INNOVATION, ENTREPRENEURSHIP AND MANAGEMENT SERIES

BIG DATA, ARTIFICIAL INTELLIGENCE AND DATA ANALYSIS SET

Volume 11

Data Analysis and Related Applications 3

Theory and Practice
New Approaches

Edited by
Yiannis Dimotikali
Christos H. Skiadas

iSTE

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coordinated by
Jacques Janssen

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First published 2024 in Great Britain and the United States by ISTE Ltd and John Wiley & Sons, Inc.

ISTE Ltd
27-37 St George's Road
London SW19 4EU
UK

www.iste.co.uk

John Wiley & Sons, Inc.
111 River Street
Hoboken, NJ 07030
USA

www.wiley.com

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Library of Congress Control Number: 2023949006

British Library Cataloguing-in-Publication Data
A CIP record for this book is available from the British Library
ISBN 978-1-78630-962-4

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PART 1

Data Analysis Classification

1

Walking into the Digital Era: Comparison of the European Union Countries in the Last Decade

This study allows us to understand how European Union countries are more or less prepared for confronting the digital era. In particular, we aim to understand whether the least developed countries are close or fairly distant from the others. For this study, data for some variables associated with digital skills, digital economy and digital society have been collected from the Eurostat database during the period 2010–2020. To analyze the data, we applied a double principal component analysis.

These results allow us to identify the differences and similarities between countries and indicators from 2010–2020, and, more precisely, to study the countries' evolution trends and the evolution of the relations between the different indicators.

1.1. Introduction

This study allows us to understand how the countries in the European Union are more or less prepared for confronting the digital era. People and societies have to deal with these new challenges not only to gain knowledge but also to promote growth, development and opportunities for everyone. In particular, it is interesting to see whether the least developed countries are close or relatively distant from the others in this route, in order to develop new strategies and to overcome detected fragilities.

Chapter written by Fernanda Otilia FIGUEIREDO and Adelaide FIGUEIREDO.

For a color version of all the figures in this chapter, see www.iste.co.uk/dimotikalis/data3.zip.

G1: Activity and employment status of individuals
V1 – % employed persons in the universe of active persons with ICT education
V2 – % males in the universe of employed persons with ICT education
V3 – % persons with tertiary education among employed persons with ICT education
V4 – % persons aged 15–34 among the employed persons with ICT education
G2: Internet at households with population aged 16–74 years
V5 – % households with Internet access
V6 – % households with broadband Internet connection
G3: Internet use by individuals
V7 – % individuals with daily Internet access in the last three months before the survey
V8 – % individuals with Internet use in the last three months before the survey
V9 – % individuals with Internet use in the last 12 months before the survey
V10 – % individuals with Internet use more than a year ago before the survey
V11 – % individuals who have never used Internet before the survey
G4: Online purchase by individuals
V12 – % individuals with last online purchase in the last three months before the survey
V13 – % individuals with last online purchase in the last 12 months before the survey
G5: Reasons of the individuals for using Internet
V14 – % individuals using Internet for finding information about goods and services
V15 – % individuals using Internet for looking for a job or sending a job application
V16 – % individuals using Internet for selling goods and services
G6: Enterprises use for selling (having e-commerce)
V17 – % enterprises with e-commerce sales of at least 1% turnover
G7: Enterprises that provided training to develop/upgrade ICT skills, excluding enterprises of the financial sector
V18 – % small enterprises provided training to ICT/IT specialists
V19 – % medium enterprises provided training to ICT/IT specialists
V20 – % SMEs provided training to ICT/IT specialists
V21 – % large enterprises provided training to ICT/IT specialists
V22 – % small enterprises provided training to other employed persons
V23 – % medium enterprises provided training to other employed persons
V24 – % SMEs provided training to other employed persons
V25 – % large enterprises provided training to other employed persons
V26 – % small enterprises provided training to their personnel
V27 – % medium enterprises provided training to their personnel
V28 – % SMEs provided training to their personnel
V29 – % large enterprises provided training to their personnel

Table 1.1. *Variables considered in the study grouped by topic*

1.1.1. *The dataset*

For this study, a large number of indicators associated with digital skills, digital economy and digital society (29 variables) have been considered, as well as all European countries for which we have data available (30 individuals). The data for these indicators were collected from the Eurostat database during the period 2010–2020.

