

Engaging Everyone with Open Data Science



Kimmo Vehkalahti Centre for Social Data Science University of Helsinki, Finland

Outline

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- 2. Open Data Science
- 3. Results
- 4. Conclusion
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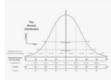
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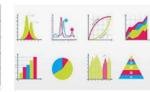


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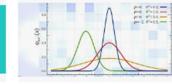
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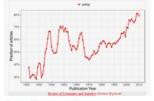
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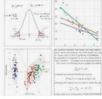
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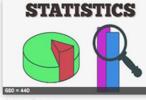


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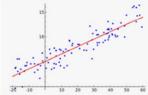
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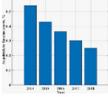
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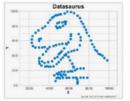
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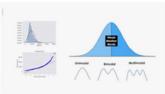
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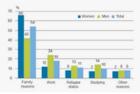
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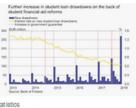
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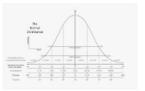
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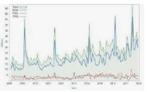
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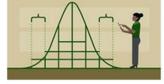
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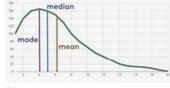
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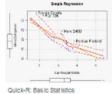
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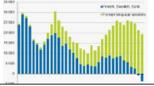
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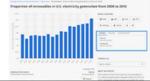








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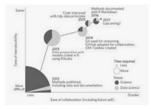


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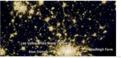
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- The ongoing "Data revolution" sets more requirements for the students and researchers on all fields of science.
- One could say (without exaggerating too much) that

We should all be data scientists.

- The term "data science" is a good synonym to statistics.
- "Statistics" vs "Data science" is also a question of brand/image.



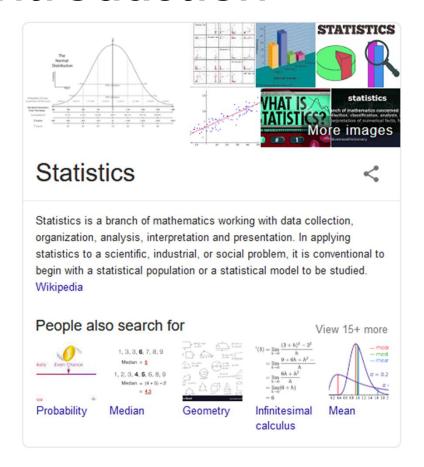
According to Wikipedia:

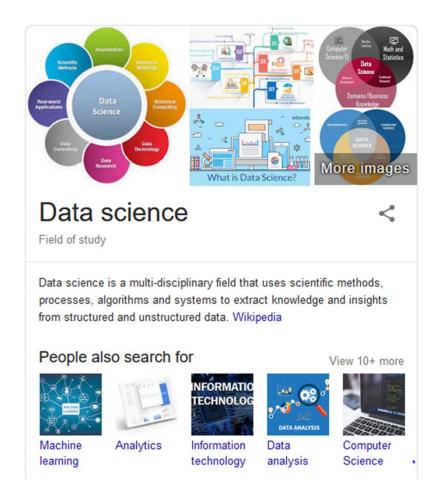
 "Statistics is a branch of mathematics working with data collection, organization, analysis, interpretation and presentation."

while

 "Data science is a multi-disciplinary field that uses scientific methods, processes, algorithms and systems to extract knowledge and insights from structured and unstructured data."

