **2. A proposed solution: Canonical variate analysis**

59 Canonical Variate Analysis (also known as canonical discriminant analysis) can be thought of
60 as a variant of Canonical Correlation Analysis (CCA), where group indicators form one variable
61 set (Gittins, 1985). CCA was developed by Hotelling (1935) as a means of identifying the linear
62 combination of one set of variables, X, that is most correlated with another linear
63 combination of a second set of variables, Y. Beaghen (1997, p. 6) emphasises that Canonical
64 Correlation has the property of biorthogonality, which is 'the property that each canonical
65 variate in the X-domain is uncorrelated with the canonical variates in the Y-domain except
66 the corresponding Y-variate'. CCA has been used in tourism research in the context of travel
67 motivations and push and pull factors (Uysal & Jurowski, 1994; Oh et al., 1995; Balogu & Uysal,
68 1996; Gonzalez & Bello, 2002), tourism behaviour (Wong & Lau, 2001), destination marketing
69 and branding (Ahmed, 1986; Hosany et al., 2006), e-relationship marketing and hotel financial
70 performance (Jang et al, 2006), hosts perceptions of impacts (Allen et al, 1988) and demand
71 (Uysal & O'Leary, 1986). However, CCA has not been used extensively, nor specifically to
72 analyse tourism photographs.

73 Muller (1982) proposed a General Linear Model (GLM) for canonical correlation techniques.
74 Developed in 1948 by Rao (1948, 2005), CVA can be thought of as being part of this family. As
75 with CCA, the technique works by constructing canonical variables, each of which can include
76 one or more of the original variables. Darlington et al. (1973) explain the mechanics as a two-
77 stage process, with two statistics. Starting with the original variables, the first canonical
78 correlation is the highest correlation possible between a weighted combination of X variables
79 and a weighted combination of Y variables. These are the first canonical variates (CVs). The
80 second canonical correlation is then calculated as the highest correlation that can be found
81 between the X and Y weighted composites that are uncorrelated with the first canonical
82 variates (Figure 1). These are known as second CVs.



83

84 Figure 1: CVA process

85

86 CVA thus works by detecting the optimum dimensionality of each variable that strengthens
87 the relationship between dependent and independent variable sets. It is based on the
88 premise of defining how much of the variance in one set of variables can be explained by the
89 second set. The most common practice to achieve this is by identifying functions where the
90 canonical correlation coefficients are statistically significant beyond some predetermined
91 level, typically .05. In so doing, using CVA helps to ensure that proper regard is given to
92 variations within each variable set (Darlington et al., 1973; Chatfield & Collins, 1980; Russell
93 et al., 2000; Bussell et al., 2008). Hair et al. (1998) recommend three criteria to use in
94 combination to decide which of the canonical functions should be interpreted: (i) the level of

95 statistical significance of the function, (ii) the magnitude of the canonical correlation, and (iii)
96 the redundancy measure for the percentage of variance accounted for from the two data sets.

97 CVA has thus far been used predominantly in the biological sciences (Albrecht, 1980; Causton,
98 2008). Few studies have used CVA in a tourism and hospitality context (rare exceptions being
99 Tran et al., 2013, Tran & Ralston, 2006) and none as a tool to analyse photographs in the
100 tourism field, despite the surge in readily available photographic data that often result in very
101 large photographic datasets (Lee, 2016).

102

103 **2.1. Justification for the use of CVA**

104 The studies by Brown et al. (1980) and Tran and Ralston (2006) both used CVA to test
105 hypotheses they had already developed based on interviews with informants. This reflects a
106 key advantage of CVA that is reported by non-social science researchers, who suggest that
107 CVA is best used when the researchers have a priori knowledge of the data (Alsberg et al.,
108 1998; Johnson et al., 2007). PCA, in contrast, is fundamentally an unsupervised technique.
109 CVA also allows any variable (be it an original variable or a canonical one) to be continuous,
110 categorical or even mixed (Darlington et al., 1973). This can be vital in the social sciences,
111 allowing 'soft' data to be brought in to help the analysis.