The variables are grouped by topic (groups G1–G7), and are listed in Table 1.1. When we refer to ICT (Information and Communication Technology) Education, in the general sense, it means providing users with a diverse set of technological tools, definitions and resources to create, store, communicate, manage and optimize information. The database aggregates the ICT education levels into two categories: upper-secondary and post-secondary non-tertiary (levels 3 and 4), and tertiary (levels 5–8). Concerning employed persons with ICT education, they are divided by two classes of age: 15–34 and 35–74. The enterprises are classified accordingly to the number of employees and self-employed persons as follows: small (10–49), medium (50–249), SMEs (10–249) and large (250 or more).

Of course, it would be interesting to include other indicators such as the percentage of the ICT sector in GPD, the R&D personnel in the ICT sector as a percentage of total R&D personnel or the business expenditure on R&D in the ICT sector as a percentage of total R&D expenditure, for instance. However, we do not have information for all countries and years during the period.

The countries (individuals) considered in this study are presented in Table 1.2. We also further analyzed six data tables, corresponding to the years 2010, 2012, 2014, 2016, 2018 and 2020, each one with the same countries and variables. As the United Kingdom was not part of the EU in 2020, we considered the values obtained in 2019, instead of 2020, so we could still include it in the analysis.

Countries	Countries	Countries
EU27 – European Union 27	FR – France	AT – Austria
BE – Belgium	HR – Croatia	PL – Poland
BG – Bulgaria	IT – Italy	PT – Portugal
CZ – Czechia	CY – Cyprus	RO – Romania
DK – Denmark	LV – Latvia	SI – Slovenia
DE – Germany	LT – Lithuania	SK – Slovakia
EE – Estonia	LU – Luxembourg	FI – Finland
IE – Ireland	HU – Hungary	SE – Sweden
GR – Greece	MT – Malta	UK – United Kingdom
ES – Spain	NL – Netherlands	NO – Norway

Table 1.2. *Countries considered in the study*

1.1.2. *Preliminary analysis of the data*

Before proceeding with a multivariate data analysis, we carried out an exploratory analysis in order to gain insight into the data. In particular, we represented the boxplots by year and for all of the variables (not presented here) and among other conclusions, it is worth mentioning here the huge number of outliers observed in the data, and reported in Table 1.3. The countries with an $*$ are severe outliers. Some countries appear as outliers with respect to some variables during several years of the period 2010–2020, such as GR, RO and BG: GR is a severe lower outlier in variable V1 (the percentage of employed persons in the universe of active persons with ICT education is small comparatively to the corresponding percentage in the other countries); RO and BG are lower outliers in variables V21, V25 and V29 (the percentage of large enterprises providing training in ICT skills to their personnel, specialists or other employed persons is small when compared to what happens in other countries). We also mention, for instance, DK and FI, who appear during some years of the period as upper outliers in variable V15 (with a large percentage of individuals using the Internet to look for a job or sending a job application compared to other countries), and countries such as BE and FI, who in 2020 were upper outliers in variables V19, V23 and V27 (i.e. they have a large percentage of medium enterprises providing ICT training when compared with other countries). Other details can be found in Table 1.3.

