

Personality Project

Big Five Test

PMC Lab

Psychometric Theory

psych package

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Using R for psychological research

A simple guide to an elegant language

This is one page of a series of tutorials for using R in psychological research. Much of material has also covered been covered in number of [short courses](#) or in a set of [tutorials](#) for specific problems.

Introduction to R

(For a very abbreviated form of this guide meant to help students do basic data analysis in a personality research course, see [a very short guide](#). In addition, [a short guide](#) to data analysis in a research methods course offers some more detail on graphing.)

There are many possible statistical programs that can be used in psychological research. They differ in multiple ways, at least some of which are ease of use, generality, and cost. Some of the more common packages used are Systat, SPSS, and SAS. These programs have GUIs (Graphical User Interfaces) that are relatively easy to use but that are unique to each package. These programs are also very expensive and limited in what they can do. Although convenient to use, GUI based operations are difficult to discuss in written form. When teaching statistics or communicating results to others, it is helpful to use examples that may be used by others using different computing environments and perhaps using different software. This set of brief notes describes an alternative approach that is widely used by practicing statisticians, the statistical environment R. This is not meant as a user's guide to R, but merely the first step in guiding people to helpful tutorials. I hope that enough information is provided in this brief guide to make the reader want to learn more. (For the impatient, [an even briefer guide](#) to analyzing data for [personality research](#) is also available.)

It has been claimed that "The R statistical programming language and computing environment has become the de-facto standard for writing statistical software among statisticians and has made substantial inroads in the social and behavioural sciences. R is a free, open-source implementation of the S language, and is available for Windows, Mac OS X, and Unix/Linux systems. There is also a commercial implementation of S called S-PLUS, but it has been eclipsed by R." From [John Fox's short course on S and R](#).

The [R project](#), based upon the S and S+ stats packages, has developed an extremely powerful set of "packages" that operate within one program. Although described as merely "an effective data handling and storage facility [with] a suite of operators for calculations on arrays, in particular, matrices" R is, in fact, a very useful interactive package for data analysis. When compared to most other stats packages used by psychologists, R has at least three compelling advantages: it is free, it runs on multiple platforms (e.g., Windows, Unix, Linux, and Mac OS X), and combines many of the most useful statistical programs into one quasi integrated program..

More important than the cost is the fact that R is open source. That is, users have the ability to inspect the code to see what is actually being done in a particular calculation. ([R is free software](#) as part of the [GNU Project](#). That is, users are free to use, modify, and distribute the program, within the limits of the [GNU non-license](#)) [The program itself and detailed installation](#)

e.g., the [psych](#) package

[Partial list of useful commands in psych](#)

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[Finding Omega](#)

[Factor Analysis](#)

[Reliability](#)

[Short Course lecture notes](#)

[APS](#) May, 2017, ([notes](#))

[World Conference on](#)

[Personality](#), March, 2013

([notes](#))

[ARP](#), June, 2011 ([notes](#))

[instructions](#) for Linux, Unix, Windows, and Macs are available through [CRAN](#) (Comprehensive R Archive Network). Somewhat pedantic instructions for installing R are in my tutorial [Getting Started with R and the psych package](#).

Although many run R as a language and programming environment, there are Graphical User Interfaces (GUIs) available for PCs, Linux and Macs. See for example, [R Commander](#) by John Fox, [RStudio](#) and [R-app](#) for the Macintosh developed by Stefano M. Iacus and Simon Urbanek. Compared to the basic PC environment, the Mac GUI is to be preferred. Many users find [RStudio](#) to be the preferred environment. It provides the same user experience on PCs and on Macs.

A note on the numbering system: The R-development core team releases an updated version of R about every six months. The version of 3.4.0 was introduced in April, 2017 replacing 3.3.3 which was released in 2016. Bug fixes are then added with a sub version number (e.g. 3.4.1 will fix any minor problems with 3.4.0). The next version of R (R 3.5.0) will be released sometime in 2017.

R is an integrated, interactive environment for data manipulation and analysis that includes functions for standard descriptive statistics (means, variances, ranges) and also includes useful graphical tools for Exploratory Data Analysis. In terms of inferential statistics R has many varieties of the General Linear Model including the conventional special cases of Analysis of Variance, MANOVA, and linear regression.

What makes R so powerful is the programming philosophy of core-R as well as the packages. Rather than give voluminous output for each function, the functions display only the most important aspects of the analysis, and save additional results as elements of the returned object. These objects may then be processed by additional functions. The power of this implementation is that specialized packages can take advantage of the more general core-R features. Thus, the correlation function, `cor`, can be used by functions that do factor analysis (`fa`) and the mean function can be used for a function to basic descriptive statistics (`describe`), which can be combined with the `by` function to do statistics broken down by groups (`describeBy`) or be combined again with functions that do correlations, to provide some basic multilevel statistics (`statsBy`). Without much effort, standard functions such as `aov` which does ANOVA, or `lme` to do linear mixed effects models can be integrated into other functions to find, for instance, intra class correlations (ICC) or multilevel reliability (`multilevel.reliability`). These functions in turn, may be used by the end user by just giving one or two commands. Because there are so many useful texts and web-based tutorials on R it is hard to suggest any particular one. A very short introduction to is the `\emph{Introduction to R}` by Venables et al. which is available as a book for a fee, or as a pdf to download from the web for free.

What makes R particularly powerful is that statisticians and statistically minded people around the world have taken advantage of the object oriented nature of R and have contributed more than 10,600 packages to the R Group and maintain a [very active news group offering suggestions and help](#). The growing collection of packages and the ease with which they interact with each other and the core R is perhaps the greatest advantage of R. Advanced features include correlational packages for multivariate analyses including Factor and Principal Components Analysis, and cluster analysis. Advanced multivariate analyses packages that have been contributed to the R-project include at least three for Structural Equation Modeling ([sem](#), [lavaan](#), and [Open-Mx](#)), Multi-level modeling (also known as Hierarchical Linear Modeling and referred to as [non linear mixed effects](#) in the `nlme4` package) and taxometric analysis. All of these are available in the free packages distributed by the R group at CRAN. Many of the functions described in this tutorial are incorporated into the [psych](#) package. Other packages useful for psychometrics are described in a task-view at CRAN. In addition to be a environment of prepackaged routines, R is a interpreted programming language that allows one to create specific functions when needed.

In addition to be a package of routines, R is a interpreted programming language that allows one to create specific functions when needed. This does not require great skills at programming and allows one to develop short functions to do repetitive tasks.

R is also an amazing program for producing statistical graphics. A collection of some of the best graphics was available at [addictedtoR](#) with a complete gallery of thumbnail of figures. This seems to have vanished. However, the site [R graph Gallery](#) is worth visiting.

[An introduction to R](#) is available as a pdf or as a paper back. (The CRAN site uses frames that redirect to the correct location. Select manuals and then an 'Introduction to R'). It is worth reading and rereading. Once R is installed on your machine, the introduction may be obtained by using the `help.start` command. More importantly for the novice, a number of very helpful tutorials have been written for R. (e.g., the tutorial by John Verzani to help [one teach introductory statistics](#) and learn R at the same time--this has now been published as a book, but earlier versions are still available online), or (by Jonathan Baron and Yuelin Li) to use [R in the Psychology lab](#). The Baron and Li tutorial was the most useful for psychologists trying to learn R but is now 6 years old. Another useful resource is [John Fox's short course on R](#) (Now 7 years old). For a more complete list of brief (<100 pages) and long (> 100 pages) tutorials, go to the "[contributed](#)" section of the CRAN.

There are a number of "reference cards" also known as "cheat sheets" that provide quick summaries of commands.

Jonathan Baron's [one pager](#)

Tom Short's [four pager](#)

Paul Torfs and Claudia Brauer [not so short introduction](#)

More locally, I have taken tutorials originally written by Roger Ratcliff and various graduate students on how to do analysis of variance using S and adapted them to the R environment. This guide was developed to help others learn R, and also to help students in [Research Methods](#), [Personality Research](#), [Psychometric Theory](#), [Structural Equation Modeling](#), or other courses do some basic statistics.

To download a copy of the software, go to the download section of the [cran.r-project.org](#) site. A [detailed pdf](#) of how to download R and some of the more useful packages is available as part of the personality-project.

[Jason French](#) maintains instructions on installing and configuring R in various Linux distributions, such as Fedora, CentOS, Ubuntu, and Debian. [See his post here](#). He also has written various tutorials on using R for regression and analysis of variance.

This set of notes originally relied heavily on "[An introduction to R](#)" by Venables, Smith and the R Development Core Team, the very helpful [Baron and Li](#) guide and the [teaching stats](#) page of John Verzani. Their pages were very useful when I started to learn R. There is a growing number of text books that introduce R. One of the classics is "Modern Applied Statistics with S" by Brian D. Ripley and William N. Venables. For the psychometrically minded, my [psychometrics text](#) (in progress) has all of its examples in R.

The [R help listserve](#) is a very useful source of information. Just lurking will lead to the answers for many questions. Much of what is included in this tutorial was gleaned from comments sent to the help list. The most frequently asked questions have been organized into a [FAQ](#). The archives of the help group are very useful and should be searched before asking for help. Jonathan Baron maintains a [searchable database](#) of the help list serve. Before asking for help, it is important to read the [posting guide](#) as well as "[How to Ask Questions the Smart Way](#)".

For a thoughtful introduction to R for SPSS and SAS users, see the [tutorials](#) developed at the University of Tennessee by Bob Muenchen. For a comparison of what is available in R to what is available in SPSS or SAS, see his table comparing the features of R to SPSS.

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General Comments

R is not overly user friendly (at first). Its error messages are at best cryptic. It is, however, very powerful and once partially mastered, easy to use. And it is free. Even more important than the cost is that it is an open source language which has become the lingua franca of statistics and data analysis. That is, as additional modules are added, it becomes even more useful. Modules included allow for multilevel (hierarchical) linear modeling, confirmatory factor analysis, etc. I believe that it is worth the time to learn how to use it. J. Baron and Y. Li's guide is very helpful. They include a one page pdf summary sheet of commands that is well worth printing out and using. A [four page summary sheet](#) of commands was contributed by Tom Short.

Using R in 12 simple steps for psychological research

(These steps are not meant to limit what can be done with R, but merely to describe how to do the analysis for the most basic of research projects and to give a first experience with R).

1. [Install R](#) on your computer or go to a machine that has it.
2. Download the [psych](#) package as well as other recommended packages from CRAN using the `install.packages` function, or using the package installer in the GUI. To get packages recommended for a particular research field, use the `ctv` package to install a particular task view. Note, these first two steps need to be done only once!
3. Activate the `psych` package or other desired packages using e.g., `library(psych)`. This needs to be done every time you start R. Or, it is possible to modify the startup parameters for R so that certain libraries are loaded automatically.
4. Enter your data using a text editor and save as a text file (perhaps comma delimited if using a spreadsheet program such as Excel or OpenOffice)
5. Read the data file or copy and paste from the clipboard (using, e.g., `read.clipboard`).
6. Find basic descriptive statistics (e.g., means, standard deviations, minimum and maxima) using `describe`.
7. Prepare a simple descriptive graph (e.g., a box plot) of your variables.
8. Find the correlation matrix to give an overview of relationships (if the number is not too great, a scatter plot matrix or SPLOM plot is very useful, this can be done with `pairs.panels`).
9. If you have an experimental variable, do the appropriate multiple regression using standardized or at least zero centered scores.
10. If you want to do a factor analysis or principal components analysis, use the `fa` or principal functions.
11. To score items and create a scale and find various reliability estimates, use `score.items` and perhaps `omega`.
12. Graph the results.

Getting started

Installing R on your computer

Although it is possible that your local computer lab already has R, it is most useful to do analyses on your own machine. In this case you will need to download the R program from the R project and install it yourself. Using your favorite web browser, go to the R home page at <http://www.r-project.org> and then choose the Download from CRAN (Comprehensive R Archive Network) option. This will take you to list of mirror sites around the world. You may download the Windows, Linux, or Mac versions at this site. For most users, downloading the binary image is easiest and does not require compiling the program. Once downloaded, go through the install options for the program. If you want to use R as a visitor it is possible to install R onto a “thumb drive” or “memory stick” and run it from there. (See the R for Windows FAQ at CRAN).

Packages and Task Views

One of the great strengths of R is that it can be supplemented with additional programs that are included as packages using the package manager. (e.g., sem or OpenMX do structural equation modeling) or that can be added using the source command. Most packages are directly available through the CRAN repository. Others are available at the BioConductor (<http://www.bioconductor.org>) repository. Yet others are available at “other” repositories. The psych package (Revelle, 2017) may be downloaded from [CRAN](#) or for Macs, the <http://personality-project.org/r> repository.

