An introduction to Psychometric Theory

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Outline of Day 1/part 1

What is psychometrics?

In physical science a first essential step in the direction of learning any subject is to find principles of numerical reckoning and methods for practicably measuring some quality connected with it. I often say that when you can measure what you are speaking about and express it in numbers you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind; it may be the beginning of knowledge, but you have scarcely in your thoughts advanced to the stage of science, whatever the matter may be. (Thomson, 1891) aka Lord Kelvin.

Taken from Michell (2003) in his critique of psychometrics: Michell, J. The Quantitative Imperative: Positivism, Naïve Realism and the Place of Qualitative Methods in Psychology, Theory & Psychology, Vol. 13, No. 1, 5-31 (2003)

What is psychometrics?

The character which shapes our conduct is a definite and durable 'something', and therefore . . . it is reasonable to attempt to measure it. (Galton, 1884)

The history of science is the history of measurement. Those departments of knowledge in which measurement could be used most readily were the first to become sciences, and those sciences are at the present time the furthest advanced in which measurement is the most extended and the most exact. Mathematics is concerned entirely with number and quantity," (Cattell, 1893, p 316).

Whatever exists at all exists in some amount. To know it thoroughly involves knowing its quantity as well as its quality (Thorndike, 1918, p 16). See also Thorndike (1904).

Observation and Measurement

> *Observation is the key to the method of science. ... Still, the mere observing and recording of natural phenomena does not make science: observations must be selectively crucial in the interests of rational generalization. (Boring, 1929, p 8),*

> *Measurement provides a precision of differentiation and definition in observation that can be had in no other way: mathematics provides the necessary means of carrying measurements through a logical development to their consequences without loss of their precision. (Boring, 1929, p15),*

As an example of the power of measurement, consider Galileo's timing balls rolling down inclined planes to find that the rate of acceleration was a constant (Settle, 1961).

What is psychometrics?

> *We hardly recognize a subject as scientific if measurement is not one of its tools (Boring, 1929)*
>
> *There is yet another [method] so vital that, if lacking it, any study is thought ... not be scientific in the full sense of the word. This further and crucial method is that of measurement. ((Spearman, 1937, p 89)*
>
> *One's knowledge of science begins when he can measure what he is speaking about and express in numbers (Eysenck, 1973, citing Thomson)*

Psychometrics: the assigning of numbers to observed psychological phenomena and to unobserved concepts.
Evaluation of the fit of theoretical models to empirical data.

Goals

1. To acquire the fundamental vocabulary and logic of psychometric theory.
2. To develop your capacity for critical judgment of the adequacy of measures purported to assess psychological constructs.
3. To acquaint you with some of the relevant literature in personality assessment, psychometric theory and practice, and methods of observing and measuring affect, behavior, cognition and motivation.
4. To instill an appreciation of and an interest in the principles and methods of psychometric theory.
5. This course is not designed to make you into an accomplished psychometrist (one who gives tests) nor is it designed to make you a skilled psychometrician (one who constructs tests)
6. It will give you limited experience with psychometric computer programs (although all of the examples will use R, it not necessary to learn R, but it sure helps.).