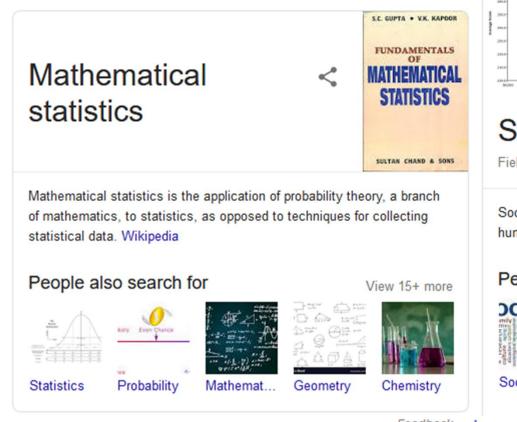
Which one of these definitions sounds more interesting? Perhaps some combination of these would better describe our field?

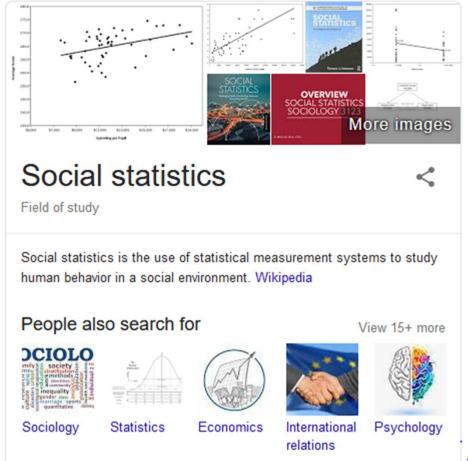














- Teaching of statistics should focus more on practical data science.
- Special emphasis needed on data wrangling:
 - Preparing the data for the analyses
 - Looking at the data via simple but clever visualizations
- Important overall learning goals:
 - Principles and practices of open science and reproducible research
 - Statistical and algorithmic thinking, sharing of code and data
- State-of-the-art tools like RStudio and R Markdown freely available!
- Thus: many reasons why I like to use the term Open Data Science.



New course established to respond to the serious need around:



- Primary target: Doctoral students of social sciences and humanities
- Suitable for "anyone" (master's / bachelor's / exchange / post docs)
- So far, 100+ participants every time (organized 3 times 2017-2018)



General learning objectives of the course were stated as follows:

 "After completing this course you will understand the principles and advantages of using open research tools with open data and understand the possibilities of reproducible research."

and

 "You will know how to use RStudio, R Markdown, and GitHub for these tasks, and know how to learn more of these open software tools. You will also know how to apply certain statistical methods of data science, that is, data-driven statistics."



Seven weeks of study online, w/ one optional computer class / week:

- 1. Start me up!
- 2. Regression and model validation
- 3. Logistic regression
- 4. Clustering and classification
- 5. Dimensionality reduction techniques
- 6. Analysis of longitudinal data

Introduction to Open Data Science

CONTENTS

Welcome to the course!

- 1. Start me up!
- 2. Regression and model validation
- 3. Logistic regression
- 4. Clustering and classification

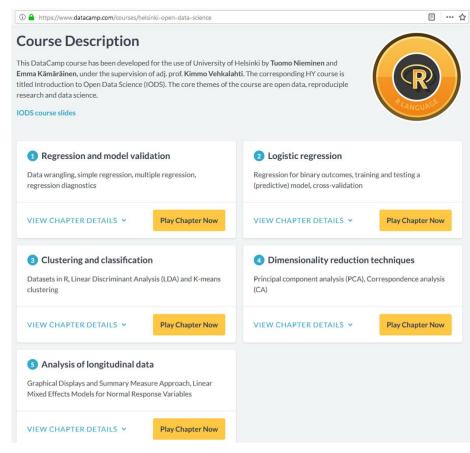
- 5. Dimensionality reduction techniques
- 6. Analysis of longitudinal data
- 7. Some books for your curiosity
- 8. Deadlines, forums, FAQ

Far from a traditional, systematic statistics course! A mixture of

- Statistical modeling (LM, GLM etc.)
- Data analysis (PCA, MCA etc.)