112 It is also argued that CVA is useful for data visualisation, particularly to evaluate inter-
113 relationships (Johnson et al., 2007) and to reveal the basic structure of complex datasets
114 (Albrecht, 1980). CVA allows the mapping of clusters in two or three dimensions (Hammer
115 and Harper, 2006). Albrecht (1980) explains how CVA helps visualise the dataset on a plot. He
116 regards CVA as a succession of rotational and rescaling transformations of the original
117 variables which protect the integrity of the data while allowing the researcher to interpret
118 them (Albrecht, 1980). He further suggests that using CVA is as if the:

119 'coordinate system defined by the original descriptor variables is suspended in air such
120 that the investigator can walk around it until the most favorable vantage point is located
121 for viewing the differences among the populations. Canonical Variate Analysis simply

122 defines the most favourable vantage point as being related to the greatest statistical
123 separation among the populations' (Albrecht, 1980, p. 687)

124 The results of CVA can be conveyed as bivariate plots of one CV versus another, or as three-
125 dimensional plots (Albrecht, 1980). This allows associations between sample groups to
126 become visible (Johnson et al., 2007). The mean of each sample class is plotted against each
127 CV, usually surrounded by a confidence area. The confidence area is circular, and Quinn and
128 Keough (2002) describe it as an 'interim' calculation of the population mean which, according
129 to Johnson et al. (2007), is equivalent to confidence intervals in the univariate situation. If
130 95% confidence circles are plotted around each mean, significantly different sample groups
131 can be identified visually on the plot (by their lack of overlap).

132

133 **2.2. An example: The use of CVA in a volunteer-employed photography (VEP) study**

134 This section presents an example of the use of CVA. The dataset used in the study was
135 collected for a tourism planning study in the St David's area of Pembrokeshire Coast National
136 Park, Wales (see Balomenou & Garrod, 2014; this paper presents a different analysis of the
137 data collected in that study). Tourists and residents were given cameras, diaries and a
138 demographic survey, and were asked to photograph positive and negative aspects of
139 holidaying and living in the area. A brief description of the dataset is presented in Table 1:

140

141 Table 1: Study dataset in numbers

Total number of participants	278
Overall return rate	64.7% (51.2% locals, 76.5% tourists)
Average survey time per participant	21 minutes
Total data collection time for main study	98 hours
Number of photographs analysed	1496

142

143 CVA analysis of this data used only the variables that were already expressed in quantitative
144 form or could sensibly be converted into such. These are shown in Table 2.

145 Table 2: Survey questions data drawn for the quantitative analysis

Tourists	Locals
Question 3: What is your main activity during your visit?	Question 2: How long have you lived in St David's peninsula?
Question 4: Why have you chosen to visit Pembrokeshire Coast National Park?	Question 4: Is your job related to the tourism industry in any way?
Question 5: What is it that you value most about this area?	Question 5: What do you think is special about Pembrokeshire Coast National Park?
Question 6: Have you visited Pembrokeshire Coast National Park before?	Question 6: What is it that you value most about this area?
Question 7: Is this the start, middle or end of your holiday?	Question 9: How might the area be improved?
Question 8: Are you going to spend all your holiday in the St David's area?	Question 10: Given the chance would you ever think of moving elsewhere in this country?
Question 10: How might the area be improved?	Question 11: Our National Parks are under a lot of pressure. Are there any aspects of the area that, if changed, would mean you wouldn't enjoy living in Pembrokeshire Coast National Park anymore?
Question 12: Our National Parks are under a lot of pressure. Are there any aspects of the area that, if changed, would mean that you would not choose to come back to Pembrokeshire Coast National Park for your holidays?	

146

147 The software used to run the CVAs for this study was devised by Dr David Causton, from the
 148 Institute of Biological, Earth and Rural Sciences at the University of Wales in Aberystwyth and
 149 has been used in multiple occasions in biology (Bussell et al., 2008; Johnson et al., 2007).
 150 Other software available in the market include CVAGen6 AND PCAGen6.

151 The data was extracted by coding the answers to these questions. There are three reasons
 152 these questions were used. First, the answers to them could be grouped effectively and
 153 researcher interpretation was minimal. Second, one of the objectives of the analysis was to
 154 compare photos captured by different user groups, so the questions and the answers needed
 155 to be comparable. Third, the decision to run a satisfactory number of tests and get the

156 maximum amount of information from the data collected: the data collected from the rest of
 157 the questions asked in the survey would be used in the analysis of the survey and the in-depth
 158 analysis of all the elements of the technique together.