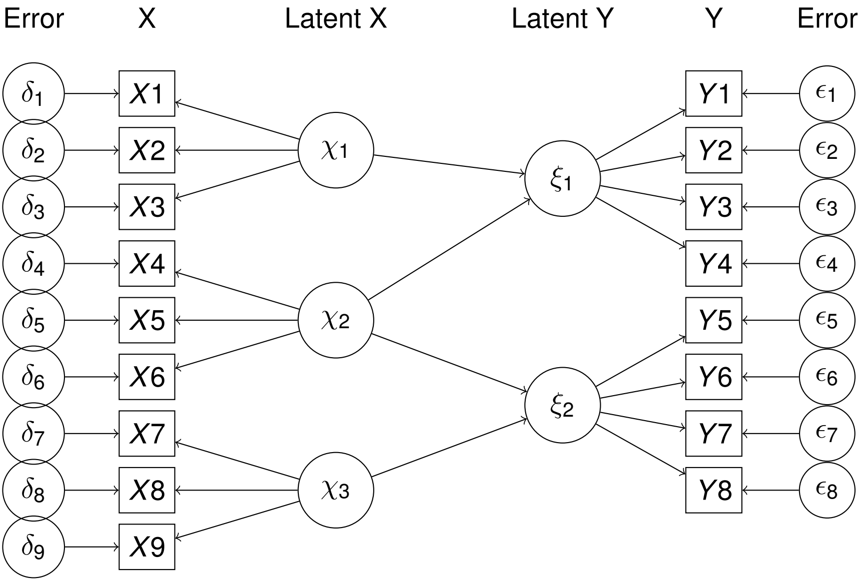
Requirements

1. Asking questions!
2. Objective Midterm exam
3. Objective Final exam
4. Final paper applying principles from the course to a problem of interest to you.
5. Sporadic applied homework and data sets

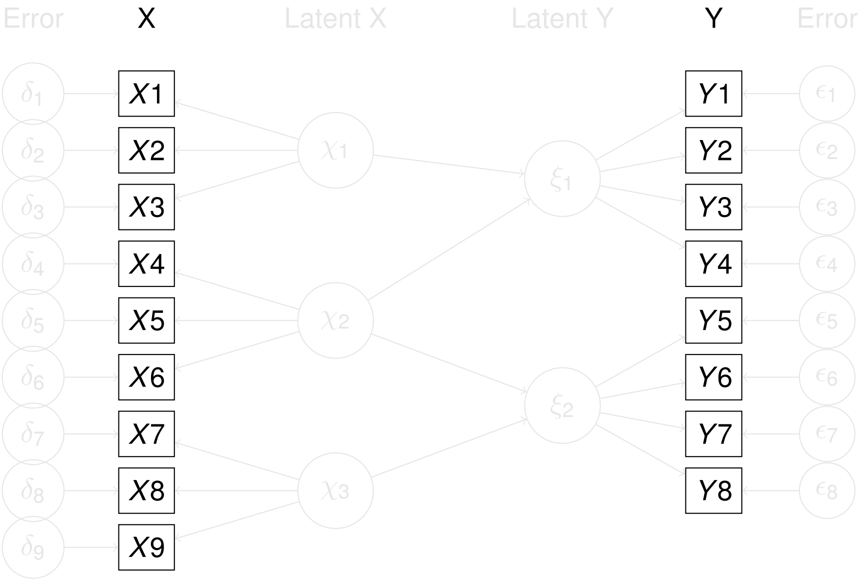
Texts (required and recommended supplements)

1. Revelle, W. (in prep). http://www.personality-project.org/r/book/[An introduction to psychometric theory with applications in R]. Springer Available on line and linked throughout the syllabus.
2. Loehlin and Beaujean (2017) Useful reading on SEM (suggested to read)
3. Nunnally and Bernstein (1994) An old classic but dreadfully out of date.

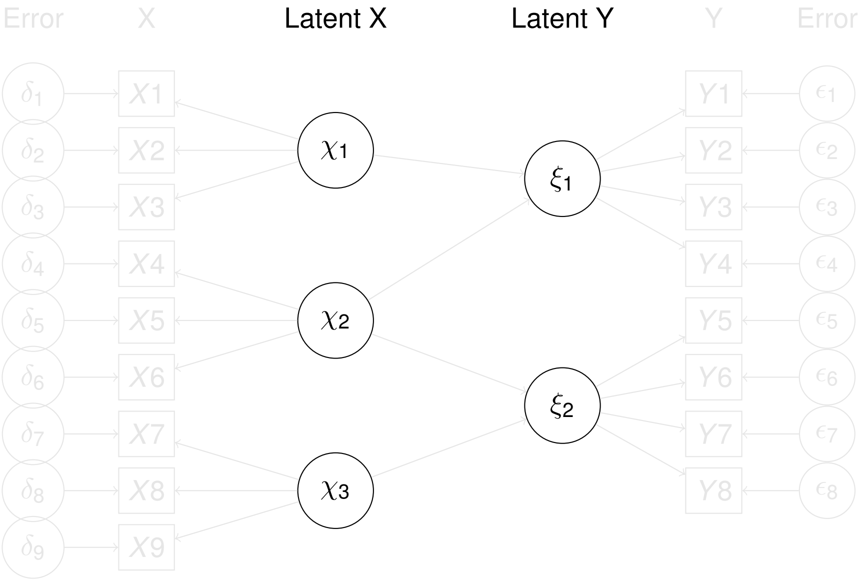
Psychometric Theory: A conceptual Syllabus