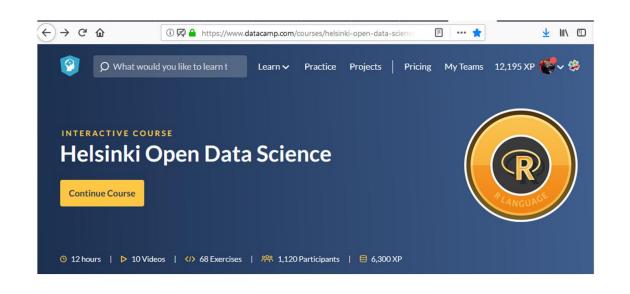


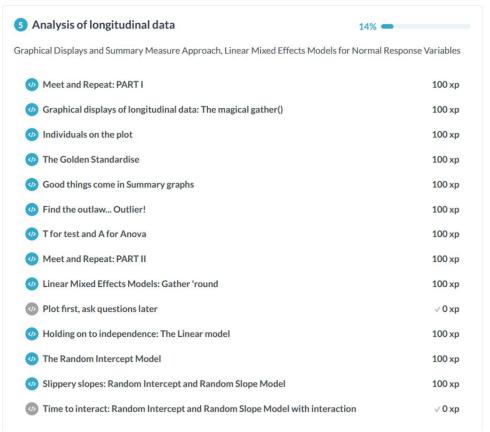
- Dedicated free DataCamp course "Helsinki Open Data Science" supports learning the R skills
- Easy, interactive way to explore and learn the weekly R tricks to be used
- R code can then be copied to Rstudio
- www.datacamp.com



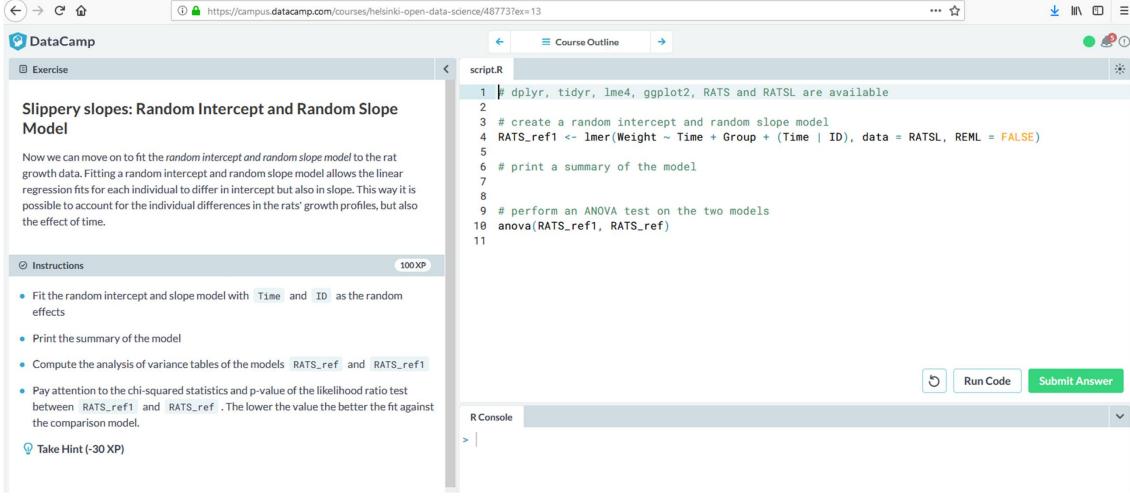


Some views of the DataCamp platform:



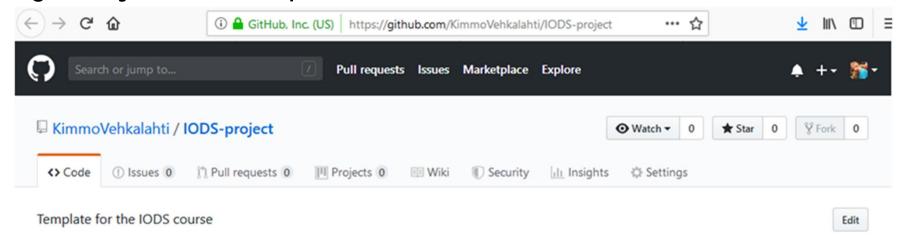






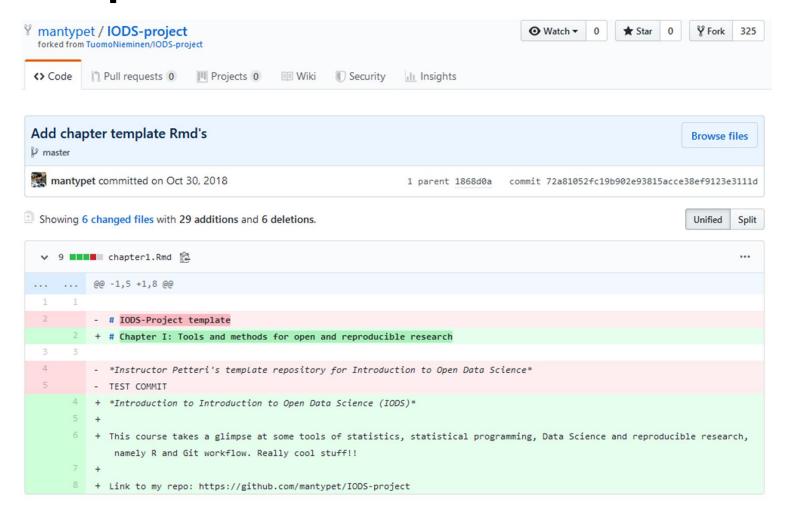


- Weekly assignments consist of data wrangling and analysis exercises.
- They are practiced on DataCamp and then completed with RStudio.
- All the students' weekly reports are saved and shared on GitHub, using ready-made templates downloaded on the first week.

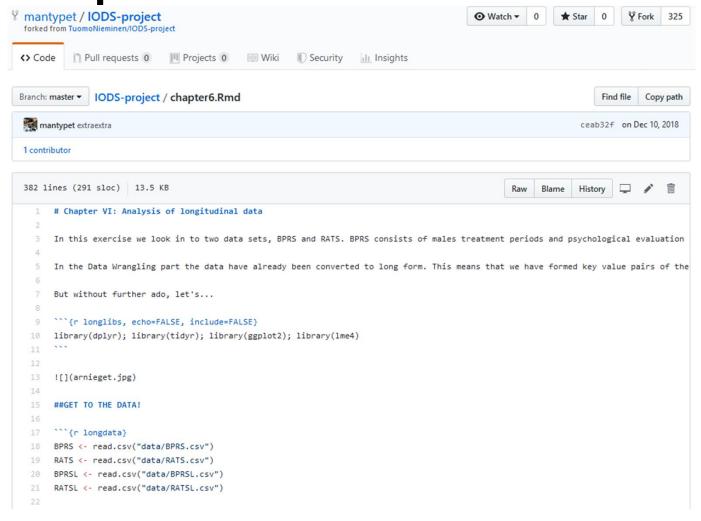


R Markdown is used and the reports are knitted into HTML files.











① ♠ https://mantypet.github.io/IODS-project/#chapter-vi-analysis-of-longitudinal-data

/mantypet.github.io/IODS-project/#chapter-vi-analysis-of-longitudinal-data

IODS course project

Petteri Mäntymaa

Last updated 2018-12-10 17:47:51

- Chapter I: Tools and methods for open and reproducible research
- Chapter II: Regression and model validation
- Chapter III: Logistic regression
- Chapter IV: Clustering and classification
 - Housing Values in Suburbs of Boston
- Chapter V: Dimensionality reduction techniques
- Chapter VI: Analysis of longitudinal data
 - GET TO THE DATA!
 - Summaries and graphical inspections of RATS

(Petteri is one of my previous & precious Teaching Assistants and very important technical developers of the IODS course.)