159 Maintaining data integrity and avoiding researcher bias was imperative. Thus, instead of the
 160 researchers constructing the variables according to their own interpretation of the face value
 161 of the photographs, the coding system was based on interviews with the general public and
 162 their assessment of the photograph content. Thirty photos were selected randomly from the
 163 dataset and copies were placed on a board that could be easily transported. The board was
 164 approximately 1m x 80cm and could hold a maximum of 30 photographs. Interviews took
 165 place in three different locations in Aberystwyth, another seaside town in the same part of
 166 Wales, among people from a similar range of age groups and user groups to those in
 167 Pembrokeshire. Stratified sampling was used, based on data drawn from the UK census
 168 regarding age and gender. Participants were simply asked to describe what they could see in
 169 five photographs of their choice.

170 Seven sets of variables were produced in the process of identifying the variables for the
 171 coding process. After each set was produced, its selection was challenged by the research
 172 team and an improved version was produced, which was again challenged and so on. The final
 173 set of 30 variables that would be used as a basis for the coding were identified in the seventh
 174 attempt and can be seen in Table 3.

175 Table 3: Thirty variables identified after the interviews

A. Overall percentage	
Water	Natural and man-made features: sea, river, marina, jetty, harbor
Sky, blue	
Sky, clouds	
People	
Trees	
Vegetation	Grass, fern, bracken
Flowers	
Beach	Shingle, sand, when tide is out
Rocks/ hills	In the distance and when this is what was captured, natural features
Signs	Road sign, walking path signs, cycling signs, advertisements, speed signs, etc

Animals	
“Coastal Path”	
Heritage buildings	St David’s Cathedral, Treffin’s Mill, Solva Mill, etc
Other buildings	
Means of transport	
Other man-made features	Roads, fences, tomb stones, car parks, rubbish bins, benches, chairs, tables
Rubbish	
Tourism paraphernalia	Wind breaks, beach mats, tents, umbrellas
<i>B. Specific, units</i>	
People	Standing, sitting, engaged in activities
Trees	
Signs	
Dogs	
Horses	
Other animals	Mammals, insects, birds, excluding people
Heritage buildings	St David’s Cathedral, Treffin’s Mill, Solva Mill, etc
Other buildings	
Rubbish bins	
Cars	
Boats	
Flowers	

176

177 Initially, 500 randomly selected photographs were coded using these 30 variables. A double-
178 blind coding process was used to enable inter-coding reliability statistics to be calculated. To
179 maintain the integrity of the dataset, CVA was applied to this dataset and it became apparent
180 that 12 variables were responsible for 95% of total variation. These 12 variables (Table 4) were
181 then used to code the rest of the dataset. This greatly reduced the amount of time and
182 resources required to code up the remaining two-thirds of the photographs.

183

184 Table 4: The final 12 variables used in the CVA coding

Variable no. 1	Blue sky (proportion of photograph area)
Variable no. 2	Cloudy sky (proportion)
Variable no. 3	People (proportion)
Variable no. 4	Animals (proportion)

Variable no. 5	Car interior (proportion)
Variable no. 6	Other man-made features (proportion)
Variable no. 7	Tourism paraphernalia (proportion)
Variable no. 8	People (number visible in photograph)
Variable no. 9	Signs (number)
Variable no.10	Horses (number)
Variable no.11	Heritage buildings (number)
Variable no.12	Flowers (number)

185

186 Twelve hypotheses were then constructed, based on information from the literature and the
 187 data from the demographic questionnaires. These hypotheses were then tested using CVA. A
 188 high proportion of the original variation (99% to 100%) could be explained in relation to
 189 hypotheses with relatively few variables. One such hypotheses will be presented here to
 190 illustrate the success of using CVA for this dataset.

191 Hypothesis 11: There are significant differences between the photographs taken by
 192 members of the local community compared to visitors according to what they value
 193 the most about the area.

