Subject

In this tutorial, we show how to use the CANONICAL DISCRIMINANT ANALYSIS component.

One of the goals of this method is to produce new variables ("latent" variables) from a set of examples classified into groups. These new variables optimize the separation between groups.

Dataset

We use the WINE_QUALITY.XLS¹ dataset. It contains 34 wines classified into 3 groups "good", "medium" and "bad". We have weather descriptors (sum of daily temperature, sun, heat and rain).

Canonical Discriminant Analysis

Download the dataset

The first step is to create a new diagram and import the dataset (FILE / NEW).



¹ From M. Tenenhaus, « Méthodes Statistiques en Gestion », Edition Dunod, 1996, p. 244 (Tableau 1) – Annual data on 1924 – 1957 period.

Performing the analysis

We insert the DEFINE STATUS component; we set QUALITY as TARGET and the other descriptors as INPUT. Then, we insert the CANONICAL DISCRIMINANT ANALYSIS component.

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	1	Results					
	Attribute	Target	Input yes yes yes	Illustrative			
	Temperature (°C)	-		-			
		Sun (h)		25	-		
		Heat (days)		-3	-		
		Rain (mm)	-	yes	-		
		Quality	yes	-	-		
JL.	Compo	nents					
Data visualization	Statistics	Nonparametri	c statisi	tics			
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Regression	Factorial analysis	PLS		1			
Clustering	Spy learning	Meta-spv learning					
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Canonical Discrimina Multiple Correspond NIPALS Principal Component	nt Analysis Iance Analysis t Analysis						

Reading the results

We obtain 3 tables: the importance of the latent variables in the separation of groups; the coefficients of the discrimination functions; the factor structure matrix i.e. the correlation between the descriptors and the latent variables.

Resutts													
Roots and Wilks' Lambda													
Root	Eigenvalue	Proporti	on Cano	nical R	Wilks Lambda	CHI-:	2	d.f.		p-value			
1	3.27886	0.95	945 0	.875382	0.205263	3 46.	7122		8	0.000000			
2	0.13857	1.00	000 0.	.348867	0.878292	2 3.	8284		3	0.280599			
Canonical Discriminant Function 🥖													
Coefficients	Unst	Unstandardized			Standardized								
Attribute	Root n °1	l Roo	tn°2	Root n °1	Root n	°2							
Temperature (°)	<mark>C)</mark> -0.00)86	0.0000	-0.7509	9 0.0	0041							
Sun (h)	-0.00)68	0.0053	-0.5476	6 O.4	1309							
Heat (days)	0.02	271	-0.1278	0,1984	4 -0.9	9362							
Rain (mm)	0.00)59	-0.0062	0,4456	6 -0.4	4690							
constant	32,911	135 -2	2, 16759		-								
Factor Structure Matrix - Correlations													
Root		Root n °1			Root n °2								
Descriptors	Total	Within	Between	Total	Within	Between							
Temperature (°	C) -0.901	-0.724	-0.987	-0.375	-0.584	-0.164							
Sun (h)	-0.897	-0.701	-0.999	0.116	0.176	0.052							
Heat (days)	-0.771	-0.525	-0.956	-0.590	-0.780	-0.292							
Rain (mm)	0.663	0.398	0.977	-0.361	-0.421	-0.212							

The unstandardized discriminant coefficients enable us to perform a projection of a new individual. For instance, on the first factor Z1, with the following values TEMPERATURE = 3000, SUN = 1100, HEAT = 20 and RAIN = 300, we compute the coordinate: $-0.0086 \times 3000 + -0.0068 \times 1100 + 0.0271 \times 20 + 0.0059 \times 300 + 32.91135 = 1.9435$

Graphical representation

We can build a graphical representation of the examples on the 2 axes Z1 and Z2. We add a SCATTERPLOT component in our diagram.

We select the appropriate variables in the list box; we can define the shape of the points according to the group value (QUALITY). We see that the first factor enables to separate the wines according their quality. We see also that the above new observation (Z1 = 1.9435) is probably a "bad" wine.

Tutorial Canonical Discriminant Analysis



R.R.