Chapter VI: Analysis of longitudinal data

In this exercise we look in to two data sets, BPRS and RATS. BPRS consists of males treatment periods and psychological evaluation scores between treatment groups. RATS is about the growth of rats in different growth profile groups.

In the Data Wrangling part the data have already been converted to long form. This means that we have formed key value pairs of the variable under interest and the variable indicating different measurement times. To simplify, we get to have the time variable as, oh well - a variable, hence can take it in to account in our investigation and analysis!

But without further ado, let's ...



GET TO THE DATA!

```
BPRS <- read.csv("data/BPRS.csv")
RATS <- read.csv("data/RATS.csv")
BPRSL <- read.csv("data/BPRSL.csv")
RATSL <- read.csv("data/RATSL.csv")
BPRS$treatment <- factor(BPRS$treatment)
BPRS$subject <- factor(BPRS$subject)
RATS$ID <- factor (RATS$ID)
RATS$Group <- factor(RATS$Group)
BPRSL$treatment <- factor(BPRSL$treatment)
BPRSL$subject <- factor(BPRSL$subject)
RATSL$ID <- factor (RATSL$ID)
RATSL$Group <- factor(RATSL$Group)
```

Summaries and graphical inspections of RATS

Let's implement the analyses of BPRS to the RATS data and check out the wrangled RATSL





- Weekly peer-reviews of 3 reports for 6 weeks.
- Grading with a scale from 0 (fail) to 5 (excellent).
- Teachers check the integrity of the peer-reviews.
- Course grade is completely based on peer-reviews.

The grades of the IODS 3.0 are briefly summarized below.

3. Results



- The course has been a HUGE success story, so we are quite happy!
- Some excerpts from anonymous student feedback: (BOLD ADDED)

"I really enjoyed this course, to be honest this is the best course that I had in Helsinki. Combining both DataCamp and Rstudio exercise was amazing idea, it helped me alot. Even though I have been using R since couple of years but during this course I learned more sophisticated ways of programming."

3. Results



More excerpts from anonymous student feedback: (BOLD ADDED)

"The course was really interesting and hands-on approach worked well. Datacamp exercises were well organised. Need for this kind of applied statistical (data science) courses where you're needed to clean your dataset and then use correct statistical methods is in high demand. You can get a feel that you're learning something actually useful for real life. Learning Github has been really huge benefit."

3. Results



More excerpts from anonymous student feedback: (BOLD ADDED)

"First of all I want to thank you all about this course which has been the funniest and most interesting ever. This was my first touch to R, GitHub and Slack. I never thought that I would get this excited about something, but I did. I noticed that the R environment is an endless world and its not as difficult as I thought at first. I will definitely continue to learn codes and statistics."

4. Conclusion



- There is a huge need for more (and more) data scientists.
- Teaching of statistics should focus more on data science, with a special emphasis on data wrangling.
- The statistics curriculum should be updated and the term "data science" used as a synonym to statistics.
- Our new course gives an excellent example of how to engage students to learn skills of reproducible, open data science.

5. References (cited in the paper)



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Engaging Everyone with Open Data Science



Thank you for your attention!



... ... Thanks! J Just a few slides from my invited talk in the 27th IWMS (Shanghai, China) in June 2019, entitled:

Multivariate Analysis for Data Scientists

Kimmo Vehkalahti

University of Helsinki, Finland

IWMS-2019: The 27th International Workshop on Matrices and Statistics

6-9 June 2019 | Shanghai, China

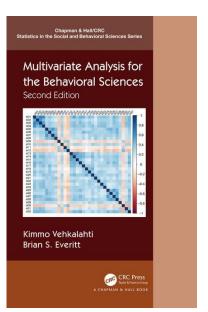
Kimmo Vehkalahti & Brian S. Everitt:

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Chapman and Hall/CRC Press, 2019

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- 14. Multidimensional Scaling and Correspondence Analysis
- 15. Exploratory Factor Analysis
- 16. Confirmatory Factor Analysis and Structural Equation Models
- 17. Cluster Analysis
- 18. Grouped Multivariate Data