The concept of a “task view” has made downloading relevant packages very easy. For instance, the `install.views("Psychometrics")` command will download over 50 packages that do various types of psychometrics. To install the Psychometrics task view.

```
install.packages("ctv")
library(ctv)
install.views("Psychometrics")
```

For any other than the default packages to work, you must activate it by either using the Package Manager or the library command, e.g.,

```
library(psych)
library(sem)
```

In what follows, I am assuming that you have installed psych and made it active using the library command. entering ? the name of a package (e.g.,)

```
?psych
```

will give a list of the functions available in that package (e.g., psych) package as well as an overview of their functionality.

```
objects(package=psych)
```

will list the functions available in a package (in this case, psych).

If you routinely find yourself using the same packages everytime you use R, you can modify the Startup process by specifying what should happen .First. Thus, if you always want to have psych available,

```
.First <- function(library(psych))
```

and then when you quit, use the save workspace option.

Help and Guidance

R is case sensitive and does not give overly useful diagnostic messages. If you get an error message, don't be flustered but rather be patient and try the command again using the correct spelling for the command. Issuing the up arrow command will

let you edit the previous command.

When in doubt, use the `help()` function. This is identical to the `?function` where `function` is what you want to know about. e.g.,

```
help(read.file) #or
read.file #another way of asking for help
```

asks for help in using the `read.table` function. the answer is in the help window.

```
apropos("read") #returns all available functions with that term in their name.
RSiteSearch("read") #opens a webbrowser and searches voluminous files
```

`RSiteSearch("keyword")` will open a browser window and return a search for “keyword” in all functions available in R and the associated packages as well (if desired) the R-Help News groups.

All packages and all functions will have an associated help window. Each help window will give a brief description of the function, how to call it, the definition of all of the available parameters, a list (and definition) of the possible output, and usually some useful examples. One can learn a great deal by using the help windows, but if they are available, it is better to study the package vignette.

Package vignettes

All packages have help pages for each function in the package. These are meant to help you use a function that you already know about, but not to introduce you to new functions. An increasing number of packages have a package vignette that give more of an overview of the program than a detailed description of any one function. These vignettes are accessible from the help window and sometimes as part of the help index for the program. The three vignettes for the `psych` package are also available from the personality project web page. (An [introduction](#), an [overview](#) of the `psych` package and Using the `psych` package as a [front end](#) to the `sem` package).

Commands are entered into the "R Console" window. You can add a comment to any line by using a `#`. The Mac version has a text editor window that allows you to write, edit and save your commands. Alternatively, if you use a normal text editor (As a Mac user, I use BBEDIT, PC users can use Notepad), you can write out the commands you want to run, comment them so that you can remember what they do the next time you run a similar analysis, and then copy and paste into the R console.

Many people find the [RStudio](#) application a very useful front end for R. It provides four windows, one that saves your commands and text, the console, a graphics window, and a data browsing window. In addition, Rstudio is the home of some very useful packages. Download R and then download Rstudio.

Although being syntax driven seems a throwback to an old, pre Graphical User Interface type command structure, it is very powerful for doing production statistics. Once you get a particular set of commands to work on one data file, you can change the name of the data file and run the entire sequence again on the new data set. This is also very helpful when doing professional graphics for papers. In addition, for teaching, it is possible to prepare a web page of instructional commands that students can then cut and paste into R to see for themselves how things work. That is what may be done with the instructions on this page. It is also possible to write text in [latex](#) with embedded R commands. Then executing the [Sweave](#) function on that text file will add the R output to the [latex](#) file. Using RStudio, similar magic is done in the RMarkdown language. This almost magical feature allows rapid integration of content with statistical techniques. More importantly, it allows for "reproducible research" in that the actual data files and instructions may be specified for all to see.

As you become more adept in using R, you will be tempted to enter commands directly into the console window. I think it is better to keep (annotated) copies of your commands to help you next time.

R commands may be thought of as imperative verbs addressed to R. Basically you are telling R to do something to some object with or more modifiers of how to do it.

Command syntax tends to be of the form:

variable = function (parameters) or better yet

variable <- function (parameters) the = and the <- symbol imply replacement, not equality

the preferred style seems to be to use the <- symbol to avoid confusion

elements of arrays are indicated within brackets []

This guide assumes that you have installed a copy of R onto your computer and you are trying out the commands as you read through this. (Not necessary, but useful.)

Help and Guidance

For a list of all the commands that use a particular word, use the apropos () command:

```
apropos(read) #lists all the commands that have the word "read" in them

apropos("read")
[1] ".readRDS"          "read.clipboard"      "read.clipboard.csv"
[4] "read.clipboard.fwf" "read.clipboard.lower" "read.clipboard.tab"
[7] "read.clipboard.upper" "read.csv"            "read.csv2"
[10] "read.dcf"          "read.delim"          "read.delim2"
[13] "read.DIF"          "read.file"           "read.file.csv"
[16] "read.fortran"       "read.ftable"         "read.fwf"
[19] "read.https"        "read.socket"         "read.table"
[22] "readBin"           "readChar"            "readCitationFile"
[25] "readline"          "readLines"           "readRDS"
[28] "readRenviro"       "Sys.readlink"
```

For more complicated functions (e.g., plot(), lm()) the help function shows very useful examples. A very nice example is demo(graphics) which shows many of the complex graphics that are possible to do. demo(lm.glm) gives many examples of the linear model/general linear model.

The example command will run through all of the examples for a particular function. Thus, the next command will show you a number of different possible formats for showing correlational scatter plot matrices (SPLOMS)

```
example(pairs.panels)
```

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Entering or getting the data

There are multiple ways of reading data into R.

From a text file

For very small data sets, the data can be directly entered into R. For more typical data sets, it is useful to use a simple text editor or a spreadsheet program (e.g., Excel or [OpenOffice](#)). You can enter data in a tab delimited form with one variable per column and columns labeled with unique name. A numeric missing value code (say -999) is more convenient than using "." ala Systat. To read the data into a rows (subjects) by columns (variables) matrix use the `read.table` command. If using a spreadsheet, just leaving the cell blank will work if you then use the `read.file.tab()` function.

A very useful command, for those using a GUI is `read.file()` which takes advantage of two different core-R functions (`file.choose` and `read.table`). `read.file()` opens a typical selection window for choosing a file. `read.file()` will correctly read in files that end in .txt, text, .sav (for spss), .csv, etc.

```
my.data <- read.file()  #will open a a search window to find the file and then read it.
#specify the name and address of the remote file
#based upon the suffix of the file, it will then call the appropriate reading procedure or
give a warning saying it doesn't know what to do.

#alternatively

datafilename <- file.choose()    # use the OS to find the file

#e.g., datafilename <- "Desktop/epi.big5.txt" #locate the local directory

person.data <- read.file(datafilename) #read the data file

#Alternatively, to read in a comma delimited file:
#person.data <- read.table(datafilename,header=TRUE,sep=",")
```

From the clipboard

For many problems you can just cut and paste from a spreadsheet or text file into R using the `read.clipboard` command from the `psych` package.

```
my.data <- read.clipboard()    #or
my.data <- read.clipboard.csv() #if comma delimited
my.data <- read.clipboard.tab() #if tab delimited (e.g., from Excel)
```

Files can be comma delimited (csv) as well. In this case, you can specify that the separators are commas. For very detailed help on importing data from different formats (SPSS, SAS, Matlab, Systat, etc.) see the [data help page](#) from Cran. The foreign package makes importing from SPSS or SAS data files fairly straightforward. However, `read.file()` will work on many file formats.

From the web

For teaching, it is important to note that it is possible to have the file be a remote file read through the web. (Note that for some commands, there is an important difference between line feeds and carriage returns. For those who use Macs as web servers, make sure that the unix line feed is used rather than old Mac format carriage returns.) For simplicity in my examples I have separated the name of the file to be read from the `read.file` command. These two commands can be combined into one. The file can be local (on your hard disk) or remote.

For most data analysis, rather than [manually enter the data into R](#), it is probably more convenient to use a spreadsheet (e.g., Excel or OpenOffice) as a data editor, save as a tab or comma delimited file, and then read the data or copy using the

`read.clipboard()` command. Most of the examples in this tutorial assume that the data have been entered this way. Many of the examples in the help menus have small data sets entered using the `c()` command or created on the fly.

Data input example

For the first example, we read data from a remote file server for several hundred subjects on 13 personality scales (5 from the Eysenck Personality Inventory (EPI), 5 from a Big Five Inventory (BFI), the Beck Depression Inventory, and two anxiety scales). The file is structured normally, i.e. rows represent different subjects, columns different variables, and the first row gives subject labels. (To read from a local file, we simply change the name of the datafilename.)

```
#specify the name and address of the remote file
datafilename <- "http://personality-project.org/r/datasets/maps.mixx.epi.bfi.data"
#datafilename <- "Desktop/epi.big5.txt" #read from local directory or
# datafilename <- file.choose()      # use the OS to find the file
#in all cases
person.data <- read.file(datafilename) #read the data file

names(person.data) #list the names of the variables
```

produces this output

```
> datafilename <- "http://personality-project.org/r/datasets/maps.mixx.epi.bfi.data"
> #datafilename <- "Desktop/epi.big5.txt" #read from local directory
> person.data <- read.file(datafilename) #read the data file
#or, search your file for the appropriate file to read
person.data <- read.file() #will open a search window

> names(person.data) #list the names of the variables
[1] "epiE"    "epiS"    "epiImp"   "epilie"   "epiNeur"  "bfaagree" "bfcon"    "bfext"
[9] "bfneur"  "bfopen"  "bdi"      "traitanx" "stateanx"
```

The data are now in the `data.table` "person.data". Tables allow one to have columns that are either numeric or alphanumeric. To address a particular row (e.g., subject = 5) and column (variable = 7) you simply enter the required fields:

```
person.data[5,8]      #the 5th subject, 8th variable or
person.data[5,"bfext"] #5th subject, "Big Five Inventory - Extraversion" variable
#or
person.data[5,]       #To list all the data for a particular subject (e.g, the 5th subject)
person.data[5:10,]    #list cases 5 - 10
person.data[5:10,"bfext"] #list just the extraversion scores for subjects 5-10
person.data[5:10,4:8]  #list the 4th through 8th variables for subjects 5 - 10.
```

In order to select a particular subset of the data, use the subset function. The next example uses subset to display cases where the lie scale was pretty high

```
subset(person.data,epilie>6) #print the data meeting the logical condition epilie>6
#also try
person.data[person.data["epilie"]>6,]
```

produces this output

```
epiE epiS epiImp epilie epiNeur bfaagree bfcon bfext bfneur bfopen bdi traitanx stateanx
16   11   5     6     7     13    126   78   112   83   132   4     45    28
212   6    4     1     7     4    147  119  102   81   142   2     26    21
```

One can also selectively display particular columns meeting particular criteria, or selectively extract variables from a dataframe.

```
subset(person.data[,2:5],epilie>5 & epiNeur<3) #notice that we are taking the logical 'and'

  epiS epiImp epilie epiNeur
12   12     3     6     1
118   8     2     6     2

subset(person.data[,3:7], epilie>6 | epiNeur ==2 ) #do a logical 'or' of the two conditions

epi <- subset(data,select=epiE:epiNeur) #select particular variables from a data frame
```

Reading data from SPSS or other stats programs

In addition to reading text files from local or remote servers, it is possible to read data saved in other stats programs (e.g., SPSS, SAS, Minitab). read commands are found in the package foreign. You will need to make it active first.

```
datafilename <- "http://personality-project.org/r/datasets/finkel.sav" #remote file
library(foreign) #make it active
eli.data <- read.spss(datafilename, use.value.labels=TRUE, to.data.frame=TRUE)
```

Data sets can be saved for later analyses using the save command and then reloaded using load. If files are saved on remote servers, use the load(url(remoteURLname)) command.

```
save(object,file="local name") #save an object (e.g., a correlation matrix) for later analysis
load(file) #gets the object (e.g., the correlation matrix back)
load(url("http://personality-project.org/r/datasets/big5r.txt")) #get the correlation matrix
```

Getting around in R

R is case sensitive so be careful when naming or calling functions and variables. Commands are entered in the command console and (at least for Macs), are colored blue while results in the results console are shown in black. Commands can be cut and pasted from a text editor (or from a browser if following along with examples) into the command console. Like Unix or OS X, using the up arrow shows previous commands.