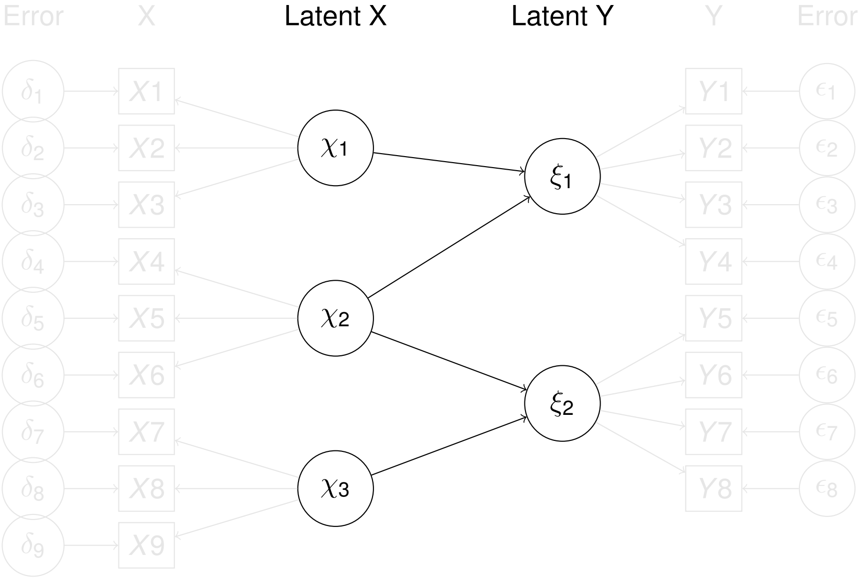
Observed Variables



Latent Variables



Theory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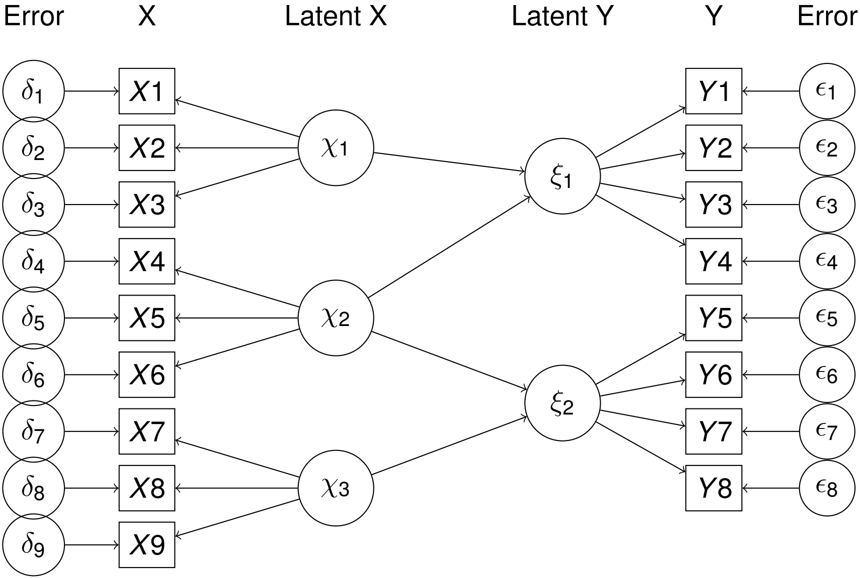