Let us close with an example of MDS from Chapter 14:

A view of the book (pp. 278-279):
 Data (dissimilarity matrix), analysis, figure, and interpretations

 A view of the same example from material freely available online on GitHub: Analysis and figure with R Markdown



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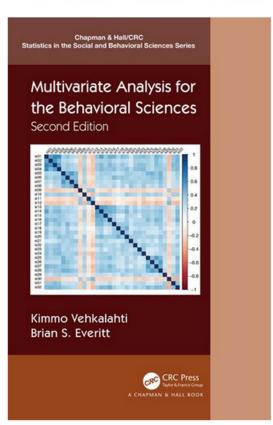
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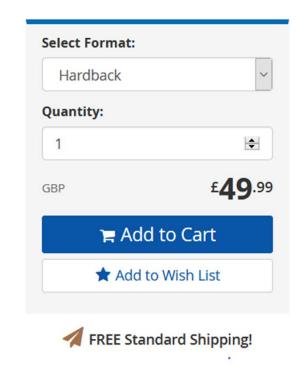
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Summary

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TABLE 14.7
Proximity Matrix of Ten Remarkable Classical Music Composers Selected and Compared by Olli Mustonen

	Bac	Hay	Moz	Bee	Sch	Bra	Sib	Deb	Bar	Šos
Bach	0									
Haydn	50	0								
Mozart	30	10	0							
Beethoven	20	15	20	0						
Schubert	40	30	25	10	0					
Brahms	40	70	40	20	15	0				
Sibelius	40	90	70	25	60	20	0			
Debussy	50	50	50	80	50	70	35	0		
Bartók	30	80	80	60	70	70	35	15	0	
Šostakovitš	30	40	50	40	60	70	20	40	20	0

14.2.4 Mapping Composers of Classical Music

Our final example of the use of classical scaling involves data on composers of classical music, taken with permission from Mustonen (1996, 156–159) and Mustonen (1995, 167–170). Seppo Mustonen (a Finnish professor of Statistics) asked his son Olli Mustonen (a Finnish pianist, conductor, and composer) to select ten remarkable composers from different era of classical music and compare those composers with each other intuitively based on their entire production and style. Olli Mustonen made his comparisons using a scale from 0 to 100 in a way that the more he considered the composers to differ, the higher the score he gave. After about half an hour's reflection, he presented the proximity matrix given in Table 14.7, where the selected composers appear roughly in chronological order. We can see that the scale was applied with intervals of five units, and that the greatest difference was 90 units, occurring between Sibelius and Haydn.

Applying classical scaling to the data in Table 14.7 leads to four negative eigenvalues for the matrix ${\bf B}$ (see Technical Section 14.1) and so the dissimilarity matrix shown there is clearly non-Euclidean. Here we will look at the fit criteria described in Technical Section 14.1 as a guide to the number of dimensions needed to adequately represent the dissimilarity values in Table 14.7. For the one-dimensional solution we obtain the values

$$P_1^{(1)} = 0.35$$
 and $P_1^{(2)} = 0.58$

while for the two-dimensional solution, the values obtained are

$$P_2^{(1)} = 0.58$$
 and $P_2^{(2)} = 0.83$

which would seem to suggest two dimensions (although the first one does not approach 0.8 before eight dimensions). Also both the alternative criteria (the

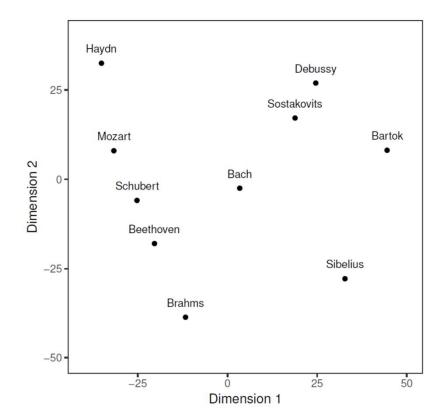


FIGURE 14.4
Resulting map from classical scaling of the classical composers.

trace and the magnitude) support the conclusion, so we shall proceed with two dimensions, following the original lines of interpretations of Mustonen (1996).