Year	Variables and associated outliers	
2010	Lower	V1(GR), V3(IT), V21(RO), V29(RO)
2012	Lower	V1(ES,GR*), V21(RO), V29(RO)
	Upper	V10(CZ)
2014	Lower	V1(PT,GR*), V7(RO), V21(RO), V29(RO)
	Upper	V10(BG)
2016	Lower	V1(GR*), V2(CY), V7(RO), V21(RO),V25(BG,RO), V29(BG,RO)
	Upper	V15(DK), V17(IE)
2018	Lower	V1(GR*,IT,PT), V3(PT), V21(RO),V25(BG,RO), V29(RO)
	Upper	V26(NO)
2020	Lower	V1(GR*,ES), V2(DK), V14(IT,RO),V19(RO), V21(RO), V23(BG,RO),V25(BG,RO), V27(BG,RO), V29(RO)
	Upper	V10(BG,IT), V15(DK,FI), V19(BE),V23(FI),V27(FI)

Table 1.3. *Variables that present several outliers along the period*

After an introduction, aiming to present this study and detailed descriptions of the dataset, as well as a preliminary data analysis, this chapter is organized as follows. Section 1.2 gives a small description of the double principal component analysis method, the statistical methodology applied in this work, and also includes part of the results obtained from the application of this method to the data. The representation and interpretation of the trajectories are provided in section 1.3, and section 1.4 concludes the chapter with some final conclusions.

1.2. Double principal component analysis: a brief description

To analyze the data, we applied a double principal component analysis (DPCA), a method of multivariate data analysis introduced in Bouroche (1975) to analyze three-way data with quantitative variables. This method can be modified to allow the analysis of categorical data. See, for instance, Lera et al. (2006).

DPCA is an extension of the principal component analysis (PCA) method, and allows us to jointly analyze several data tables with information collected on the same variables and individuals, in several instants of time, for instance. In this study, we have six data tables, corresponding to the years 2010, 2012, 2014, 2016, 2018 and 2020, all with the same countries and variables.

The application of the DPCA method comprises four steps: (1) interstructure, i.e. the analysis of the global evolution of the data along the period of time; (2) analysis of the clouds of individuals; (3) intrastructure, i.e. the choice of the best common space to represent the individuals and the variables; and (4) representation and interpretation of the trajectories of the individuals and variables.

From Figure 1.1, we can observe that the years appear in chronological order along the first axis. As can be expected, there are big changes between the periods of 2010 and 2020.

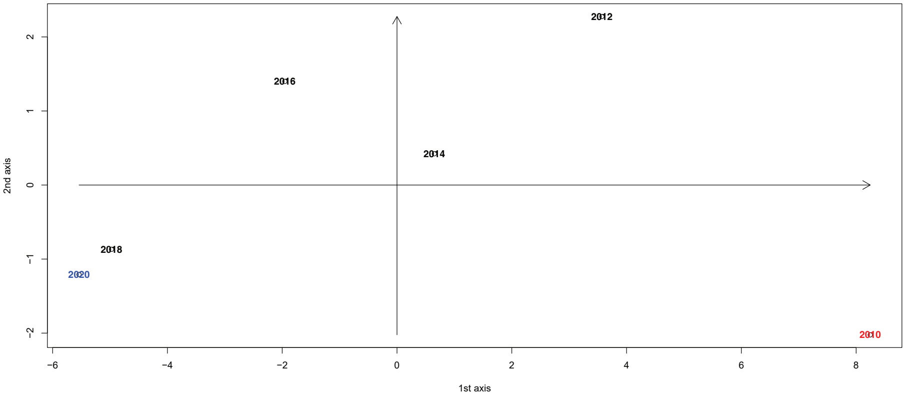


Figure 1.1. *Representation of the interstructure*

The analysis of individuals' clouds and, in particular, the percentage of explained inertia when they are projected in a subspace of a smaller dimension, lead us to select the plan of the first two principal axes obtained from the PCA of the year 2014 to represent the individuals and variables for all years. This system of principal axes minimizes the average loss of information, i.e. it globally maximizes the percentage of explained inertia. The projection of the countries and variables in this plan globally explains 76.6% of the total inertia. If we consider three axes, the percentage of the explained inertia increases to 81%, but the balance between the gain and the increase of complexity to interpret the trajectories lead us to choose only two axes. The results corresponding to the last step of the method are presented in the next section.

