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Online Art Buying Decision Support: A Multivariate Approach

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Abstract

We introduce a new perspective in visualizing rankings of online sales platforms created as a decision support tool on behalf of international fine art buyers and collectors. By means of Multiple Correspondence Analysis, a descriptive statistics multivariate data analysis method, groups of top ranked online sellers are extracted and mapped taking into consideration all available ranking variables: Visits Movement, Purchases, Buyer and Visitor Experience. This research enables prospective online art buyers to take evidence-based decisions derived from multivariate ranking data originating from internet seller platform surveys.

Keywords: art sales, e-business ranking, ranking data, multiple correspondence analysis, decision support

Introduction – Online Sales and Ranking Visualizations

Online art sales (OAS) are becoming increasingly popular worldwide and progressively attract numerous individual collectors and institutional art buyers (Crow, 2007; Gameran & Crow, 2011; Khaire, 2015) due mainly to the impact of internet on the democratization of information (Horowitz, 2012) and globalization of markets (Velthuis, 2014; Velthuis & Curioni, 2015). Successful art auction houses with long history in the field, as well as modern platforms for the promotion of artists and exhibitions, have intensified internet use as a means of communication, promotion and sales of works of art (Kang & Chen, 2017; Lee & Lee, 2018).
In addition, specialized publishers and art houses are exploring trends of this diverse market by exploiting electronic polls, periodically publishing reports and results, analyzing preferences of online customers. The unconventional nature of the field, lead prominent, long established art houses to host, among others, Art Law, Art Business and Art Management graduate seminars and Master's degrees (Tuttle et *al.*, 2017).
In a data overloaded internet art sales environment, we introduce a new perspective on rankings data visualization of OAS platforms so to aid and support the online art buying decision process [Chen et *al*., 2009]. Ranking data generally result from settings where it is desired to position a set of objects or elements with relevance to some criteria (Alvo & Philip, 2014). The vast majority of studies on online buying support have been quantitative research focusing on identifying and evaluating buyers survey results (Kim et *al.*, 2008; Coulson-Thomas, 2010; Lee et *al.*, 2011; Liu et *al*., 2013; Chen et *al*., 2016).
In our work, we map OAS firm groups incorporating qualitative data on Visits, Purchases, Buyer and Visitor Experience with the aid of a multivariate exploratory statistics method named Multiple Correspondence Analysis -MCA (Le Roux & Rouanet, 2010). The method examines the symmetric association structure between categorical variables and produces along informative output tables, additional, insightful graphs that focus on specific characteristics of the phenomenon under consideration.
MCA has been utilized in similar applications on ranking data (Alvo & Ertas, 1992) in research fields such as Sports (van Raalte et *al.*,1992), Education (Sachs & Chan, 2003), Marketing (Driesener & Romaniuk, 2006), Food (van Herk & van de Velden, 2007) and Transportation (Wen & Yeh, 2010). Furthermore, in similar research cases, MCA has been reported as a decision support tool in fields such as Agriculture (Solano et *al.*, 2000), E-Commerce (van Dam & van de Velden, 2015), Management (Furrer et *al.*, 2008), Marketing (Stalidis et *al.* 2015) and Transport (Diana & Pronello, 2010).
The expected benefits are that the procedure generates reusable R code regardless of the size and creation date of the data set. Other important aspects of the procedure include the capability to focus on specific parts of the data set relating to certain categories and that the input is expandable, so that future work may examine the time dimension as well.
An additional goal of the current research in whether the categories of all ranking variables are significantly different from each other by examining their corresponding confidence ellipses (Le Roux & Rouanet, 2010).

Data and Method

Hiscox, a leading international art insurer publishes annually online art sales (OAS) and business reports that include information and ratings for the world's most popular art sales web portals (Hiscox 2018). The source data of this research is included in the 2018 Hiscox report and in particular is reflected in a scoreboard of 831 art buyers of the top 25 firms active in the field of art sales.

As the publisher of the data states, their survey was conducted in January 2018. The Hiscox online art sales platform ranking is based on the qualitative responses of art shoppers when polled about their visiting and buying habits as well as their perception and satisfaction of visiting and purchasing from different online art platforms. Also, due to the characteristics of the sample (77% are European and American art buyers), there is a possible bias towards online art platforms based in the aforementioned countries, therefore the ranking is not certainly reflective of the reputation of national online art sales portals in countries such as China, or online platforms spreading through a comprehensive range of art business, and where fine art sales is a less significant segment of their portfolio (Hiscox 2018).