The resulting map of composers is shown in Figure 14.4. The first dimension (from left to right) appears to be related to time, with one significant exception: the "timeless" Bach is placed in the middle. The second dimension (from top to bottom) can be interpreted as a transition from "light" music to "heavy" music. Indeed, the *Viennese Classics* (Haydn, Mozart, Schubert, and Beethoven) form a logical chain, accompanied by Brahms, who, together with Sibelius, is located in the "heavyweight division". The modern composers (Debussy, Šostakovitš, and Bartók) seem to form a cluster of their own, and it is perfectly understandable that, of these composers, it is Šostakovitš who gets settled nearest to Bach. A rather lonely Sibelius is placed at a considerable distance from all other composers.

Let us close with an example of MDS from Chapter 14:

A view of the book (pp. 278-279):
 Data (dissimilarity matrix), analysis, figure, and interpretations

 A view of the same example from material freely available online on GitHub: Analysis and figure with R Markdown

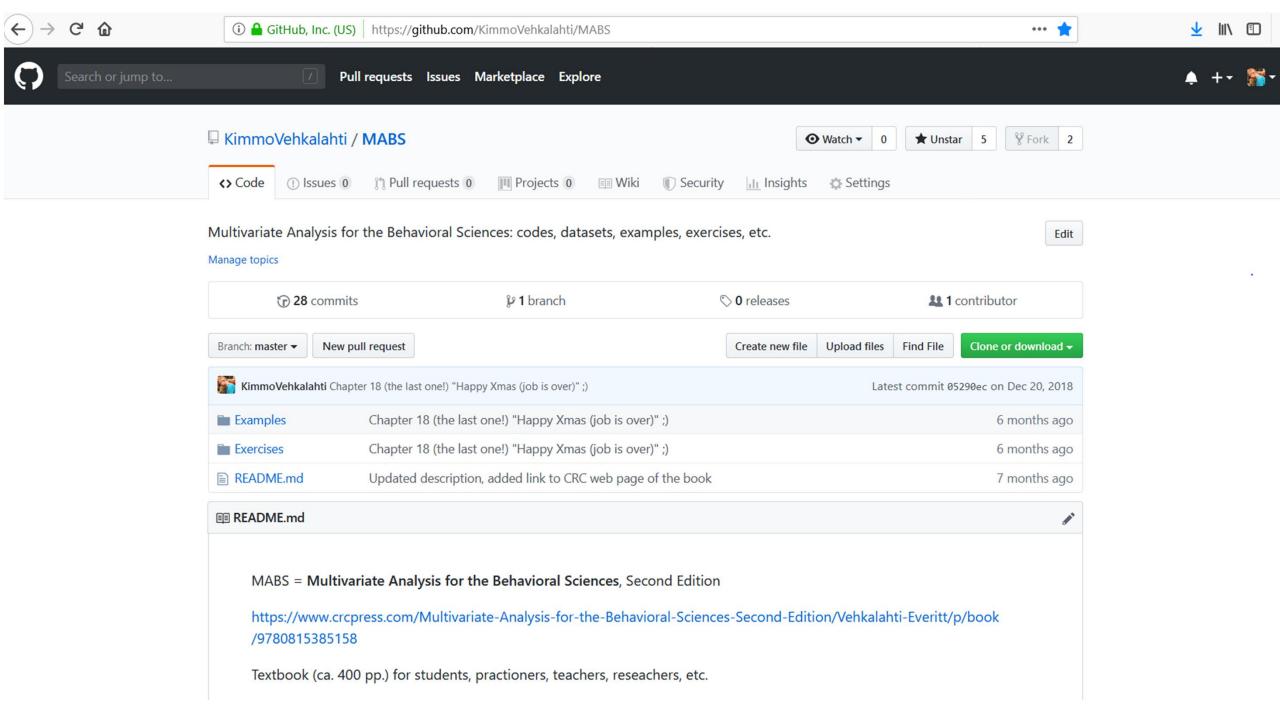
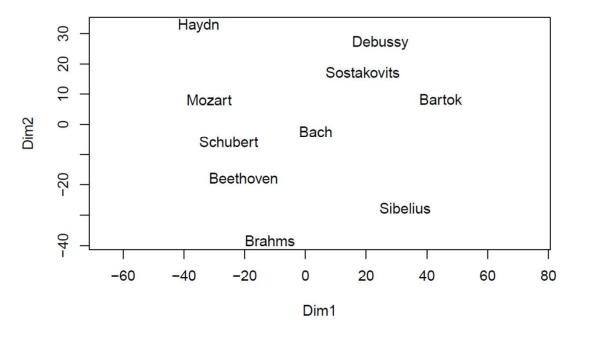