It is a useful habit to be consistent in your own naming conventions. Some use lower case letters for variables, Capitalized for data frames, all caps for functions, etc. It is easier to edit your code if you are reasonably consistent. Comment your code as well. This is not just so others can use it, but so that you can remember what you did 6 months later.

```
ls() #shows the variables in the workspace
help (name) #provides help about a function "name"

? name #does the same

rm(variable) #removes that variable

rm(list = ls()) #removes all variables from the work space
attach("table") #makes the elements of "table" available to be called directly (make sure to always detach later. The use of attach ...

names(table) #what are the variables inside the table
```

```

variable <-c(value1,value2,value3 ...)  #assigns values to a variable.
# column bind (combine) variables to make up a new array with these variables

newvariable <- cbind (variable1, variable2, variable3 ... variable n)

# e.g.

ls()      #show the variables in the workspace

datafilename <- "http://personality-project.org/R/datasets/maps.mixx.epi.bfi.data"
person.data <- read.table(datafilename,header=TRUE) #read the data file
names(person.data) #list the names of the variables

attach(person.data)      #make the separate variable available -- always do detach when finished.
                        #The with construct is better.

new.epi <- cbind(epiE,epiS,epiImp,epilie,epiNeur)      #form a new variable "epi"
epi.df <- data.frame(new.epi)      #actually, more useful to treat this variable as a data frame

bfi.df <- data.frame(cbind(bfext,bfneur,bfagree,bfcon,bfopen))
                        #create bfi as a data frame as well

detach(person.data)  # very important to detach after an attach

```

The use of the attach -- detach sequence has become less common and it is more common to use the with command. The syntax of this is clear

with(some data frame, { do the commands between the brackets}) #and then close the parens

```

#alternatively:
with(person.data,{
  epi <- cbind(epiE,epiS,epiImp,epilie,epiNeur)      #form a new variable "epi"
  epi.df <- data.frame(epi)      #actually, more useful to treat this variable as a data frame

  bfi.df <- data.frame(cbind(bfext,bfneur,bfagree,bfcon,bfopen))
                        #create bfi as a data frame as well
  epi.df <- data.frame(epi)      #actually, more useful to treat this variable as a data frame

  bfi.df <- data.frame(cbind(bfext,bfneur,bfagree,bfcon,bfopen))
                        #create bfi as a data frame as well

  describe(bfi.df)
} #end of the stuff to be done within the with command
) #end of the with command

```

However, intermediate results created inside the with () command are not available later. The with construct is more appropriate when doing some specific analysis. However, this is R, so there is yet another way of doing this that is very understandable:

```

#alternatively:
epi.df <- data.frame(with(person.data,{ cbind(epiE,epiS,epiImp,epilie,epiNeur)} )) #actually, more useful to treat this variable as a da

bfi.df <- data.frame(with(person.data,cbind(bfext,bfneur,bfagree,bfcon,bfopen)) )
                        #create bfi as a data frame as well

```

```
epi.df <- data.frame(epi)      #actually, more useful to treat this variable as a data frame
```

Yet another way to call elements of a variable is to address them directly, either by name or by location:

```
epi <- person.data[c("epiE","epiS","epiImp","epilie","epiNeur")] #form a new variable "epi"
epi.df <- data.frame(epi)      #actually, more useful to treat this variable as a data frame

bfi.df <- data.frame(person.data[c(9,10,7,8,11)]) #create bfi as a data frame as well
```

It is also possible to edit the data:

```
ls()      #show the variables
y <- edit(person.data)
          #show the data.frame or matrix x in a text editor and save changes to y
fix(person.data)
          #show the data.frame or matrix x in a text editor
invisible(edit(x))
          #creates an edit window without also printing to console -- directly make changes.
          #Similar to the most basic spreadsheet. Very dangerous!
head(x)   #show the first few lines of a data.frame or matrix
tail(x)   #show the last few lines of a data.frame or matrix
str(x)    #show the structure of x
```

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Data manipulation

The normal mathematical operations can be done on all variables. e.g.

```
attach(person.data) #make the variables inside person data available
imp2 <- epiImp*epiImp #square epiImp
s1 <- epiS+epiImp      #sum sociability and impulsivity
statetotrait <- stateanx/traitanx #find the ratio of state to trait anxiety
})
weirdproduct <- epi*bfi #multiply respective elements in two tables
meanimp <- mean(imp)
stdevimp <- sd(imp)
standarizedimp <- scale(imp,scale=TRUE) #center and then divide by the standard deviation
detach(person.data) #and make sure to detach the variable when you are finished with it
```

Logical operations can be performed. Two of the most useful are the ability to replace if a certain condition holds, and to find subsets of the data.

```

person.data[person.data == -9] <- NA
#replace all cases where a particular code is observed with NA

males=subset(person.data |gender ==1)
#x=subset(y|condition)

```

The power of R is shown when we combine various data manipulation procedures. Consider the problem of scoring a multiple choice test where we are interested in the number of items correct for each person. Define a scoring key vector and then score as 1 each item match with that key. Then find the number of 1s for each subject. We use the Iris data set as an example.

```

iris2 <- round(iris[1:10,1:4]) #get a sample data set
key <- iris2[1,] #make up an arbitrary answer key
score <- t(t( rowSums((iris2 == c(key[1]))+0))) #look for correct item and add them up
mydata <- data.frame(iris2,score) #
key #what is the scoring key
mydata #show the data with the number of items that match the key

```

(Thanks to Gabor Grothendieck and R help for this trick. Actually, to score a multiple choice test, use `score.multiple.choice` in the `psych` package.)

Basic descriptive statistics

[Back to Top](#) Core R includes the basic statistical functions one would want to provide summaries of the data. The `summary` command is not particularly helpful and the `mean`, `min`, `max`, `sum`, etc commands will be of a complete data set, not a single column.

```

ls() #list the variables in the work space

ls()
[1] "bfi.df"      "datafilename" "epi"          "epi.df"       "person.data"

summary(epi.df) #standard descriptive stats using the summary command

      epiE      epiS      epiImp      epilie      epiNeur
Min.   : 1.00  Min.   : 0.000  Min.   :0.000  Min.   :0.000  Min.   : 0.00
1st Qu.:11.00  1st Qu.: 6.000  1st Qu.:3.000  1st Qu.:1.000  1st Qu.: 7.00
Median :14.00  Median : 8.000  Median :4.000  Median :2.000  Median :10.00
Mean   :13.33  Mean   : 7.584  Mean   :4.368  Mean   :2.377  Mean   :10.41
3rd Qu.:16.00  3rd Qu.: 9.500  3rd Qu.:6.000  3rd Qu.:3.000  3rd Qu.:14.00
Max.   :22.00  Max.   :13.000  Max.   :9.000  Max.   :7.000  Max.   :23.00

summary(person.data["epiImp"]) #descriptive stats for one variable -- note the quote marks

      epiImp
Min.   :0.000
1st Qu.:3.000
Median :4.000
Mean   :4.368
3rd Qu.:6.000
Max.   :9.000

#The following do what their name implies
max()

```

```

min()
mean()
median()
sum()
var()      #produces the variance covariance matrix
sd()        #standard deviation
mad()       #(median absolute deviation)
fivenum()   #Tukey fivenumbers min, lowerhinge, median, upper hinge, max

#e.g.

with(person.data, {      #make the variables inside of data available to be called by name
  max(epsImp)
  min(epsImp)
  mean(epsImp)
  median(epsImp)
  var(epsImp)
  sqrt(var(epsImp))
  sum(epsImp)
  sd(epsImp)
  mad(epsImp)
  fivenum(epsImp)
})

detach(person.data)      #always match an attach with a corresponding detach

Produces this output

> attach(person.data)      #make the variables inside of data available to be called by name
> max(epsImp)
[1] 9
> min(epsImp)
[1] 0
> mean(epsImp)
[1] 4.367965
> median(epsImp)
[1] 4
> var(epsImp)
[1] 3.546621
> sqrt(var(epsImp))
[1] 1.883248
> sum(epsImp)
[1] 1009
> sd(epsImp)
[1] 1.883248
> mad(epsImp)
[1] 1.4826
> fivenum(epsImp)
[1] 0 3 4 6 9
> detach(person.data)      #always match an attach with a corresponding detach
>

```

This approach (attach ... detach) is awkward at best.

Many if not most psychologists will probably prefer the output provided by the describe function in the psych package:

```
describe(epi.df)
```

	var	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
epiE	1	231	13.33	4.14	14	13.49	4.45	1	22	21	-0.33	-0.06	0.27
epiS	2	231	7.58	2.69	8	7.77	2.97	0	13	13	-0.57	-0.02	0.18
epiImp	3	231	4.37	1.88	4	4.36	1.48	0	9	9	0.06	-0.62	0.12
epilie	4	231	2.38	1.50	2	2.27	1.48	0	7	7	0.66	0.24	0.10
epiNeur	5	231	10.41	4.90	10	10.39	4.45	0	23	23	0.06	-0.50	0.32

Standardization and zero centering scale) that does this automatically

```
epiz <- scale(epi)           #centers (around the mean) and scales by the sd
epic <- scale(epi,scale=FALSE) #centers but does not Scale
```

Compare the two results. In the first, all the means are 0 and the sds are all 1. The second also has been centered, but the standard deviations remain as they were.

```
describe(epiz)
describe(epic)

> describe(epiz)
      var    n mean sd median trimmed  mad   min   max range  skew kurtosis   se
epiE    1 231    0  1  0.16   0.04 1.08 -2.98 2.10  5.08 -0.33   -0.06 0.07
epiS    2 231    0  1  0.15   0.07 1.10 -2.82 2.01  4.84 -0.57   -0.02 0.07
epiImp   3 231    0  1 -0.20   0.00 0.79 -2.32 2.46  4.78  0.06   -0.62 0.07
epilie   4 231    0  1 -0.25  -0.07 0.99 -1.59 3.09  4.68  0.66    0.24 0.07
epiNeur  5 231    0  1 -0.08   0.00 0.91 -2.12 2.57  4.69  0.06   -0.50 0.07

> describe(epic)
      var    n mean  sd median trimmed  mad   min   max range  skew kurtosis   se
epiE    1 231    0 4.14  0.67   0.16 4.45 -12.33  8.67   21 -0.33   -0.06 0.27
epiS    2 231    0 2.69  0.42   0.18 2.97  -7.58  5.42   13 -0.57   -0.02 0.18
epiImp   3 231    0 1.88 -0.37  -0.01 1.48  -4.37  4.63    9  0.06   -0.62 0.12
epilie   4 231    0 1.50 -0.38  -0.11 1.48  -2.38  4.62    7  0.66    0.24 0.10
epiNeur  5 231    0 4.90 -0.41  -0.02 4.45 -10.41 12.59   23  0.06   -0.50 0.32
```

#to print out fewer decimals, the round(variable,decimals) function is used. This next example also introduces the apply function which applies a particular function to the rows or columns of a matrix or data.frame.

```
round(apply(epi,2,mean),1)
round(apply(epi,2,var),2)
round(apply(epi,2,sd),3)
```

Another example of the apply function:

```
apply(epi,2,fivenum)           #give the lowest, 25%, median, 75% and highest value (compare to summary)
```

The describe function.