194 Although it does not explain the highest proportion of the variation, it is used to indicate how
 195 CVA successfully analyses this complicated and rich dataset. The CVA thus compared
 196 photographs taken by locals and tourists according to people’s perception about what they
 197 most value about the area. Eight groups were thus formed, as shown in Table 5:

198 Table 5: CVA 11 populations

Locals	Tourists
No overdevelopment	No overdevelopment
Quality of life	Quality of life
Location	Location
Community	Other

199

200

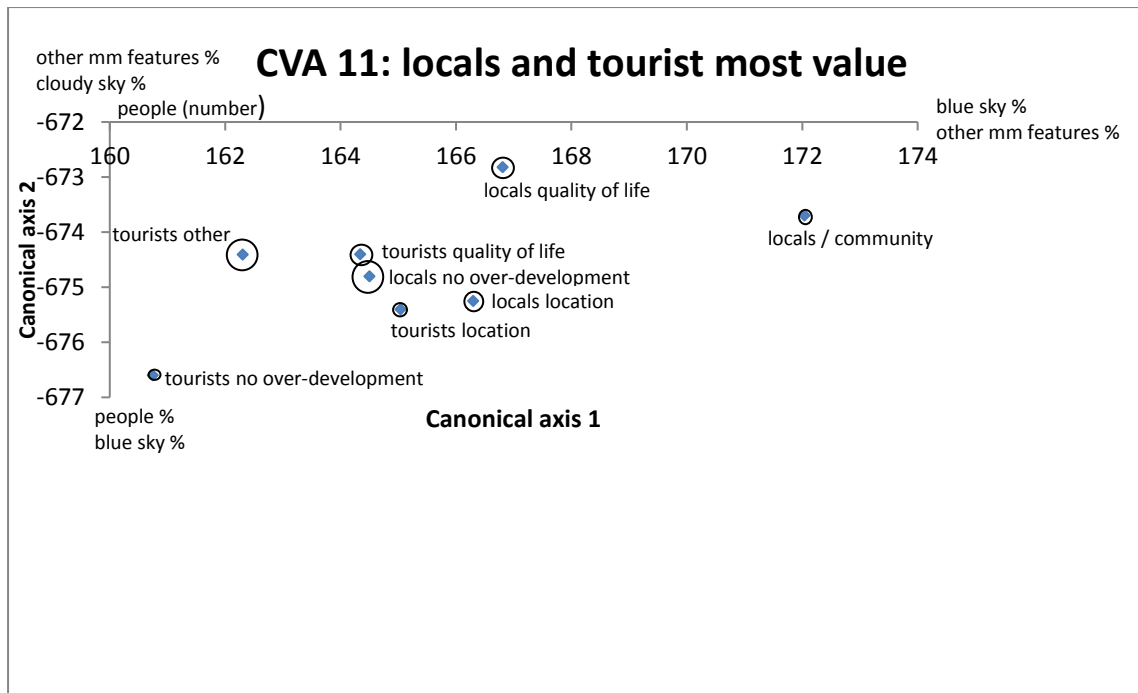
201 Table 6: Eigenvalues and canonical correlations

202	Root No.	Eigenvalue	Pct.	Cum. Pct.
203	1	0.1299	57.5923	57.5923
204	2	0.0449	19.9005	77.4927
205	3	0.0230	10.1863	87.6791
206	4	0.0132	5.8513	93.5304
207	5	0.0101	4.4707	98.0011
208	6	0.0033	1.4810	99.4822
209	7	0.0012	0.5178	99.9999

210

211 The CVA plot (Figure 2) explains 87.7% of the total original variation. There are significant
212 differences between the photographs taken by residents compared to visitors, according to
213 what they value the most about the area. The only two groups whose photographs were not
214 significantly different were locals who appreciate the limited scale of development in the
215 area, and tourists who appreciate the quality of life in the area.

216



217

218 Figure 2: CVA 11 - what locals and tourists most value

219

220 The two groups that were placed opposite on both axes were ‘tourists who most valued that
 221 the area is not overdeveloped’ and ‘locals who most valued the sense of community in the
 222 area’. Participants who fell into the first of these groups tended to include more people in
 223 their photographs, and participants in the second group tend to include more blue sky and
 224 man-made features.