Multiple Correspondence Analysis is a well-established multivariate dimension reduction method commonly used to visualize and interpret categorical data in social and life sciences (Le Roux & Rouanet 2010). Among other outcomes (part of which are included in the Appendix), an interpretation and decision support tool, pertaining to the main plot in MCA, is a two dimensional symmetric map (see Figure 2) where both individuals (rows/OAS firms) and variable (column/ranking) categories are plotted in principal coordinates (Greenacre & Blasius 2006) forming a horseshoe type graph (Diaconis et *al.* 2008).

Data Transformations & Variables Considered

All five of the variables in the examined data file are related to visitor and buyer opinions. Specifically, variable MOV corresponds to the movement of the on-line art store since past year (2017), VIS to VISitor rank, PUR to PURchase rank, VEXP to Visitor EXPerience rank and BEXP to Buyer EXPerience rank (*Table 1*).

Table 1: The examined variables

Parameter	Code
Movement from 2017	MOV
Visitor rank	VIS
Purchase rank	PUR
Visitor experience rank	VEXP
Buyer experience rank	BEXP
Source: Online art trade report 2018 from Hiscox	

The initial data file reflects the views of 831 art buyers and visitors and costs of the top 25 online art sellers, based on 5 ranking variables shown above. The top lines in the original file are presented below (Figure 1).

2018 rank	Company	Movement from 2017	Visitor rank	Purchase rank	Vistor experience rank	Buyer experience rank	Average rank
1	Christie's (online)*	0 ◆	3	3	2	1	2.3
2	Artsy	+1 ▲	2	1	3	4	2.5
3	Sotheby's (online)*	-1 ▼	4	4	1	2	2.8
4	Artnet	+1 ▲	1	2	5	8	4.0
5	1stdibs	-1 ▼	5	5	7	10	6.8

Figure 1: Top lines in the initial data file

Any application of MCA expects all numerical variables be transformed into categorical. In our case, all variables are transformed utilizing their quartiles (Q25, Q50,Q75) that divide and evenly distribute data values, following the naming conventions shown below (Table 1).

Table 2: Quantification of Rankings Variables

	Category Description Suffixes	
% - QRT	MOV	VIS, PUR VEXP, BEXP
25	Dn	Low
75	No	Mid
25	Up	High

Thus, for variable MOV, "Down" (Dn) occurrences are assigned to lower 25% category (labeled MOV.Dn), "No Change" occurrences are assigned to mid 75% category (MOV.No) and Up occurrences to upper 25% category (MOV.Up). Likewise, for raking variables: Visitor Rank (VIS), Purchase Rank (PUR), Visitor Experience rank (VEXP) and Buyer Experience rank (BEXP), Low, Mid and High categories are assigned based on their distributions for quartiles Q1 (Low), Q2 & Q3 (Mid) and Q4 (High) respectively.

Results – Main Raking Trends

The application of Multiple Correspondence Analysis, when plotting both individuals (OAS firms) and variable categories (user and buyer's rankings) reveals a clear picture of the main trends in the original data source, enabling both buyers and firms' decision makers to get the big picture of the specific online market.
In the biplot below (Figure 2), the first factorial plane takes into account 50,26% of the total variability of the examined data set as also indicated in the Appendix of the current work. Based on the interpretation tables that accompany MCA's results, insight on important characteristics of each firm grouping can be drawn by focusing on important trends as pointed out by index cos2, the quality of representation of variables or categories, or, their squared correlations that measure the degree of association between variable categories and a particular axis (see Individuals and Categories tables in the Appendix). When a (ranking) category or OAS firm is well represented by two dimensions, the sum of their cos2 index is near one.
.