Although the summary function gives Tukey's 5 number summaries, many psychologists will find the describe function in the psych more useful.

```
describe(epi.df)      #use the describe function
```

	var	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
epiE	1	231	13.33	4.14	14	13.49	4.45	1	22	21	-0.33	-0.06	0.27
epiS	2	231	7.58	2.69	8	7.77	2.97	0	13	13	-0.57	-0.02	0.18
epiImp	3	231	4.37	1.88	4	4.36	1.48	0	9	9	0.06	-0.62	0.12
epilie	4	231	2.38	1.50	2	2.27	1.48	0	7	7	0.66	0.24	0.10
epiNeur	5	231	10.41	4.90	10	10.39	4.45	0	23	23	0.06	-0.50	0.32

Simple graphical descriptions: the stem and leaf diagram

```
stem(person.data$bfneur)      #stem and leaf diagram
```

The decimal point is 1 digit(s) to the right of the |

```

3 | 45
4 | 26778
5 | 000011122344556678899
6 | 000011111222233344567888899
7 | 000001112223444456666777889999
8 | 00111122333444445556677789
9 | 00011122233334445556677888888899
10 | 00000011112222233334444444555667778899
11 | 000122222444556677899
12 | 03333577889
13 | 0144
14 | 224
15 | 2

```

Correlations

```
round(cor(epi.df),2)
```

#correlation matrix with values rounded to 2 decimals

	epiE	epiS	epiImp	epilie	epiNeur
epiE	1.00	0.85	0.80	-0.22	-0.18
epiS	0.85	1.00	0.43	-0.05	-0.22
epiImp	0.80	0.43	1.00	-0.24	-0.07
epilie	-0.22	-0.05	-0.24	1.00	-0.25
epiNeur	-0.18	-0.22	-0.07	-0.25	1.00

```
round(cor(epi.df,bfi.df),2)
```

#cross correlations between the 5 EPI scales and the 5 BFI scales

	bfext	bfneur	bfagree	bfcon	bfopen
epiE	0.54	-0.09	0.18	-0.11	0.14
epiS	0.58	-0.07	0.20	0.05	0.15
epiImp	0.35	-0.09	0.08	-0.24	0.07
epilie	-0.04	-0.22	0.17	0.23	-0.03
epiNeur	-0.17	0.63	-0.08	-0.13	0.09

Testing the significance of a set of correlations

The `cor` function does not report the probability of the correlation. The `cor.test` in Core R will test the significance of a single correlation. For those who are more accustomed to testing many correlations, `corr.test` in `psych` will report the raw correlations, the pairwise number of observations, and the p-value of the correlation, either for a single correlation or corrected for multiple tests using the Holm correction.

```
corr.test(sat.act)

> corr.test(eps.df)
Call:corr.test(x = eps.df)
Correlation matrix
      epsE  epsS epsImp epslie epsNeur
epsE    1.00  0.85   0.80  -0.22  -0.18
epsS    0.85  1.00   0.43  -0.05  -0.22
epsImp   0.80  0.43   1.00  -0.24  -0.07
epslie  -0.22 -0.05  -0.24   1.00  -0.25
epsNeur -0.18 -0.22  -0.07  -0.25   1.00
Sample Size
      epsE epsS epsImp epslie epsNeur
epsE    231  231   231   231   231
epsS    231  231   231   231   231
epsImp   231  231   231   231   231
epslie   231  231   231   231   231
epsNeur  231  231   231   231   231
Probability values (Entries above the diagonal are adjusted for multiple tests.)
      epsE epsS epsImp epslie epsNeur
epsE    0.00  0.00   0.00   0.00   0.02
epsS    0.00  0.00   0.00   0.53   0.00
epsImp   0.00  0.00   0.00   0.00   0.53
epslie   0.00  0.43   0.00   0.00   0.00
epsNeur  0.01  0.00   0.26   0.00   0.00
```

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Graphical displays

A quick overview of some of the graphic facilities. See the [r.graphics](#) and the [plot regressions](#) and how to [plot temporal data](#) pages for more details.

For a stunning set of graphics produced with R and the code for drawing them, see addicted to R: [R Graph Gallery](#) : Enhance your data visualisation with R.

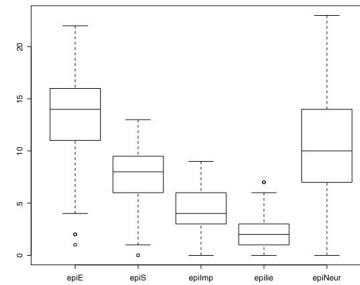
```
#see the graphic window for the output
```

```

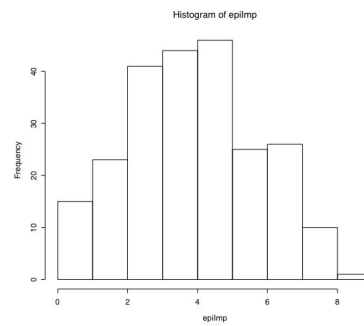
boxplot(eps)      #boxplot of the five epi scales
hist(epsE)        #simple histogram
plot(epsE,epsImp)  #simple scatter plot
pairs(eps.df)      #splom plot

```

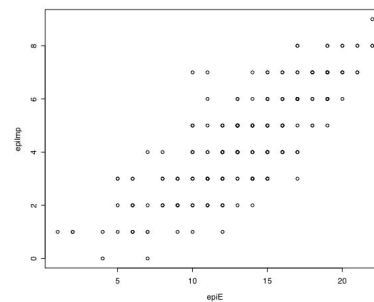
boxplot(eps)



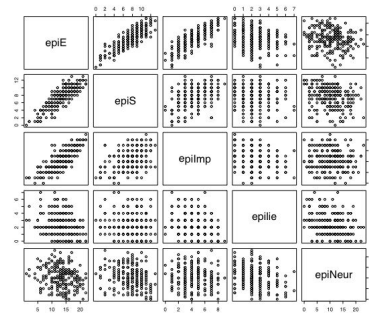
hist(epsE)



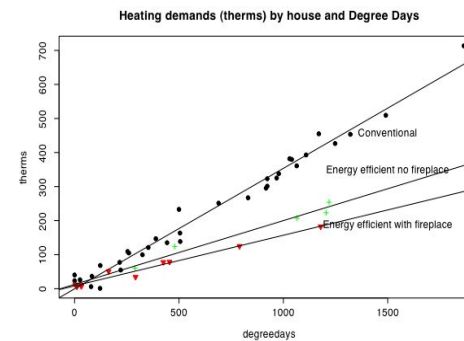
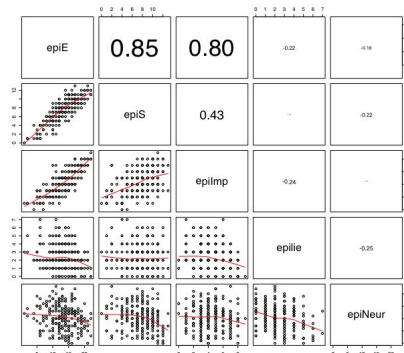
plot(epsE,epsImp) #Simple scatter plot



pairs(eps) # Basic ScatterPlot Matrix (SPLOM)



More advanced plotting (see [r.graphics](#) and [r.plotregressions](#) for details)



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Inferential Statistics -- Analysis of Variance

The following are examples of Analysis of Variance. A more complete listing and discussion of these examples including the output is in the [R.anova](#) page. This section just gives example instructions. See also the [ANOVA section of Jonathan Baron's page](#).

One Way ANOVA

```
#tell where the data come from
datafilename="http://personality-project.org/r/datasets/R.appendix1.data"
data.ex1=read.table(datafilename,header=T) #read the data into a table
```

```
aov.ex1 = aov(Alertness~Dosage,data=data.ex1) #do the analysis of variance
summary(aov.ex1) #show the summary table
print(model.tables(aov.ex1,"means"),digits=3)
#report the means and the number of subjects/cell
boxplot(Alertness~Dosage,data=data.ex1)
#graphical summary appears in graphics window
```

[Two Way \(between subjects\) Analysis of Variance \(ANOVA\)](#) The standard 2-way ANOVA just adds another Independent Variable to the model. The example data set is stored at the personality-project.

```
datafilename="http://personality-project.org/R/datasets/R.appendix2.data"
data.ex2=read.table(datafilename,header=T) #read the data into a table
data.ex2 #show the data
aov.ex2 = aov(Alertness~Gender*Dosage,data=data.ex2) #do the analysis of variance
summary(aov.ex2) #show the summary table
print(model.tables(aov.ex2,"means"),digits=3)
#report the means and the number of subjects/cell
boxplot(Alertness~Dosage*Gender,data=data.ex2)
#graphical summary of means of the 4 cells
attach(data.ex2)
interaction.plot(Dosage,Gender,Alertness) #another way to graph the means
detach(data.ex2)
```

[One way repeated Measures](#) Repeated measures are some what more complicated. However, Jason French has prepared a very useful [tutorial](#) on using R for repeated measures.

```
#Run the analysis:
datafilename="http://personality-project.org/r/datasets/R.appendix3.data"
data.ex3=read.table(datafilename,header=T) #read the data into a table
data.ex3 #show the data
aov.ex3 = aov(Recall~Valence+Error(Subject/Valence),data.ex3)
summary(aov.ex3)
print(model.tables(aov.ex3,"means"),digits=3)
#report the means and the number of subjects/cell
boxplot(Recall~Valence,data=data.ex3) #graphical output
```

[Two way repeated measures](#) This gets even more complicated.

```
datafilename="http://personality-project.org/r/datasets/R.appendix4.data"
data.ex4=read.table(datafilename,header=T) #read the data into a table
data.ex4 #show the data
aov.ex4=aov(Recall~(Task*Valence)+Error(Subject/(Task*Valence)),data.ex4 )

summary(aov.ex4)
print(model.tables(aov.ex4,"means"),digits=3)
#report the means and the number of subjects/cell
boxplot(Recall~Task*Valence,data=data.ex4) #graphical summary of means of the 6 cells
attach(data.ex4)
interaction.plot(Valence,Task,Recall) #another way to graph the interaction
detach(data.ex4)
```

[4 way anova: 2 repeated measures and two between subjects](#)

```
datafilename="http://personality-project.org/r/datasets/R.appendix5.data"
data.ex5=read.table(datafilename,header=T) #read the data into a table
```

```
#data.ex5                                #show the data
aov.ex5 =
aov(Recall~(Task*Valence*Gender*Dosage)+Error(Subject/(Task*Valence))+
  (Gender*Dosage),data.ex5)

summary(aov.ex5)
print(model.tables(aov.ex5,"means"),digits=3)
#report the means and the number of subjects/cell
boxplot(Recall~Task*Valence*Gender*Dosage,data=data.ex5)
#graphical summary of means of the 36 cells
boxplot(Recall~Task*Valence*Dosage,data=data.ex5)
#graphical summary of means of 18 cells
```

Reorganizing the data for within subject analyses

The prior examples have assumed one line per unique subject/variable combination. This is not a typical way to enter data. A more typical way (found e.g., in Systat) is to have one row/subject. We need to "stack" the data to go from the standard input to the form preferred by the analysis of variance. Consider the following analyses of 27 subjects doing a memory study of the effect on recall of two presentation rates and two recall intervals. Each subject has two replications per condition. The first 8 columns are the raw data, the last 4 columns collapse across replications. The data are found in a file on the personality project server.

```
datafilename="/Users/bill/Desktop/R.tutorial/datasets/recall1.data"
recall.data=read.table(datafilename,header=TRUE)
recall.data #show the data
```

We can use the "stack()" function to arrange the data in the correct manner. We then need to create a new data.frame (recall.df) to attach the correct labels to the correct conditions. This seems more complicated than it really is (although it is fact somewhat tricky). It is useful to list the data after the data frame operation to make sure that we did it correctly. (This and the next two examples are adapted from Baron and Li's page.) We make use of the rep(), c(), and factor() functions.

rep (operation,number) repeats an operation number times

c(x,y) forms a vector with x and y elements

factor (vector) converts a numeric vector into factors for an ANOVA

More detail on this technique, with comparisons of the original data matrix to the stacked matrix to the data structure version is shown on the [r.anova](http://www.personality-project.org/r/r.guide.html) page.

```
raw=recall.data[,1:8] #just trial data
#First set some specific parameters for the analysis -- this allows
numcases=27 #How many subjects are there?
numvariables=8 #How many repeated measures are there?
numreplications=2 #How many replications/subject?
numlevels1=2 #specify the number of levels for within subject variable 1
numlevels2=2 #specify the number of levels for within subject variable 2

stackedraw=stack(raw) #convert the data array into a vector
#add the various coding variables for the conditions
#make sure to check that this coding is correct

recall.raw.df=data.frame(recall=stackedraw,
  subj=factor(rep(paste("subj", 1:numcases, sep=""), numvariables)),
  replication=factor(rep(rep(c("1","2"), c(numcases, numcases)),
    numvariables/numreplications)),
  time=factor(rep(rep(c("short", "long"),
```

```

c(numcases*numreplications, numcases*numreplications)),numlevels1)),
study=rep(c("d45", "d90") ,c(numcases*numlevels1*numreplications,
numcases*numlevels1*numreplications)))

recall.aov= aov(recall.values ~ time * study + Error(subj/(time * study)), data=recall.raw.df)
#do the ANOVA
summary(recall.aov) #show the output
print(model.tables(recall.aov,"means"),digits=3) #show the cell means for the anova table

```

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Linear regression

Many statistics used by psychologists and social scientists are special cases of the linear model (e.g., ANOVA is merely the linear model applied to categorical predictors). Generalizations of the linear model include an even wider range of statistical models.

Consider the following models:

$y \sim x$ or $y \sim 1 + x$ are both examples of simple linear regression with an implicit or explicit intercept.

$y \sim 0 + x$ or $y \sim -1 + x$ or $y \sim x - 1$ linear regression through the origin

$y \sim A$ where A is a matrix of categorical factors is a classic ANOVA model.

$y \sim A + x$ is ANOVA with x as a covariate

$y \sim A * B$ or $y \sim A + B + A * B$ ANOVA with interaction terms

...