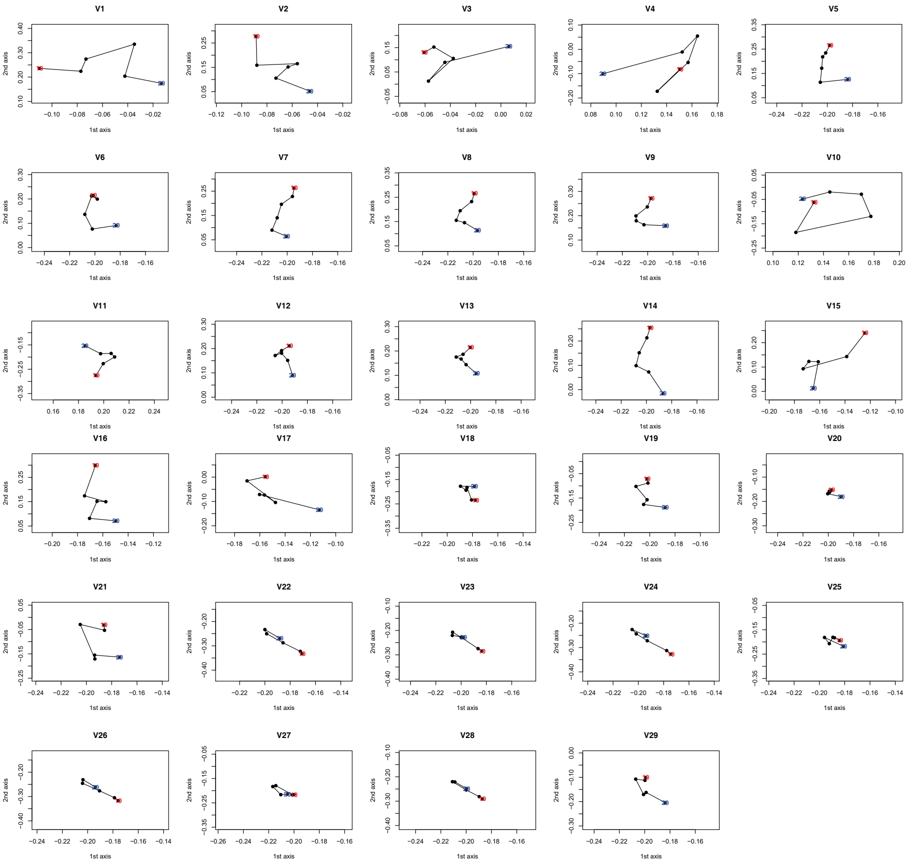
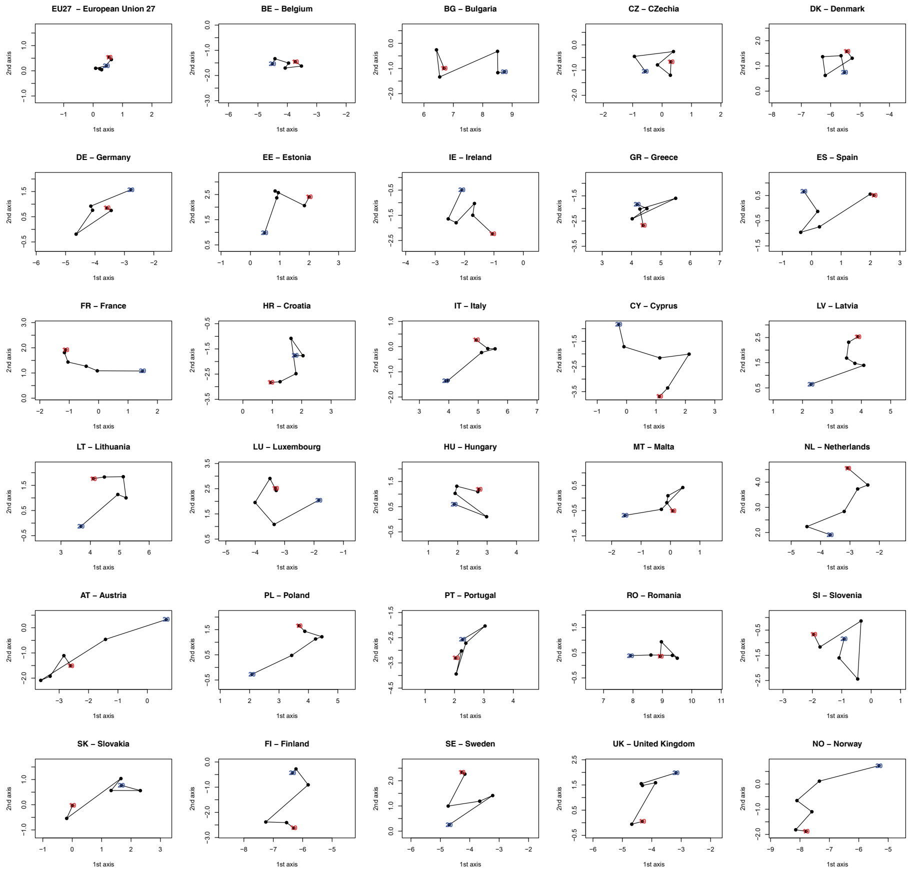