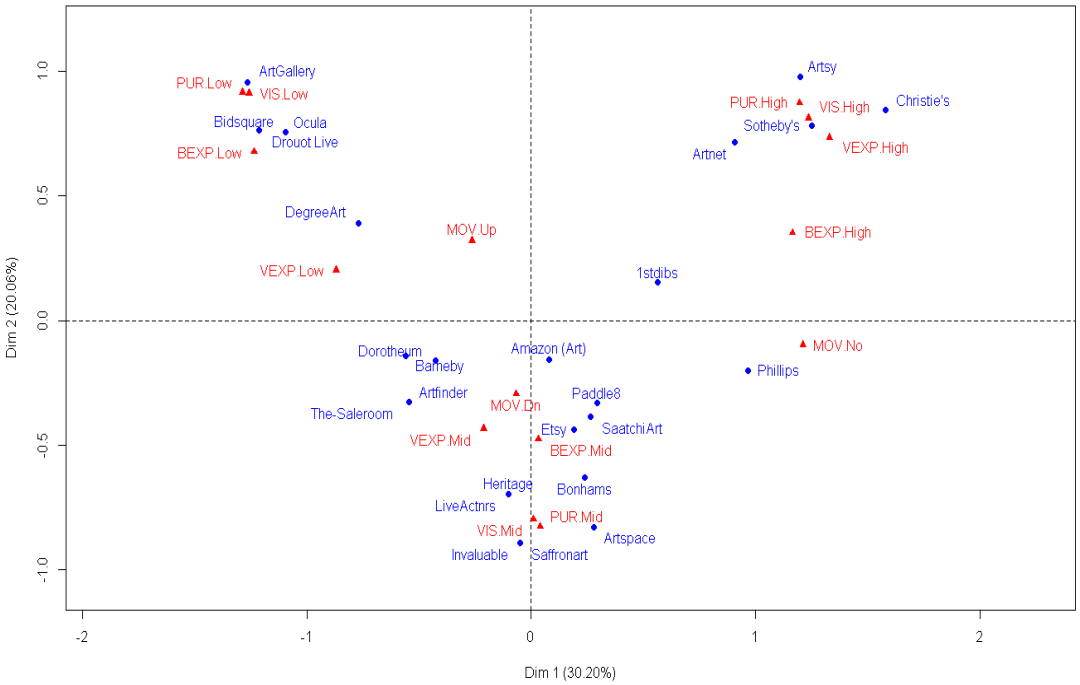

Figure 2: The first factorial map (total inertia : 50,26%)

In the top right/first quartile in the graph above (Figure 2), Arsy, Christie's, Sotheby's Artnet prevail, showing High scores in all ranking variables ({VIS, PUR, VEXP, BEXP}.high) and essentially no Movement since last year (MOV.No).
On the other hand, OAS. firms in the top left/second quartile, namely ArtGallery, Bidsquare, Ocula, Drouot and DegreeArt are positioned in the low rankings region ({VIS, PUR, VEXP, BEXP}.low) in all four of the examined ranking variables, combined with increasing trends (MOV.Up).
Lower quartiles (Q3 and Q4) include the rest, all middle-ranked firms ({VIS, PUR, VEXP, BEXP}.Mid), mainly moving downwards in rankings (MOV.Dn). These OAS firms are Dorotheum, Amazon (Art), Barneby, Philips, Artfinder, Paddle8, The-Saleroom, Etsy, Saatchi Art, Heritage, Bohnams, Live Auctioneers, Artspace, Invaluable and Saffronart. From its rankings, 1stbits seems to belong to this group of firms as well.
Graphs produced by MCA are procedurally accompanied by corresponding interpretation tables (see Appendix: Interpretation Aid for MCA Results) providing the researcher with valuable insights needed to unveil possible hidden information in the original data set.
As mentioned previously, a secondary goal of this decision support procedure is to determine whether the categories of a ranking or other variable are significantly different from each other. In this direction separate graphs of category clusters for each variable would be helpful, in the form of confidence ellipses, here of 95% confidence. These ellipses are depicted below (Figure 3) and can be constructed with the use of a specific implementation of MCA (Husson et *al.* 2017).