These models can be fitted with the linear model function (`lm`) and then various summary statistics are available of the fit. The data set is our familiar set of Eysenck Personality Inventory and Big Five Inventory scales with Beck Depression and state and trait anxiety scales as well. The first analysis just regresses BDI on EPI Neuroticism, then we add in Trait Anxiety, and then the $N * \text{trait Anx}$ interaction. Note that we need to 0 center the predictors when we have an interaction term if we expect to interpret the additive effects correctly. Centering is done with the `scale()` function. Graphical summaries of the regression show four plots: residuals as a function of the fitted values, standard errors of the residuals, a plot of the residuals versus a normal distribution, and finally, a plot of the leverage of subjects to determine outliers. Models 5 and 6 predict bdi using the BFI, and model 7 (for too much fitting) looks at the epi and bfi and the interactions of their scales. What follows are the commands for a number of demonstrations. Samples of the commands and the output may be found in the [regression](#) page. [Further examples](#) show how to find regressions for multiple dependent variables or to find the regression weights from the correlation matrix rather than the raw data.

```

datafilename="http://personality-project.org/r/datasets/maps.mixx.epi.bfi.data"
#where are the data
personality.data =read.table(datafilename,header=TRUE) #read the data file
names(personality.data) #what variables are in the data set?

```

```

attach(personality.data)  #make the variables easier to use
model1 = lm(bdi~epiNeur) #simple regression of beck depression on Neuroticism
summary(model1)          # basic statistical summary

#pass parameters to the graphics device
op <- par(mfrow = c(2, 2), # 2 x 2 pictures on one plot
          pty = "s")      # square plotting region,
                          # independent of device size

plot(model1)              #diagnostic plots in the graphics window

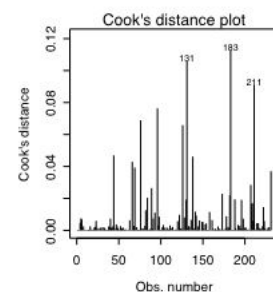
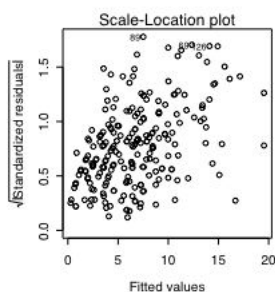
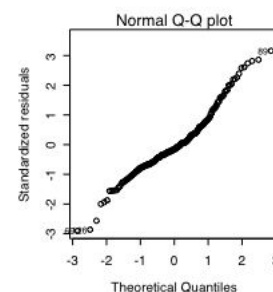
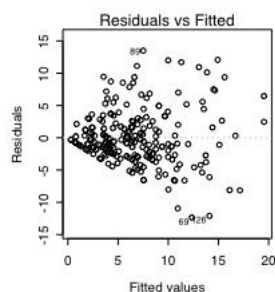
model2=lm(bdi~epiNeur+traitanx) #add in trait anxiety
summary(model2)            #basic output
plot(model2)

anova(model1,model2)       #compare the difference between the two models
model2.5=lm(bdi~epiNeur*traitanx)
#test for the interaction, note that the main effects are incorrect
#because we need to 0 center the data
summary(model2.5)
anova(model2,model2.5)     #compare the two models

#rescale the data to do the analysis
cneur=scale(epiNeur,scale=F) #0 center epiNeur
zneur=scale(epiNeur,scale=T) #standardize epiNeur
ctrain = scale(traitanx,scale=F) #0 center traitAnx

model3=lm(bdi~cneur+ctrain+cneur*ctrain)
summary(model3)            #explicitly list the additive and interactive terms
plot(model3)

```



```
model4=lm(bdi~cneur*ctrain)
```

```
summary(model4) #note how this is exactly the same as the previous model

epi=cbind(epiS,epiImp,epilie,epiNeur)
#form a new variable "epi" without overall extraversion
epi=as.matrix(epi) #actually, more useful to treat this variable as a matrix

bfi=as.matrix(cbind(bfext,bfneur,bfagree,bfcon,bfopen)) #create bfi as a matrix as well
epi=scale(epi,scale=T) #standardize the epi
bfi=scale(bfi,scale=T) #standardize the bfi

model5=lm(bdi~bfi) #model beck depression by the Big 5 inventory
summary(model5)
model6=lm(bdi~bfi+epi)
summary(model6)

model7 = lm(bdi~bfi*epi)
#additive model of epi and bfi as well as the interactions between the sets
summary(model7) #given as an example of overfitting
## At end of plotting, reset to previous settings:
par(op)
```

[Further examples](#) show how multiple regression can be done with multiple dependent variables at the same time and how regressions can be done based upon the correlation matrix rather than the raw data.

In order to visualize interactions, it is useful to [plot regression lines separately for different groups](#). This is demonstrated in some detail in a real example based upon heating demands of two houses.

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Multivariate procedures in R

Scale Construction and Reliability

(This section, written four years ago, shows how to do the analyses in "vanilla R". I recommend installing the psych package from CRAN and using the more powerful functions in that package.)

One of the most common problems in personality research is to combine a set of items into a scale. Questions to ask of these items and the resulting scale are a) what are the item means and variances. b) What are the intercorrelations of the items in the scale. c) What are the correlations of the items with the composite scale. d) what is an estimate of the internal consistency reliability of the scale. (For a somewhat longer discussion of this, see the [internal structure of tests](#).)

The following steps analyze a small subset of the data of a large project (the synthetic aperture personality measurement project at the Personality, Motivation, and Cognition lab). The data represent responses to five items sampled from items

measuring extraversion, emotional stability, agreeableness, conscientiousness, and openness taken from the IPIP (International Personality Item Pool) for 200 subjects.

```
#get the data
datafilename="http://personality-project.org/R/datasets/extraversion.items.txt"
#where are the data

items=read.table(datafilename,header=TRUE) #read the data

attach(items) #make this the active path
E1=q_262 -q_1480 +q_819 -q_1180 +q_1742 +14
#find a five item extraversion scale
#note that because the item responses ranged from 1-6, to reverse an item
#we subtract it from the maximum response possible + the minimum.
#Since there were two reversed items, this is the same as adding 14

E1.df = data.frame(q_262 ,q_1480 ,q_819 ,q_1180 ,q_1742 ) #put these items into a data frame

summary(E1.df) #give summary statistics for these items
round(cor(E1.df,use="pair"),2) #correlate the 5 items, rounded off to 2 decimals,
#use pairwise cases
round(cor(E1.df,E1,use="pair"),2) #show the item by scale correlations
#define a function to find the alpha coefficient

alpha.scale=function(x,y) #create a reusable function to find coefficient alpha
#input to the function are a scale and a data.frame of the items in the scale
{
  Vi=sum(diag(var(y,na.rm=TRUE))) #sum of item variance
  Vt=var(x,na.rm=TRUE) #total test variance
  n=dim(y)[2] #how many items are in the scale? (calculated dynamically)
  ((Vt-Vi)/Vt)*(n/(n-1)) #alpha
}

E.alpha=alpha.scale(E1,E1.df)
#find the alpha for the scale E1 made up of the 5 items in E1.df
detach(items)
#take them out of the search path
```

Produces the following output:

```
summary(E1.df) #give summary statistics for these items
  q_262      q_1480      q_819      q_1180      q_1742
Min.   :1.00   Min.   :0.000   Min.   :0.000   Min.   :0.000   Min.   :0.000
1st Qu.:2.00   1st Qu.:2.000   1st Qu.:4.000   1st Qu.:2.000   1st Qu.:3.750
Median :3.00   Median :3.000   Median :5.000   Median :4.000   Median :5.000
Mean   :3.07   Mean   :2.885   Mean   :4.565   Mean   :3.295   Mean   :4.385
3rd Qu.:4.00   3rd Qu.:4.000   3rd Qu.:5.000   3rd Qu.:4.000   3rd Qu.:6.000
Max.   :6.00   Max.   :6.000   Max.   :6.000   Max.   :6.000   Max.   :6.000

round(cor(E1.df,use="pair"),2)
```

```

#correlate the 5 items, rounded off to 2 decimals, use complete cases
q_262 q_1480 q_819 q_1180 q_1742
q_262  1.00  -0.26  0.41  -0.51  0.48
q_1480 -0.26  1.00  -0.66  0.52  -0.47
q_819  0.41  -0.66  1.00  -0.41  0.65
q_1180 -0.51  0.52 -0.41  1.00  -0.49
q_1742 0.48  -0.47  0.65  -0.49  1.00

round(cor(E1.df,E1,use="pair"),2)      #show the item by scale correlations
[,1]
q_262  0.71
q_1480 -0.75
q_819  0.80
q_1180 -0.78
q_1742 0.80

alpha.scale=function (x,y)
#find coefficient alpha given a scale and a data.frame of the items in the scale
+ {
+   Vi=sum(diag(var(y,na.rm=TRUE)))      #sum of item variance
+   Vt=var(x,na.rm=TRUE)                 #total test variance
+   n=dim(y)[2]                          #how many items are in the scale? (calculated dynamically)
+   ((Vt-Vi)/Vt)*(n/(n-1))}             #alpha
+
+
+

E.alpha=alpha.scale(E1,E1.df,5)
#find the alpha for the scale E1 made up of the 5 items in E1.df

E.alpha
[1] 0.822683

```

Using the alpha function from psych

Alternatively, this same analysis could have been done using the alpha function from the psych package:

```

E1.df <- with(items,data.frame(q_262 ,q_1480 ,q_819 ,q_1180 ,q_1742 ))
#another way to create the data.frame
alpha(E1.df)

```

Reliability analysis
Call: alpha(x = E1.df)

raw_alpha	std.alpha	G6(smc)	average_r	mean	sd
0.82	0.83	0.83	0.49	3.6	0.52

Reliability if an item **is** dropped:

	raw_alpha	std.alpha	G6(smc)	average_r
q_262	0.82	0.82	0.80	0.53
q_1480-	0.79	0.80	0.76	0.49
q_819	0.77	0.77	0.74	0.46
q_1180-	0.79	0.79	0.77	0.49
q_1742	0.77	0.78	0.77	0.46

Item statistics

```

      n    r  r.cor r.drop mean sd
q_262 200 0.70 0.58 0.52 3.1 1.5
q_1480- 200 0.76 0.70 0.60 2.9 1.4
q_819 200 0.82 0.78 0.69 4.6 1.2
q_1180- 200 0.77 0.69 0.62 3.3 1.5
q_1742 200 0.80 0.74 0.67 4.4 1.4

```

```

Non missing response frequency for each item
      0    1    2    3    4    5    6 miss
q_262 0.00 0.18 0.20 0.22 0.22 0.12 0.06 0
q_1480 0.00 0.18 0.25 0.18 0.26 0.08 0.03 0
q_819 0.00 0.02 0.06 0.12 0.17 0.42 0.22 0
q_1180 0.01 0.14 0.19 0.16 0.30 0.14 0.06 0
q_1742 0.00 0.04 0.08 0.13 0.22 0.26 0.27 0

```

Warning message:

In alpha(E1.df) :

Some items were negatively correlated with total scale and were automatically reversed

Scoring multiple choice tests

If you are using multiple choice tests and want to score the items following a key, it is possible to use the power of R for data manipulation:

Consider the problem of scoring a multiple choice test where we are interested in the number of items correct for each person. Define a scoring key vector and then score as 1 each item match with that key. Then find the number of 1s for each subject. We use the Iris data set as an example.

```

iris2 <- round(iris[1:10,1:4]) #get a sample data set
key <- iris2[1,] #make up an arbitrary answer key
score <- t(t( rowSums((iris2 == c(key[]))+0))) #look for correct item and add them up
mydata <- data.frame(iris2,score) #
key #what is the scoring key
mydata #show the data with the number of items that match the key

```

(Thanks to Gabor Grothendieck and R help for this trick.) A more typical example using the score.multiple.choice function can be done on the iqitems example in psych

```

data(iqitems)
iq.keys <- c(4,4,3,1,4,3,2,3,1,4,1,3,4,3)
score.multiple.choice(iq.keys,iqitems)
#convert them to true false
iq.scrub <- scrub(iqitems,isvalue=0) #first get rid of the zero responses
iq.tf <- score.multiple.choice(iq.keys,iq.scrub,score=FALSE)
#convert to wrong (0) and correct (1) for analysis
describe(iq.tf)

```

Call: score.multiple.choice(key = iq.keys, data = iqitems)

(Unstandardized) Alpha:

[1] 0.63

Average item correlation:

[1] 0.11

```

item statistics
  key    0    1    2    3    4    5    6 miss    r    n mean    sd    skew kurtosis    se
iq1    4 0.04 0.01 0.03 0.09 0.80 0.02 0.01    0 0.59 1000 0.80 0.40 -1.51    0.27 0.01
iq8    4 0.03 0.10 0.01 0.02 0.80 0.01 0.04    0 0.39 1000 0.80 0.40 -1.49    0.22 0.01
iq10   3 0.10 0.22 0.09 0.37 0.04 0.13 0.04    0 0.35 1000 0.37 0.48  0.53   -1.72 0.02
iq15   1 0.03 0.65 0.16 0.15 0.00 0.00 0.00    0 0.35 1000 0.65 0.48 -0.63   -1.60 0.02
iq20   4 0.03 0.02 0.03 0.03 0.85 0.02 0.01    0 0.42 1000 0.85 0.35 -2.00    2.01 0.01
iq44   3 0.03 0.10 0.06 0.64 0.02 0.14 0.01    0 0.42 1000 0.64 0.48 -0.61   -1.64 0.02
iq47   2 0.04 0.08 0.59 0.06 0.11 0.07 0.05    0 0.51 1000 0.59 0.49 -0.35   -1.88 0.02
iq2    3 0.07 0.08 0.31 0.32 0.15 0.05 0.02    0 0.26 1000 0.32 0.46  0.80   -1.37 0.01
iq11   1 0.04 0.87 0.03 0.01 0.01 0.01 0.04    0 0.54 1000 0.87 0.34 -2.15    2.61 0.01
iq16   4 0.05 0.05 0.08 0.07 0.74 0.01 0.00    0 0.56 1000 0.74 0.44 -1.11   -0.77 0.01
iq32   1 0.04 0.54 0.02 0.14 0.10 0.04 0.12    0 0.50 1000 0.54 0.50 -0.17   -1.97 0.02
iq37   3 0.07 0.10 0.09 0.26 0.13 0.02 0.34    0 0.23 1000 0.26 0.44  1.12   -0.74 0.01
iq43   4 0.04 0.07 0.04 0.02 0.78 0.03 0.00    0 0.50 1000 0.78 0.41 -1.35   -0.18 0.01
iq49   3 0.06 0.27 0.09 0.32 0.14 0.08 0.05    0 0.28 1000 0.32 0.47  0.79   -1.38 0.01

> #convert them to true false
> iq.scrub <- scrub(iqitems,isvalue=0) #first get rid of the zero responses
> iq.tf <- score.multiple.choice(iq.keys,iq.scrub,score=FALSE)
#convert to wrong (0) and correct (1) for analysis
> describe(iq.tf)
  var    n mean    sd median trimmed mad min max range    skew kurtosis    se
iq1    1 965 0.83 0.38      1    0.91  0  0  1    1 -1.75    1.08 0.01
iq8    2 972 0.82 0.38      1    0.90  0  0  1    1 -1.68    0.83 0.01
iq10   3 900 0.41 0.49      0    0.39  0  0  1    1  0.36   -1.88 0.02
iq15   4 968 0.67 0.47      1    0.72  0  0  1    1 -0.73   -1.46 0.02
iq20   5 972 0.88 0.33      1    0.97  0  0  1    1 -2.31    3.36 0.01
iq44   6 971 0.66 0.47      1    0.71  0  0  1    1 -0.69   -1.52 0.02
iq47   7 955 0.61 0.49      1    0.64  0  0  1    1 -0.47   -1.78 0.02
iq2    8 929 0.34 0.47      0    0.30  0  0  1    1  0.68   -1.54 0.02
iq11   9 964 0.90 0.30      1    1.00  0  0  1    1 -2.63    4.93 0.01
iq16  10 953 0.78 0.41      1    0.85  0  0  1    1 -1.35   -0.19 0.01
iq32  11 962 0.56 0.50      1    0.58  0  0  1    1 -0.26   -1.93 0.02
iq37  12 928 0.27 0.45      0    0.22  0  0  1    1  1.01   -0.99 0.01
iq43  13 958 0.81 0.39      1    0.89  0  0  1    1 -1.61    0.60 0.01
iq49  14 939 0.34 0.47      0    0.30  0  0  1    1  0.69   -1.53 0.02

```

Factor Analysis

Core R includes a maximum likelihood factor analysis function (factanal) and the psych package includes five alternative factor extraction options within one function, fa. For the following analyses, we will use data from the Motivational State Questionnaire (MSQ) collected in several studies. This is a subset of a larger data set (with N>3000 that has been analyzed for the structure of mood states (Rafaeli, Eshkol and Revelle, William (2006), A premature consensus: Are happiness and sadness truly opposite affects? Motivation and Emotion, 30, 1, 1-12.). The data set includes EPI and BFI scale scores (see previous examples).

```

#specify the name and address of the remote file
datafilename="http://personality-project.org/r/datasets/maps.mixx.msq1.epi.bf.txt"
#note that it is also available as built in example in the psych package named msq
msq =read.table(datafilename,header=TRUE) #read the data file
mysq=msq[,2:72] #select the subset of items in the MSQ

mysq[mysq=="9"] = NA # change all occurrences of 9 to be missing values
mysq <- data.frame(mysq) #convert the input matrix into a data frame for easier manipulation

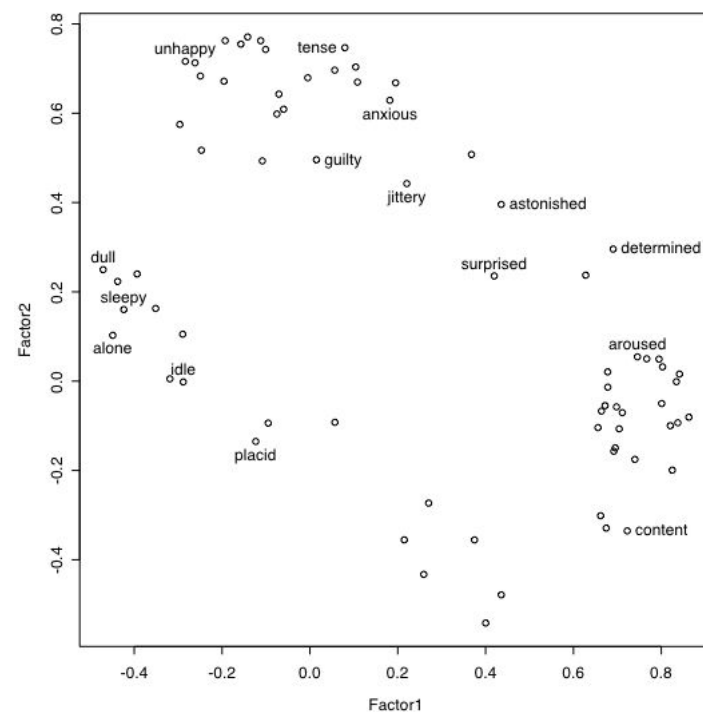
names(mysq) #what are the variables?
describe(mysq) #basic summary statistics — check for miscodings

```

```

cleaned <- na.omit(mysmq)      #remove the cases with missing values
f2 <- fa(cleaned,2,rotation="varimax")      #factor analyze the resulting item
#(f2)                          #show the result
load=loadings(f2)
print(load,sort=TRUE,digits=2,cutoff=0.01) #show the loadings
plot(load)                          #plot factor 1 by 2
identify(load,labels=names(msq))
      #put names of selected points onto the figure -- to stop, click with command key
plot(f2,labels=names(msq))

```



It is also possible to find and save the covariance matrix from the raw data and then do subsequent analyses on this matrix. This clearly saves computational time for large data sets. This matrix can be saved and then reloaded.

```

msqcovar=cov(mysmq,use="pair") #find the covariance matrix for later factoring
f3=factanal(x, factors=3, data = NULL, covmat = msqcovar, n.obs = 300,start=NULL,
rotation = "varimax")
f4=factanal(x, factors=4, data = NULL, covmat = msqcovar, n.obs = 300,start=NULL,
rotation = "varimax")

```

The fa function will do maximum likelihood but defaults to do a minimum residual (min-res) solution with an oblimin rotation. The similarity of the three different solutions may be found by using the factor.congruence function.

```
factor.congruence(list(f2,f3,f4))
```

	MR1	MR2	Factor1	Factor2	Factor3	Factor1	Factor2	Factor3	Factor4
MR1	1.00	-0.01	0.99	-0.09	-0.14	0.99	-0.09	-0.02	-0.64
MR2	-0.01	1.00	-0.11	0.99	-0.25	-0.08	0.99	-0.37	0.18
Factor1	0.99	-0.11	1.00	-0.18	-0.07	0.99	-0.18	0.06	-0.64
Factor2	-0.09	0.99	-0.18	1.00	-0.14	-0.15	1.00	-0.27	0.29
Factor3	-0.14	-0.25	-0.07	-0.14	1.00	-0.03	-0.13	0.95	0.46
Factor1	0.99	-0.08	0.99	-0.15	-0.03	1.00	-0.15	0.06	-0.56
Factor2	-0.09	0.99	-0.18	1.00	-0.13	-0.15	1.00	-0.25	0.25
Factor3	-0.02	-0.37	0.06	-0.27	0.95	0.06	-0.25	1.00	0.19
Factor4	-0.64	0.18	-0.64	0.29	0.46	-0.56	0.25	0.19	1.00

Very Simple Structure

There are multiple ways to determine the appropriate number of factors in exploratory factor analysis. Routines for the [Very Simple Structure](#) (VSS) criterion allow one to compare solutions of varying complexity and for different number of factors. Alternatives include the scree test. To use these routines on a data set with items, myitems,:

```
library(psych)
my.vss <- VSS(mydata,n=8,rotate="none",diagonal=FALSE,...) #compares up to 8 factors
op <- par(mfrow=c(1,2)) #make a two panel graph
VSS.plot(my.vss) #shows a simple summary of VSS
VSS.scree(cor(mydata),main="scree plot of principal components of mydata")
```

Omega: General Factor Saturation of a test

McDonald has proposed coefficient omega as an estimate of the general factor saturation of a test. [Revelle and Zinbarg \(2009\)](#) discuss multiple estimates of reliability, [Zinbarg, Revelle, Yovel and Li \(2005\)](#) compare McDonald's Omega to Chronbach's alpha and Revelle's beta. They conclude that omega is the best estimate. (See also [Zinbarg et al., 2006](#))

[One way to find omega](#) is to do a factor analysis of the original data set, rotate the factors obliquely, do a Schmid Leiman transformation, and then find omega. Here we present code to do that. This code is included in the [psych](#) package of routines for personality research that may be loaded from the CRAN repository or, for the the recent development version, from the local repository at <http://personality-project.org/r>.

Beta: General Factor Saturation of a test

Beta, an alternative to omega, is defined as the worst split half reliability. It can be estimated by using ICLUST ([Revelle, 1979](#)), a hierarchical clustering algorithm originally developed for main frames and written in Fortran and that is now part of the psych package. (For a very complimentary review of why the ICLUST algorithm is useful in scale construction, see [Cooksey and Soutar, 2005](#)). What took multiple years and about 2500 lines of code in Fortran took about 4 days and 100 lines of R.

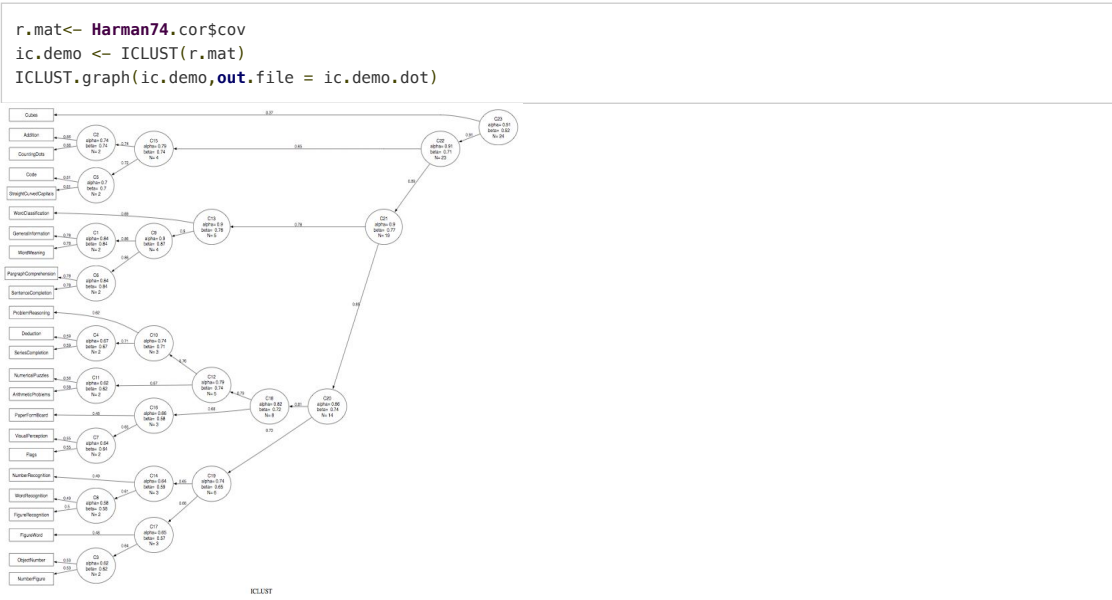
Factor rotations

Rotations available in the basic R installation are Varimax and Promax. A powerful additional set of oblique transformations including Oblimin, Oblimax, etc. are available in the GPArotations package from Cran. Using this package, it is also possible to do a Schmid Leiman transformation of a hierarchical factor structure to estimate the general factor loadings and general factor saturation of a test. (see [Omega](#)).