Figure 1.2. *Variables' trajectories*

1.3. Representation of the trajectories

The representation and interpretation of the trajectories is an important step in DPCA. It allows us to identify the differences and similarities between individuals (countries), and analyze the evolution of the correlations between the different variables during the 2010–2020 period. These trajectories are presented in Figures 1.2 and 1.3. All of the graphics have the same scale, i.e. the range in the first axis is the same, as well as the range in the second axis, to have comparable graphics. We have highlighted the year 2010 in red and the year 2020 in blue.

Looking at Figure 1.2, among the variables that present closed trajectories (i.e. they are variables with correlation values with the other variables stable along the period), we highlight the variables V18, V20, V25 and V27, related to the percentage of small or medium enterprises providing training in ICT skills to specialists or to their personnel employees or large enterprises who provide training to other employed persons. All of the other variables have extended trajectories, i.e. they are variables with relevant changes in their correlations with the others along the period. Among them, we highlight the variables V1, V2, V3 and V4 from group 1 (Activity and employment status of individuals), the variable V10 – % of individuals with Internet more than a year ago, the variables V15 and V16 from group 5 (Reasons for using Internet) and the variable V17 – % enterprises with e-commerce having received orders online, at least 1%.



EU27 – European Union 27
BE – Belgium
BG – Bulgaria
CZ – CZechia
DK – Denmark
DE – Germany
EE – Estonia
IE – Ireland
GR – Greece
ES – Spain
FR – France
HR – Croatia
IT – Italy
CY – Cyprus
LV – Latvia
LT – Lithuania
LU – Luxembourg
HU – Hungary
MT – Malta
NL – Netherlands
AT – Austria
PL – Poland
PT – Portugal
RO – Romania
SI – Slovenia
SK – Slovakia
FI – Finland
SE – Sweden
UK – United Kingdom
NO – Norway

Figure 1.3. *Countries' trajectories*

As shown in Figure 1.3, in general, most of the countries present large or extended trajectories, at least along one of the axes, and in particular, we highlight the trajectories of BG, ES, FR, CY, NL, AT, PL and NO. With very closed trajectories, we highlight EU27 and BE. The countries PT and GR also exhibit some instability in their trajectories.

For the interpretation of the trajectories, we only considered the countries that contributed the most to the axes, with their trajectories represented together in Figures 1.4–1.5, and the variables correlated more so with them.

Concerning the first axis, which explains 65.3% of the total inertia, almost all of the variables have high correlations with the axis in all years, except V1, V2 and V3. Therefore, we only highlight the variables with correlations above 0.8 in absolute value. The first axis opposes the group of countries NO, FI, DK, SE, DE and BE that have large values in the variables V5–V7, V9, V12–V14 and V19–V29 and small values in variable V11, to the group of countries RO, BG, IT, GR, LT and PL that present large values in the variable V11 and small values in the others.