Table 14.7: Proximity Matrix of Ten Remarkable Classical Music Composers Selected and Compared by Olli Mustonen

```
composers <- c("Bach", "Haydn", "Mozart", "Beethoven", "Schubert", "Brahms",</pre>
              "Sibelius", "Debussy", "Bartok", "Sostakovits")
OMD <- matrix(
c(0, 50, 30, 20, 40, 40, 40, 50, 30, 30,
  50, 0, 10, 15, 30, 70, 90, 50, 80, 40,
            0, 20, 25, 40, 70, 50, 80, 50,
  20, 15, 20, 0, 10, 20, 25, 80, 60, 40,
  40, 30, 25, 10, 0, 15, 60, 50, 70, 60,
  40, 70, 40, 20, 15, 0, 20, 70, 70, 70,
  40, 90, 70, 25, 60, 20, 0, 35, 35, 20,
  50, 50, 50, 80, 50, 70, 35, 0, 15, 40,
  30, 80, 80, 60, 70, 70, 35, 15, 0, 20,
 30, 40, 50, 40, 60, 70, 20, 40, 20, 0
 ), nrow = 10, ncol = 10, byrow = TRUE, dimnames = list(composers, composers))
n \leftarrow dim(OMD)[1]
OMDS <- cmdscale(d = OMD, k = n-1, eig = TRUE, list. = TRUE)
## Warning in cmdscale(d = OMD, k = n - 1, eig = TRUE, list. = TRUE): only 5
## of the first 9 eigenvalues are > 0
as.matrix(format(OMDS$eig, scientific = FALSE, justify = "right", nsmall = OL, digits = 0))
        [,1]
   [1,] " 7459"
    [2,] " 4830"
    [3,] " 2288"
   [4,] " 752"
   [5,] " 514"
   [6,] " 0"
   [7,] " -661"
## [8,] " -906"
## [9,] " -937"
## [10,] "-2912"
pk1 <- cumsum(abs(OMDS$eig))/sum(abs(OMDS$eig))</pre>
pk2 <- cumsum(OMDS$eig^2)/sum(OMDS$eig^2)
pk1
## [1] 0.35 0.58 0.69 0.72 0.75 0.75 0.78 0.82 0.86 1.00
pk2
## [1] 0.58 0.83 0.88 0.89 0.89 0.89 0.89 0.90 0.91 1.00
```

Figure 14.4

```
OwMDS <- wcmdscale(d = OMD, k = n-1, eig = TRUE)
plot(OwMDS, cex = 1.0)</pre>
```



谢谢

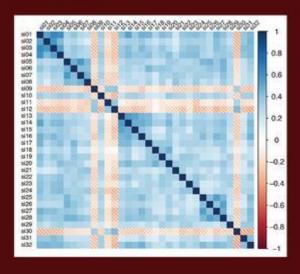
Thanks!



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