225 To verify the validity of the coding of the photographs, a third of the photographs were blind-
 226 double coded by an independent researcher. The researcher coded the 500 randomly chosen
 227 photographs the principal researcher had used to narrow down the number of the original 33
 228 variables to 12. Both sets of coding were plotted and similarity was observed.

229

230 3. Insights and future research

231 The case study identifies three benefits of using CVA in analysing ‘big’ visual data. Firstly, it
 232 shows how CVA can be used to justify a reduction in the dimensionality of multivariate data.
 233 In this case, the identified variables were reduced from 30 to 12. This made a considerable

234 reduction in coding time. It took the researchers almost two months to code 30 variables for
235 500 photos, implying the need for approximately another four months to complete the
236 remaining 996. Using CVA allowed the elimination of variables that were common to all
237 participants and could not be used to differentiate between photographs, thus reducing the
238 number of variables that needed to be coded up.

239 Secondly, the richness of the dataset was not compromised in the process. Despite the
240 reduction in the number of the variables, the reduced variable set was responsible for 95% of
241 the total original variation. Future researchers can be confident that by using a robust coding
242 technique followed up by CVA, they can reduce the dimensionality of their dataset without
243 compromising its depth and richness.

244 Thirdly, an advantage of CVA is that the photos can be traced back to those who took them.
245 This enabled the discrimination and identification of structures and inter-relationships within
246 the multivariate statistical population (Bussell et al., 2008). These were associated with
247 particular sorts of people and differences of opinion among different user groups of the same
248 area. The analysis of the photographs indicated, *inter alia*, that there are significant
249 differences between people who were born in the area compared with those who moved in
250 the area, locals and tourists who were happy to see the character of the area change and
251 those who were not, tourists depending on the stage of their holiday, and so on.

252 CVA is subject to some limitations, including that it is the CVs that are the ones to be
253 interpreted, rather than the original variables, and that interpretation takes place in pairs.
254 Considering that solutions depend on the level of correlation between and within sets, it is
255 likely that a modification in a variable of the one set will have implications to the structure of
256 the other set.

257 The findings presented here are invaluable, given the purpose of the study, which was to
258 attempt to identify differences in the destination image construed by visitors, that perceived
259 by residents, and that proposed by marketers (an aim also adopted by Michaelidou et al.,
260 (2013). Indeed, Markwell (1997), Urry (2002), and Urry and Larsen (2011) have all observed
261 that the tourism industry can shape a destination image in ways that may be dissonant with
262 that of residents or, indeed, be consistent with the actual experience of tourists. MacKay and

263 Couldwell (2004), meanwhile, suggest that keeping a visual inventory of the visitors' images
264 of a site can be especially useful for informing marketing efforts. The management
265 implications of this kind of analysis of 'big' visual data are thus substantial. Future research
266 can attempt to identify an 'optimal' image for use in marketing a destination to a target
267 market: one that has all the components that will appeal particularly to their aesthetics. It
268 would therefore be useful to examine whether marketing campaigns can be more effective if
269 they employ such techniques. The analysis of differences in resident and tourist perceptions
270 of the impacts of tourism can also be useful to complement tourism planning decision-
271 making.

272

273 **4. Conclusions**

274 This research note has demonstrated the utility of CVA as a dimensionality-reduction
275 technique for use with 'big' visual data. Such data is increasingly becoming available, both
276 through the use of PGI techniques and 'found' data available in various media, notably the
277 huge amount of user-generated content on photograph-sharing websites. Using CVA in this
278 way can make the meaningful analysis of such data considerably less resource-hungry,
279 rendering it more tenable for use by destination marketing organisations, tourism planning
280 departments, tour operators and other stakeholders. In an era of ever-shrinking research
281 budgets this represents too an important an option to be overlooked, as it has tended to be
282 to date. CVA also has distinct advantages over PCA and Factor Analysis in achieving this task,
283 including the calculation of a meaningful correlation statistic, preservation of data integrity
284 and the availability of graphical display of data patterns and inter-relationships, making the
285 findings intelligible to a wide audience. As such, this research note argues that CVA opens up
286 the potential for visual tourism research methods as never seen before.

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