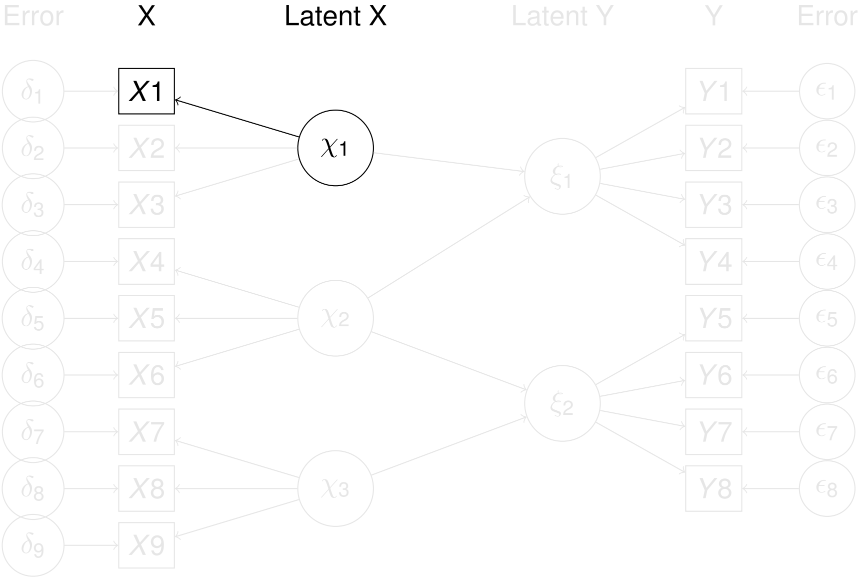
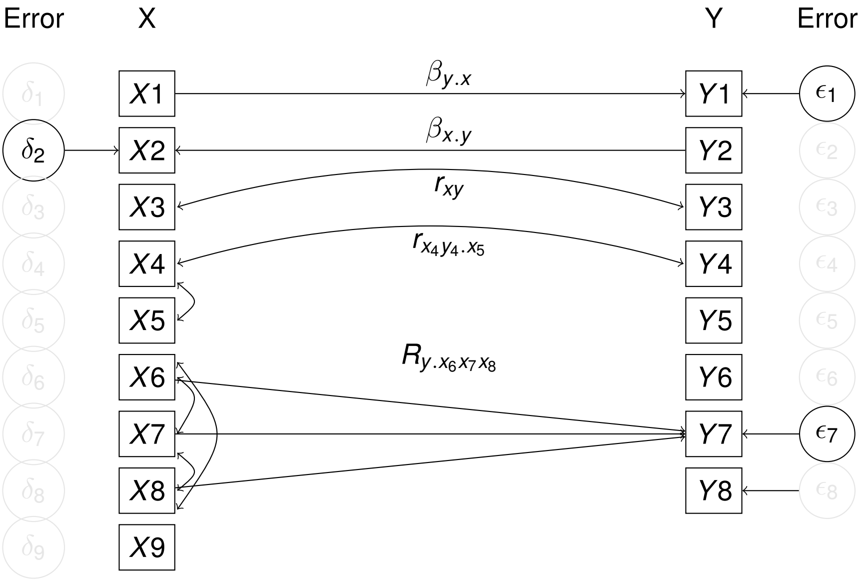
Psychometric Theory: A conceptual Syllabus



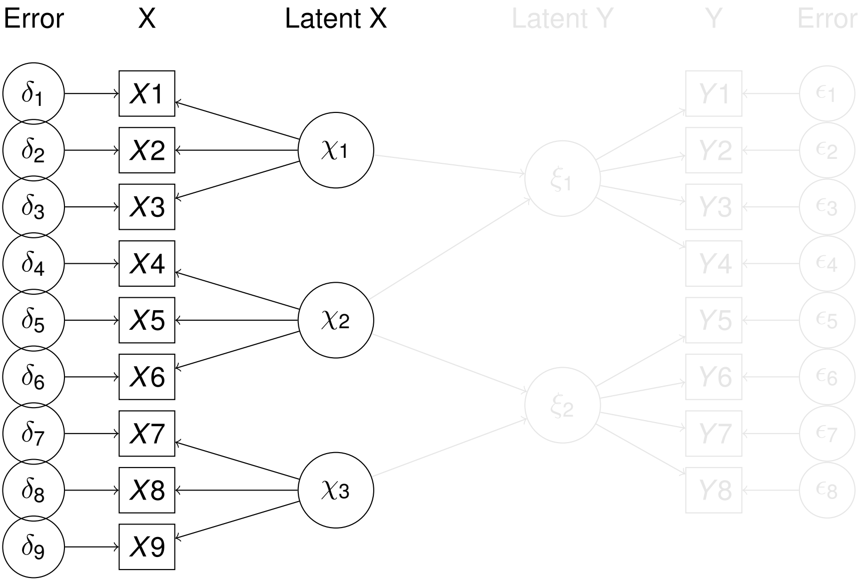
A theory of data and fundamentals of scaling