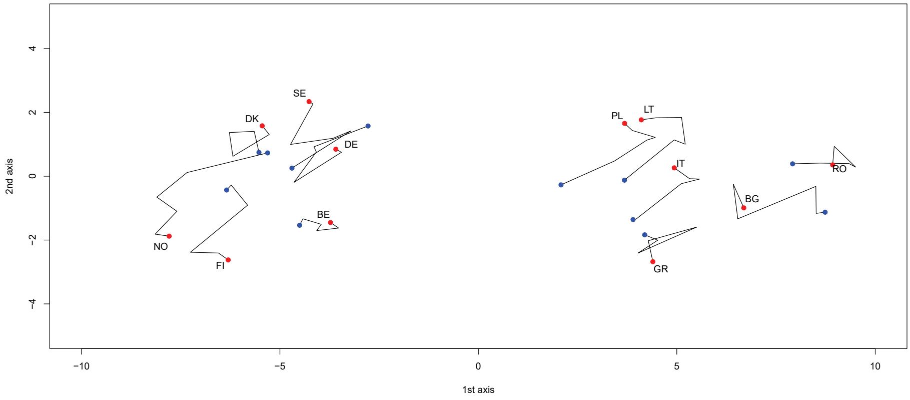


Figure 1.4. *Interpretation of trajectories in the first axis (65.3% inertia)*

The second axis only explains 11.3% of the total inertia, and few variables have significant correlations with this axis. Thus, we highlight the variables with correlations above 0.5 in absolute value. The second axis opposes the group of countries PT, HR, FI, CY, AT and BE, all of which have high values in the variables V24, V26 and V28 (years 2010, 2012 and 2014), V23–V24 (years 2010 and 2012) and small values in variable V1 (years 2010, 2012, 2014 and 2016), compared to the group of countries NL, LU, EE, LT and LV, all of which present high values in variable V1 and small values in the others.

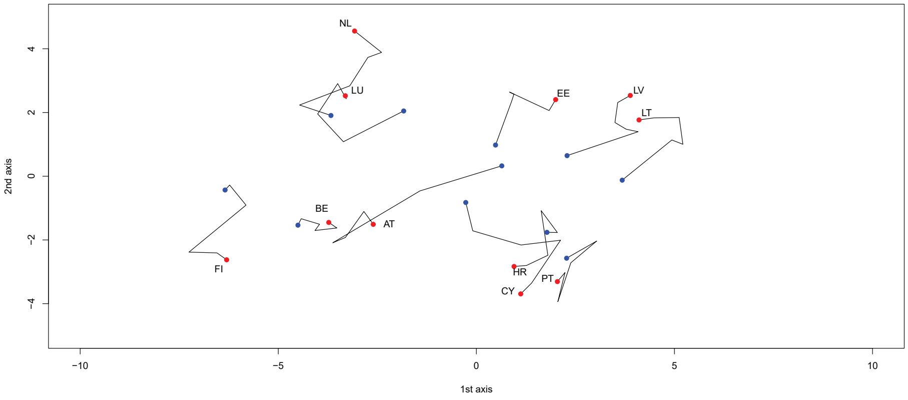


Figure 1.5. *Interpretation of trajectories in the second axis (11.3% inertia)*

1.4. Some final conclusions

The results of this study allow us to identify some existing differences or similarities between groups of European countries during the period 2010–2020 under analysis, concerning ICT skills and employment, Internet usage and digital development.

As expected, this study confirms our perception that the countries of the north and central Europe are very prepared for confronting the challenges of the digital age, since they have already greatly invested in providing training in ICT skills to their populations and how everyone is comfortable using the Internet for a variety of purposes: communication, purchase, selling, finding, and so on. Among these countries, the most similar are the following subgroups of countries: (DE and SE), (NO and DK), FI and BE.

On the other hand, the countries of the East and South of Europe are less prepared, having made little investment in ICT education and, in most of them, a large part of the population has never used the Internet. Among these countries, the closest are the subgroups (PL and LT), (IT and GR), BG and RO.