Cluster Analysis

A common data reduction technique is to cluster cases (subjects). Less common, but particularly useful in psychological research, is to cluster items (variables). This may be thought of as an alternative to factor analysis, based upon a much simpler model. The cluster model is that the correlations between variables reflect that each item loads on at most one cluster, and that items that load on those clusters correlate as a function of their respective loadings on that cluster and items that define different clusters correlate as a function of their respective cluster loadings and the intercluster correlations. Essentially, the cluster model is a factor model of complexity one (see VSS).

An example of clustering variables can be seen using the [ICLUST](#) algorithm to the 24 tests of mental ability of Harman and then using the Graphviz program to show the results.



Multidimensional scaling

Given a set of distances (dis-similarities) between objects, is it possible to recreate a dimensional representation of those objects?

Model: Distance = square root of sum of squared distances on k dimensions $d_{xy} = \sqrt{\sum (x_i - y_i)^2}$

Data: a matrix of distances

Find the dimensional values in k = 1, 2, ... dimensions for the objects that best reproduces the original data.

Example: Consider the distances between nine American cities. Can we represent these cities in a two dimensional space.

See the pages on [multidimensional scaling](#) and [Thurstonian scaling](#).

Jan de Leeuw at UCLA is converting a number of mds packages including the ALSCAL program for R. See his page at <http://www.cuddyvalley.org/psychoR/code>. ALSCAL generalizes the INDSCAL algorithm for individual differences in multiple dimensional scaling.

Further topics

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Structural Equation Modeling

Structural equation models combine measurement models (e.g., reliability) with structural models (e.g., regression). The sem package, developed by John Fox, the lavaan package by Yves Rosseel, and the OpenMx package by Steve Bolker allow for most structural equation models. To use then, add the sem, lavaan or OpenMx packages.

Structural Equation Modeling may be thought of as regression corrected for attenuation. The sem package developed by John Fox uses the RAM path notation of Jack McCordle and is fairly straightforward. Fox has prepared a [brief description of SEM techniques](#) as an appendix to his statistics text. The examples in the package are quite straightforward. A text book, such as John Loehlin's Latent Variable Models (4th Edition) is helpful in understanding the algorithm.

[Demonstrations](#) of using the sem package for several of the Loehlin problems are discussed in more detail on a separate page. In addition, lecture notes for a course on sem (primarily using R) are available at the [syllabus for my sem](#) course.

Multilevel Models/ Hierarchical Level Models

HLM can be done using the lme package. See the discussion in the R newsletter, Vol 3/3 by Lockwood, Doran, and McCaffrey. Also see the relevant pdf [appendix](#) of John Fox's [text on applied regression](#).

[Item Response Theory using R](#)

Item Response Theory is a model that considers individual differences in ability as well as item difficulty. It is sometimes called the "new" psychometrics (as contrasted to "classic" [psychometrics](#) of traditional test theory.) Essentially, classic psychometrics estimates person scores by assuming items are random replicates of each other. Precision of measurement is expressed in terms of the reliability which is the ratio of "true" score variance to total test variance. Reliability is thus a between person concept. IRT estimates person scores as well as item difficulty (endorsement) scores. Precision of measurement may be estimated in terms of the patterns of scores of a single individual and does not require between person variability. Although the "new" and "classic" psychometrics give very similar estimates of person scores, the ability to do tailored tests and to consider the metric properties of the scales makes IRT very useful. IRT models differ in their complexity. The one parameter model assumes items all have equal discriminability and differ only in their difficulty. The two parameter model assumes items differ in difficulty and discriminability, the three parameter model assumes items differ in the ease of guessing. Although developed for binary items (correct versus incorrect), generalizations of IRT to multiresponse formats are very useful.

For a detailed demonstration of how to do 1 parameter IRT (the Rasch Model) see Jonathan Baron and Yuelin Li's [tutorial on R](#). A more useful package for latent trait modeling (e.g., Rasch modeling and item response theory) (ltm) has now been released by Dimitris Rizopoulos. Note that to use this package, you must first install the MASS, gtools, and msm packages.

The ltm package allows for 1 parameter (Rasch) and two parameter (location and discrimination) modeling of a single latent trait assessed by binary items varying in location and discrimination. Procedures include graphing the results as well as anova comparisons of nested models.

The 2 parameter IRT model is essentially a reparameterization of the factor analytic model and thus can be done through factor analysis. This is done in the irt.fa and score.irt functions in psych.

Simulating data structures and probability tables

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There are at least 20 distributions available including the normal, the binomial, the exponential, the logistic, Poisson, etc. Each of these can be accessed for density ('d'), cumulative density ('p'), quantile ('q') or simulation ('r' for random deviates). Thus, to find out the probability of a normal score of value x from a distribution with mean=m and sd = s, pnorm(x,mean=m, sd=s), eg.

```
pnorm(1,mean=0,sd=1)
[1] 0.8413447
```

which is the same as

```
pnorm(1)      #default values of mean=0, sd=1 are used)
pnorm(1,1,10) #parameters may be passed if in default order or by name
```

Examples of using R to demonstrate the [central limit theorem](#) or to produce circumplex structure of personality items are useful ways to teach sampling theory or to explore artifacts in measurement.

Simulating a simple correlation between two variables based upon their correlation with a latent variable:

```
samplesize=1000
size.r=.6
theta=rnorm(samplesize,0,1)      #generate some random normal deviates
e1=rnorm(samplesize,0,1)         #generate errors for x
e2=rnorm(samplesize,0,1)         #generate errors for y
weight=sqrt(size.r)              #weight as a function of correlation
x=weight*theta+e1*sqrt(1-size.r) #combine true score (theta) with error
y=weight*theta+e2*sqrt(1-size.r)
cor(x,y)                         #correlate the resulting pair
df=data.frame(cbind(theta,e1,e2,x,y)) #form a data frame to hold all of the elements
round(cor(df),2)                 #show the correlational structure
pairs.panels(df)                 #plot the correlational structure (assumes psych package)
```

The use of the mvtnorm package and the rmvnorm(n, mean, sigma) function allows for creating random covariance matrices with a specific structure.

e.g., using the sample sizes and rs from above:

```
library(mvtnorm)
samplesize=1000
size.r=.6
sigmamatrix <- matrix( c(1,sqrt(size.r),sqrt(size.r),sqrt(size.r),1,size.r,
                        sqrt(size.r),size.r,1),ncol=3)
xy <- rmvnorm(samplesize,sigma=sigmamatrix)
round(cor(xy),2)
pairs.panels(xy)                #assumes the psych package
```

[Another simulation](#) shows how to create a multivariate structure with a particular measurement model and a particular structural model. This example produces data suitable for demonstrations of regression, correlation, factor analysis, or structural equation modeling.

The particular example assumes that there are 3 measures of ability (GREV, GREQ, GREA), two measures of motivation (achievement motivation and anxiety), and three measures of performance (Prelims, GPA, MA). These titles are, of course, arbitrary and can be changed easily. These (simulated) data are used in various lectures of mine on Factor Analysis and Psychometric Theory. Other examples of simulation of item factor structure include creating circumplex structured correlation matrices.

Simulations may also be used to teach [concepts in experimental design](#) and analysis. Several simulations of the additive and interactive effects of personality traits with situational manipulations of mood and arousal compare alternative ways of analyzing data.

Finally, a simple simulation to generate and test [circumplex](#) versus structures in two dimensions has been added.

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Adding new commands (functions) packages or libraries

A very powerful feature of R is that it is extensible. That is, one can write one's own functions to do calculations of particular interest. These functions can be saved as external file that can be accessed using the source command. For example, 10 years ago, I frequently used a set of routines that found the alpha reliability of a set of scales, or drew scatter plots with histograms on the diagonal and font sizes scaled to the absolute value of the correlation. Another set of routines applied the Very Simple Structure (VSS) criterion for determining the optimal number of factors. I originally stored these two sets of files ([vss.r](#) and [useful.r](#)) and then added them into my programs by using the source command.

However, an even more powerful option is to create packages of frequently used code. These packages can be stored on local "repositories" if they appeal to members of small work groups, or can be added to the CRAN master repository. Guidelines for creating packages are found in the basic help menus. [Notes on how to create a specific package](#) (i.e., the psych package) and install it as a repository are meant primarily for Mac users. More extensive discussions for PCs have also been developed.

The package "psych" was added to CRAN in June of 2007 and is now (May, 2017) up to version 1.7.5. (I changed the numbering system to reflect year and month of release as I passed the 100th release). As I find an analysis that I need to do that is not easily done using the standard packages, I supplement the psych package. I encourage the reader to try it. The manual is available [on line](#) or as part of the package.

To add a package from CRAN (e.g, sem, GPArotation, psych), go to the R package installer, and select install. Then, using the R package Manager, load that package.

Although it is possible to add the [psych package](#) from the personality-project.org web page, it is a better idea to use [CRAN](#). For Mac users who want the "bleeding edge" development version, select the other repository option in the R Package Installer and set it to <http://personality-project.org/r>. A list of available packages stored there will be displayed. Choose the one you want and then load it with the R package manager. Currently, there is only one package (psych) there. This version will be the current development version will be at least as new as what is on the CRAN site. You must specify that you want a source file if use the personality-project.org/r repository. As of now (May, 2017), the [psych package](#) contains more than a 400 functions including the following ones:

[psych-package](#)

[%+%](#)

[alpha.scale](#)

[circ.sim](#)

A package for personality, psychometric, and psychological research

A function to add two vectors or matrices

Cronbach alpha for a scale

Generate simulated data structures for circumplex or simple structure

[circ.simulation](#)
[circ.tests](#)
[cluster.cor](#)
[cluster.fit](#)
[cluster.loadings](#)
[correct.cor](#)
[count.pairwise](#)
[describe](#)
[describe.by](#)
[eigen.loadings](#)
[error.crosses](#)
[factor.congruence](#)
[factor.fit](#)
[factor.model](#)
[fa](#)
[factor.pa](#)
[factor.residuals](#)
[factor.rotate](#)
[factor2cluster](#)
[fisherz](#)
[geometric.mean](#)
[harmonic.mean](#)
[ICLUST](#)
[ICLUST](#)
[ICLUST.cluster](#)
[ICLUST.graph](#)
[ICLUST.sort](#)
[irt.fa](#)
[irt.0p](#)
[irt.1p](#)
[irt.2p](#)
[irt.discrim](#)
[irt.item.diff.rasch](#)
[irt.person.rasch](#)
[kurtosi](#)
[make.hierarchical](#)
[mat.regress](#)
[multi.hist](#)
[omega](#)
[paired.r](#)
[pairs.panels](#)
[panel.cor](#)
[panel.hist](#)
[phi](#)
[phi2poly](#)
[polychoric](#)