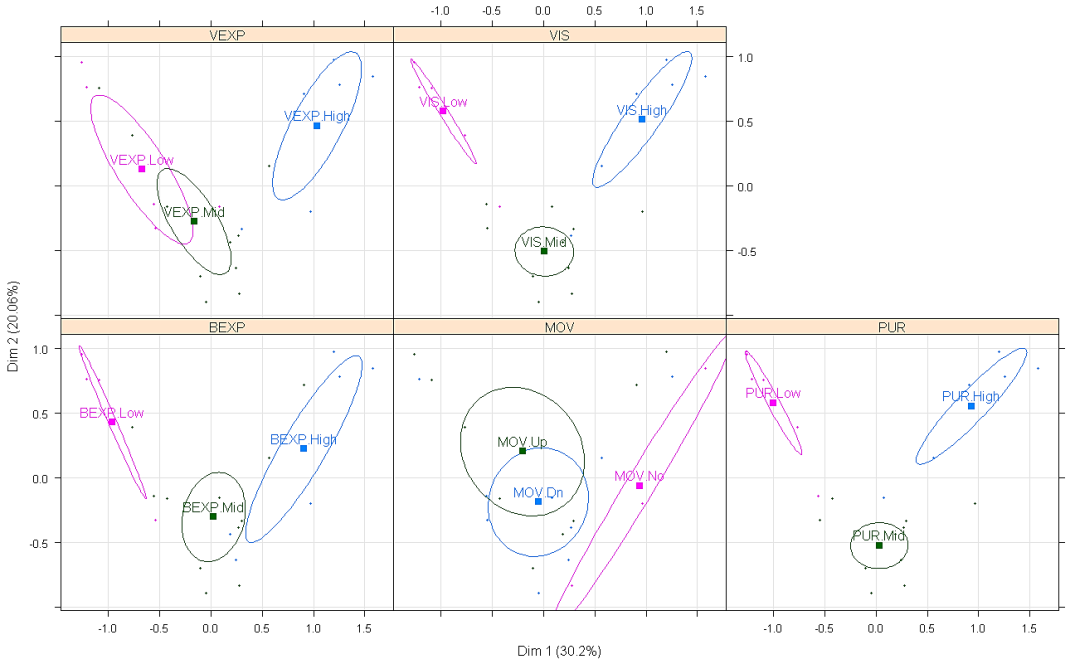

Figure 3: Confidence Ellipses of categories (95%) of all variables

As seen in the preceding figure, categories of variables Visitor Rank (VIS), Purchase Rank (PUR) and (BEXP) are significantly different from each other. On the other hand, category High Visitor Experience rank (VEXP.high) seems to map significantly apart from partly overlapping Middle (VEXP.Mid) and Low Visitor Experience (VEXP.Low) and similarly, category No Movement (MOV.No) is significantly detached from Up and Down Movement categories that map adjacent to each other.
A useful next step for future research would be an attempt to extract a more crisp, detailed view of the positioning of OAS firms by plotting a clustering dendrogram using the MCA coordinates already calculated and used in the procedures described above. This procedure will allow to define positioning of firms into clusters of common characteristics.

Concluding Remarks

Results emerging from the present study, suggest that MCA is a suitable tool for the decision support process of prospective online art buyers. This is the first work applying a multivariate data analysis method on online art sales related to survey data from an international source of art buyers ratings. Further research could also be conducted for cross validation and establishing of concise responder groupings, with the use of clustering techniques, such as k-means or hierarchical clustering.

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Appendix: Interpretation Aid for MCA results (first & second axis)

Eigenvalues

	Dim.1	Dim.2
Variance	0.604	0.401
% of var.	30.201	20.056
Cumulative % of var.	30.201	**50.257**

Individuals (the 10 first)

	Dim.1	ctr	**cos2**	Dim.2	ctr	**cos2**
1stdibs	0.563	2.099	0.168	0.153	0.233	0.012
Amazon (Art)	0.078	0.041	0.003	-0.155	0.239	0.013
Artfinder	-0.546	1.971	0.157	-0.327	1.067	0.057
ArtGallery	-1.264	10.579	0.573	0.957	9.125	0.328
Artnet	0.909	5.478	0.354	0.715	5.105	0.219
Artspace	0.278	0.513	0.035	-0.829	6.861	0.312
Artsy	1.201	9.549	0.517	0.977	9.517	0.342
Barneby	-0.561	2.083	0.166	-0.141	0.199	0.011
Bidsquare	-1.095	7.945	0.513	0.756	5.702	0.244
Bonhams	0.241	0.383	0.040	-0.630	3.963	0.276

Categories (the 10 first)

	Dim.1	ctr	**cos2**	v.test	Dim.2	ctr	**cos2**	v.test
MOV.Dn	-0.066	0.064	0.003	-0.288	-0.294	1.900	0.068	-1.278
MOV.No	1.212	5.837	0.200	2.193	-0.097	0.056	0.001	-0.175
MOV.Up	-0.264	1.017	0.055	-1.147	0.321	2.256	0.081	1.393
VIS.High	1.238	12.173	0.484	3.407	0.813	7.908	0.209	2.238
VIS.Low	-1.258	12.568	0.499	-3.462	0.912	9.948	0.263	2.510
VIS.Mid	0.009	0.001	0.000	0.047	-0.796	16.429	0.686	-4.059
PUR.High	1.198	11.396	0.453	3.297	0.873	9.123	0.241	2.404
PUR.Low	-1.286	13.146	0.522	-3.541	0.916	10.047	0.265	2.523
PUR.Mid	0.041	0.029	0.002	0.209	-0.826	17.685	0.739	-4.211
VEXP.High	1.331	14.073	0.559	3.664	0.735	6.457	0.170	2.022