We also observe that in countries such as PT, AT, CY, HR, BE and FI, where the percentage of employed persons with ICT education is yet small, a large percentage of small and medium enterprises provide training to their personnel or to other employed persons to develop or upgrade ICT skills. The opposite happens, for instance, in the countries LT, LV, EE, LU and NL.

1.5. Acknowledgements

This work was supported by the National Funds through the Portuguese funding agency, FCT – Fundação para a Ciência e a Tecnologia, within the framework of the projects UIDB/00006/2020 (CEAUL) and LA/P/0063/2020 (INESC TEC).

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2

Multivariate Kernel Discrimination Applied to Bank Loan Classification

The purpose of this chapter is to apply a kernel discriminant analysis to classify bank loans and determine which loans are at risk of default. This study begins by introducing the concept of kernel density estimation, which is a widely used non-parametric technique to obtain an estimate for the probability density function. This procedure is based on two main parameters: the kernel function and the bandwidth, the latter being the crucial parameter. The multivariate kernel density estimator is later applied to discriminant analysis to obtain kernel discrimination. This is a method that classifies observations into a predetermined number of distinct and disjointed classes. Finally, we apply multivariate kernel discriminant analysis to a sample of bank loans to determine which loans can be classified as defaulted. This model can help predict the likelihood that future loans may default.

2.1. Introduction

As the name implies, credit risk analysis is used to assess the likelihood of a borrower's repayment failure and the loss caused to the financer when default occurs. This concept greatly affects the long-term success of any bank or financial institution. In Malta, the non-performing loan ratio stood at 3% in December 2019 (Central Bank of Malta). This ratio reflects the country's credit quality of loans. Banks need to determine the probability of non-performing loans of companies to decrease the prospect of weakened liquidity. The aim of this study is to create a model that predicts whether a company will be able to pay its outstanding loan, based on several variables. To obtain such a model, we apply the multivariate kernel discriminant analysis. This technique uses kernel density estimation, as well as non-parametric discriminant analysis.

Chapter written by Mark Anthony CARUANA and Gabriele LENTINI.

Rosenblatt (1956), Whittle (1958), Parzen (1962) and Watson and Leadbetter (1963) studied and presented a number of results regarding univariate kernel density estimation. Moreover, Cacoullos (1966) extended Parzen's results to the multivariate case. Loftsgaarden and Quensenberry (1965) and Epanechnikov (1969) also applied multivariate non-parametric kernel density estimation.

The quality of multivariate kernel density estimation depends mainly on the choice of the bandwidth matrices. The univariate plug-in bandwidth estimator provided by Sheather and Jones (1991) was extended to the multivariate case by Wand and Jones (1993). Moreover, a number of authors, including Chacón and Duong (2010, 2012) and Horová et al. (2013), also contributed to the field of optimal bandwidth selection by applying a number of novel techniques.

Multivariate kernel density estimation has been applied to discriminant analysis. The properties of this technique feature in Murphy and Maron (1986) and Silverman (1986). Over the past several years, kernel discriminant analysis has been applied to several fields. For example, Liberati et al. (2012) and Widiharih et al. (2018) both used kernel discriminant analysis to address the problems of credit risk analysis in banking and making efficient credit granting decisions. Some further applications of kernel discriminant analysis include Hand (1983) and Chen et al. (2005) in medicine, Martin (2011) in agriculture and Farida and Aidi (2016) in education.

This section concludes by giving a brief overview of the structure of this chapter. In section 2.2, we discuss multivariate kernel density estimation. In section 2.3, we outline the properties of kernel discriminant analysis. In section 2.4, we apply these techniques to a local dataset that contains not only the data of a number of local companies but also the status of their bank loan (whether the company is in default or otherwise). Further details concerning the said dataset are provided in section 2.4. As mentioned earlier, the main aim will be to create a model which uses kernel discriminant analysis, which can identify firms that are close to bankruptcy. In this section, we split the data into the training set and test set. We train the model using the former dataset and test the model performance using the latter dataset. Section 2.5 contains some concluding remarks and suggestions for future research.