Simulations of circumplex and simple structure
 Apply four tests of circumplex versus simple structure
 Find correlations of composite variables from a larger matrix
 cluster Fit: fit of the cluster model to a correlation matrix
 Find item by cluster correlations, corrected for overlap and reliability
 Find dis-attenuated correlations and give alpha reliabilities
 Count number of pairwise cases for a data set with missing (NA) data.
 Basic descriptive statistics useful for psychometrics
 Basic summary statistics by group
 Extract eigen vectors, eigen values, show loadings
 Plot x and y error bars
 Coefficient of factor congruence
 How well does the factor model fit a correlation matrix. Part of the VSS package
 Find $R = F'F + U_2$ is the basic factor model
 Minimum Residual, Principal Axis, GLS, MLE factor analysis
 Principal Axis Factor Analysis
 $R^* = R - F'F$
 "Hand" rotate a factor loading matrix
 Extract cluster definitions from factor loadings
 Fisher z transform of r
 Find the geometric mean of a vector or columns of a data.frame.
 Find the harmonic mean of a vector, matrix, or columns of a data.frame
 ICLUST: Item Cluster Analysis - Hierarchical cluster analysis using psychometric principles
 iclust: Item Cluster Analysis - Hierarchical cluster analysis using psychometric principles
 Function to form hierarchical cluster analysis of items
 create control code for ICLUST graphical output
 sort items by absolute size of cluster loadings
 Item Response Theory using factor analysis of tetrachoric or polychoric correlations
 Item Response Theory estimate of theta (ability) using a Rasch (like) model
 Item Response Theory estimate of theta (ability) using a Rasch (like) model
 Item Response Theory estimate of theta (ability) using a Rasch (like) model
 Simple function to estimate item difficulties using IRT concepts
 Simple function to estimate item difficulties using IRT concepts
 Item Response Theory estimate of theta (ability) using a Rasch (like) model
 Kurtosis of a vector, matrix, or data frame
 Create a population or sample correlation matrix with hierarchical structure.
 Multiple Regression from matrix input
 Multiple histograms on one screen
 Calculate the omega estimate of factor saturation
 Test the difference between paired correlations
 SPLOM, histograms and correlations for a data matrix
 SPLOM, histograms and correlations for a data matrix
 SPLOM, histograms and correlations for a data matrix
 Find the phi coefficient of correlation between two dichotomous variables
 Convert a phi coefficient to a polychoric correlation
 Find polychoric correlations

principal	Principal components analysis
psych	A package for personality, psychometric, and psychological research
psycho.demo	Create demo data for psychometrics
read.clipboard	shortcut for reading from the clipboard
schmid	Apply the Schmid Leiman transformation to a correlation matrix
score.alpha	Score scales and find Cronbach's alpha as well as associated statistics
score.items	Score item composite scales and find Cronbach's alpha as well as associated statistics
skew	Calculate skew for a vector, matrix, or data.frame
VSS	Apply the Very Simple Structure criterion to determine the appropriate number of factors.
VSS.parallel	Compare real and random VSS solutions
VSS.plot	Plot VSS fits
VSS.scree	Plot a scree test
VSS.simulate	create VSS like data

The manual for the psych package is available at [CRAN](#) as well as [here](#)

To install the psych package using a Mac, go to the Package Installer Menu option, choose binary, and then psych and it should get the package. To get the most recent release of psych, you can go the personality-project.org repository. (Use other repository in the download packages menu.) Uncheck the "binary" option. This is a source file.

To install on a PC, just use the version on CRAN. Use the package installer option and choose psych.

Once installed, the package can be activated by using the package manager (or just issuing the package(psych) command.

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A (partial) list of useful commands

See [A short summary](#) of useful R commands for more detail. In addition, the [Rpad.pdf reference card](#) file is a very important aid to remembering the many commands available.

Input and display

```

read.table(filename,header=TRUE)      #read files with labels in first row
read.table(filename,header=TRUE,sep=',') #read a tab or space delimited file
                                       #read csv files (comma separated)

x=c(1,2,4,8,16 )                      #create a data vector with specified elements
y=c(1:8,1:4)                          #creat a data vector with 12 entries
matr=rbind(1:8,1:4)                   #create two rows in a 2 * 8 matrix
matc=cbind(1:8,1:4)                   #create two columns in a 8 * 2 matrix
n=10
x1=c(rnorm(n))                        #create a n item vector of random normal deviates
y1=c(runif(n))+n                      #create another n item vector that has n added to each random uniform distribution
z=rbinom(n,size,prob)                 #create n samples of size "size" with probability prob from the binomialitem

```

```

sample(x, size, replace = FALSE, prob = NULL)
#take a sample (with or without replacement) of size from x

vect=c(x,y) #combine them into one vector of length 2n
mat=cbind(x,y) #combine them into a n x 2 matrix (column wise)
mat[4,2] #display the 4th row and the 2nd column
mat[3,] #display the 3rd row
mat[,2] #display the 2nd column
mat=cbind(rep(1:4,2),rep(4:1,2)) #create a 8 * 2 matrix with repeating elements
subset(data,logical) #those objects meeting a logical criterion
subset(data.df,select=variables,logical)
#get those objects from a data frame that meet a criterion

```

moving around

```

ls() #list the variables in the workspace
rm(x) #remove x from the workspace
rm(list=ls()) #remove all the variables from the workspace
attach(mat) #make the names of the variables in the matrix available
detach(mat) #releases the names
new=old[,-n] #drop the nth column
new=old[n,] #drop the nth row
new=subset(old,logical) #select those cases that meet the logical condition
complete = subset(data,complete.cases(data))
#find those cases with no missing values
new=old[n1:n2,n3:n4] #select the n1 through n2 rows of variables n3 through n4)

```

data manipulation

```

x.df=data.frame(x1,x2,x3 ...) #combine different kinds of data into a data frame
as.data.frame()
is.data.frame()
x=as.matrix()
scale() #converts a data frame to standardized scores
factor() #converts a numeric variable into a factor (essential for ANOVA)
gl(n,k,length) #makes an n-level,k replicates, length long vector of factors
y <- edit(x) #opens a screen editor and saves changes made to x into y
fix(x) #opens a screen editor window and makes and saves changes to x

```

Statistics and transformations

```

max()
min()
mean()
median()
sum()
var() #produces the variance covariance matrix
sd() #standard deviation
mad() #(median absolute deviation)
fivenum() #Tukey five numbers min, lowerhinge, median, upper hinge, max
scale(data,scale=T) #centers around the mean and scales by the sd
colSums(), rowSums(), colMeans(), rowMeans() #see also apply(x,l,sum)
rowsum(x,group) #sum by group

cor(x,y,use="pair")
#correlation matrix for pairwise complete data, use="complete" for complete cases

t.test(x,y) #x is a data vector, y is a grouping vector independent groups
t.test(x,y,pair=TRUE) #x is a data vector, y is a grouping vector -- paired groups
pairwise.t.test(x,g) does multiple comparisons of all groups defined by g

```

```

aov(x~y,data=datafile) #where x and y can be matrices
aov.ex1 = aov(Alertness~Dosage,data=data.ex1)
#do the analysis of variance or
aov.ex2 = aov(Alertness~Gender*Dosage,data=data.ex2)
#do a two way analysis of variance
summary(aov.ex1)
#show the summary table
print(model.tables(aov.ex1,"means"),digits=3)
#report the means and the number of subjects/cell
boxplot(Alertness~Dosage,data=data.ex1)
#graphical summary appears in graphics window

lm(x~y,data=dataset) #basic linear model where x and y can be matrices

lm(Y~X) #Y and X can be matrices
lm(Y~X1+X2)
lm(Y~X|W) #separate analyses for each level of W
solve(A,B) #inverse of A * B - used for linear regression
solve(A) #inverse of A

```

Useful additional commands

```

colSums(x, na.rm = FALSE, dims = 1)
rowSums(x, na.rm = FALSE, dims = 1)
colMeans(x, na.rm = FALSE, dims = 1)
rowMeans(x, na.rm = FALSE, dims = 1)
rowsum(x, group, reorder = TRUE, ...)
#finds row sums for each level of a grouping variable
apply(X, MARGIN, FUN, ...)
#applies the function (FUN) to either rows (1) or columns (2) on object X
apply(x,1,min)
#finds the minimum for each row
apply(x,2,max)
#finds the maximum for each column
col.max(x)
#another way to find which column has the maximum value for each row
which.min(x)
which.max(x)
z=apply(big5r,1,which.min)
#tells the row with the minimum value for every column

```

Graphics

```

stem() #stem and leaf diagram

par(mfrow=c(2,1)) #number of rows and columns to graph

boxplot(x,notch=T,names= grouping, main="title") #boxplot (box and whiskers)

hist() #histogram
plot()
plot(x,y,xlim=range(-1,1),ylim=range(-1,1),main=title)
par(mfrow=c(1,1)) #change the graph window back to one figure
symb=c(19,25,3,23)
colors=c("black","red","green","blue")
charact=c("S","T","N","H")
plot(x,y,pch=symb[group],col=colors[group],bg=colors[condit],cex=1.5,main="main title")
points(mPA,mNA,pch=symb[condit],cex=4.5,col=colors[condit],bg=colors[condit])

```

```

curve()
  abline(a,b)
  abline(a, b, untf = FALSE, ...)
  abline(h=, untf = FALSE, ...)
  abline(v=, untf = FALSE, ...)
  abline(coef=, untf = FALSE, ...)
  abline(reg=, untf = FALSE, ...)

identify()
  plot(eatar,eanta,xlim=range(-1,1),ylim=range(-1,1),main=title)
  identify(eatar,eanta,labels=labels(energysR[,1]) )
  #dynamically puts names on the plots

locate()

pairs()                                #SPLOM (scatter plot Matrix)

matplot ()                            #ordinate is row of the matrix
biplot ()                             #factor loadings and factor scores on same graph
coplot(x~y|z)                         #x by y conditioned on z
symb=c(19,25,3,23)                   #choose some nice plotting symbols
colors=c("black","red","green","blue") #choose some nice colors

barplot()                            #simple bar plot
interaction.plot ()                  #shows means for an ANOVA design

plot(degreedays,therms)              #show the data points
by(heating,Location,function(x) abline(lm(therms~degreedays,data=x)))
  #show the best fitting regression for each group

x= recordPlot()                     #save the current plot device output in the object x
replayPlot(x)                       #replot object x
dev.control                          #various control functions for printing/saving graphic files

pnorm(1,mean=0,sd=1)
[1] 0.8413447

```

same as

```

pnorm(1)          #default values of mean=0, sd=1 are used)
pnorm(1,1,10)    #parameters may be passed if in default order or by name

```

Examples of using R to demonstrate the [central limit theorem](#) or to produce circumplex structure of personality items are useful ways to teach sampling theory or to explore artifacts in measurement.

Simulating a simple correlation between two variables based upon their correlation with a latent variable:

```

samplesize=1000
size.r=.6
theta=rnorm(samplesize,0,1)    #generate some random normal deviates
e1=rnorm(samplesize,0,1)       #generate errors for x
e2=rnorm(samplesize,0,1)       #generate errors for y
weight=sqrt(size.r)            #weight as a function of correlation
x=weight*theta+e1*sqrt(1-size.r) #combine true score (theta) with error
y=weight*theta+e2*sqrt(1-size.r)
cor(x,y)                       #correlate the resulting pair
df=data.frame(cbind(theta,e1,e2,x,y)) #form a data frame to hold all of the elements
round(cor(df),2)               #show the correlational structure
pairs.panels(df)               #plot the correlational structure (assumes psych package)

```

The use of the mvtnorm package and the rmvnorm(n, mean, sigma) function allows for creating random covariance matrices with a specific structure.

e.g., using the sample sizes and rs from above:

```
library(mvtnorm)
samplesize=1000
size.r=.6
sigmamatrix <- matrix( c(1,sqrt(size.r),sqrt(size.r),sqrt(size.r),1,size.r,
                        sqrt(size.r),size.r,1),ncol=3)
xy <- rmvnorm(samplesize,sigma=sigmamatrix)
round(cor(xy),2)
pairs.panels(xy)           #assumes the psych package
```

Useful R links

Readings and software:

Comprehensive R Archive
Network ([CRAN](#))

[An introduction to R](#)

[R Studio](#)

[A 6 page " R cheat sheet"](#)

An [introduction](#) to the
psych package

An [overview](#) of the psych
package

Structural Equation
modelling:

[sem](#)

[lavaan](#)

[psych for sem](#)

How to [do a factor analysis](#)

EFA and factor extension
([fa](#))

Multilevel modeling:

[Multilevel](#)

Linear and Non Linear

Mixed Effects [nlme](#)

[statsBy](#)

How to use R for [multilevel
modeling and reliability](#)

Item Response Models:

[Latent Trait Model \(ltm\)](#)

[mirt](#)

[mokken](#)

irt by factor analysis ([irt.fa](#))

More on the psych package

The [psych package](#) is a work in progress. The current released version is 1.7.8. Updates are added sporadically, but usually at least once a quarter. The development version is always available at the [pmc repository](#). How To tutorials include: [Getting Started](#), [Finding Omega](#), [Factor Analysis](#), and [Reliability](#)

If you want to help us develop our understanding of personality, please take our test at [SAPA Project](#).

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As is true of all webpages, this is a work in progress.

Design: [HTML5 Up!](#) | Modified by Jason A. French and William Revelle

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