2.2. Multivariate kernel density estimation

Let p denote the total number of variables in the dataset and let n denote the total number of companies in the dataset.

Let X_i be a random variable representing the i^{th} variable. Moreover, let $\boldsymbol{X}$ be a random vector, where $\boldsymbol{X} = \left(X_1, X_2, \cdots, X_p\right)^T$ and $\mathbf{x}_n = \left(\mathrm{x}_{\mathrm{n1}}, \mathrm{x}_{\mathrm{n2}}, \cdots, \mathrm{x}_{\mathrm{np}}\right)^T$ will be the vector that contains all of the observations of the n$^{\text{th}}$ company. Let $\mathbb{x}$ be the $n \times p$ matrix which contains all the observations of the dataset, such that:

$$\mathbb{x} = \begin{pmatrix} \mathbf{x}_{11} & \cdots & \mathbf{x}_{1\mathrm{p}} \\ \vdots & \ddots & \vdots \\ \mathbf{x}_{\mathrm{n}1} & \cdots & \mathbf{x}_{\mathrm{np}} \end{pmatrix}.$$

Multivariate kernel density estimation is composed of two main components: the kernel function, which will now be denoted by K, and the bandwidth, which will now be denoted by $\boldsymbol{H}$. In a multivariate setting, the bandwidth is a $p \times p$ matrix, where p represents the dimension of the data, i.e. the number of variables being studied. The approach chosen for multivariate kernel density estimation highly depends on the type of bandwidth matrix considered. When $\boldsymbol{H}$ is taken to be diagonal, this is usually referred to as a constrained bandwidth matrix. Otherwise, it is referred to as an unconstrained bandwidth matrix. The diagonal bandwidth matrix is thus a special case of the unconstrained bandwidth matrix.

2.2.1. *Kernel density estimator*

For the multivariate case with a bandwidth matrix $\boldsymbol{H}$, the kernel density estimator is defined as follows:

$$\hat{f}(\boldsymbol{x}; \boldsymbol{H}, \boldsymbol{X}_1, \boldsymbol{X}_2, \cdots, \boldsymbol{X}_n) = \frac{1}{n} \sum_{i=1}^{n} K_{\boldsymbol{H}}(\boldsymbol{x} - \boldsymbol{X}_{\boldsymbol{i}}),$$

where n represents the sample size and $K_{\boldsymbol{H}}(\boldsymbol{x})$ is said to be the scaled kernel, which is defined as:

$$K_{\boldsymbol{H}}(\boldsymbol{x}) = |\boldsymbol{H}|^{-\frac{1}{2}} K\left(\boldsymbol{H}^{-\frac{1}{2}} \boldsymbol{x}\right),$$

where $|\boldsymbol{H}|^{-\frac{1}{2}}$ is the inverse of the square root of the determinant of the matrix $\boldsymbol{H}$ and $\boldsymbol{H}^{-\frac{1}{2}}$ is the inverse of the matrix square root. Therefore, the kernel density estimator can be written as:

$$\hat{f}(\boldsymbol{x}; \boldsymbol{H}, \boldsymbol{X}_1, \boldsymbol{X}_2, \cdots, \boldsymbol{X}_n) = \frac{1}{n|\boldsymbol{H}|^{\frac{1}{2}}} \sum_{i=1}^{n} K\left(\boldsymbol{H}^{-\frac{1}{2}}(\boldsymbol{x} - \boldsymbol{X}_{\boldsymbol{i}})\right),$$

where K is the multivariate kernel function. K is assumed to be the symmetric function. Furthermore, $\int_{\mathbb{R}^p} K(\boldsymbol{z}) d\boldsymbol{z} = 1$ and $K(\boldsymbol{z}) \geq 0 \; \forall \boldsymbol{z} \in \mathbb{R}^p$, implying that K satisfies the properties of a multivariate probability density function. There are various types of functions that satisfy the above-mentioned properties, which include the standard multivariate normal kernel density function and the multivariate