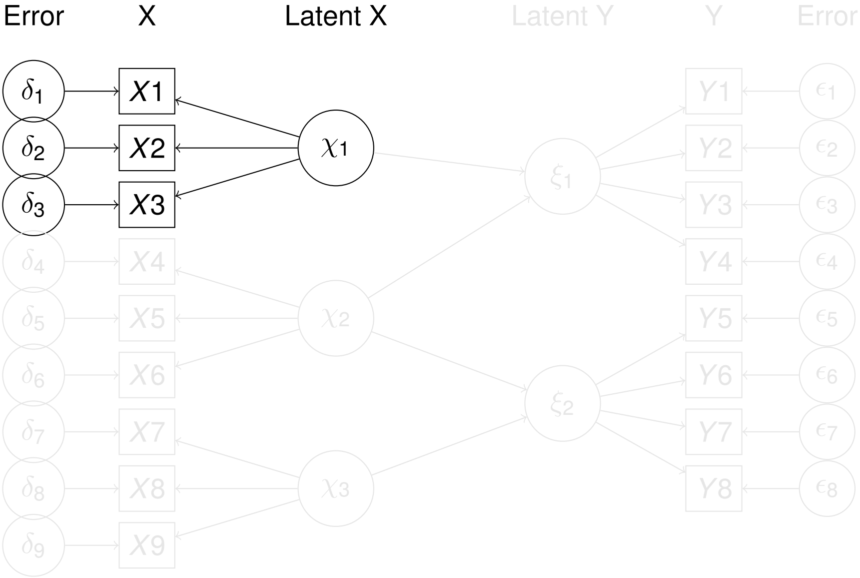
Correlation, Regression, Partial Correlation, Multiple Regression



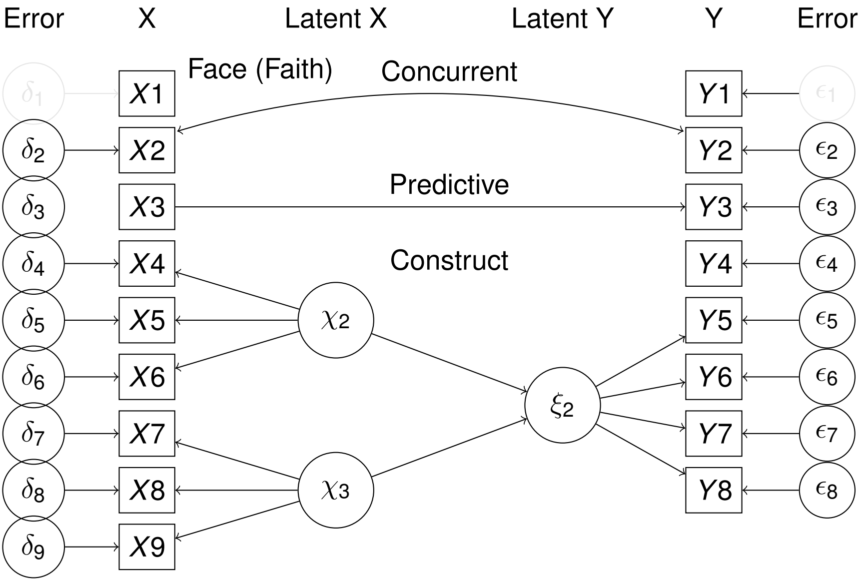
Measurement: A latent variable approach.



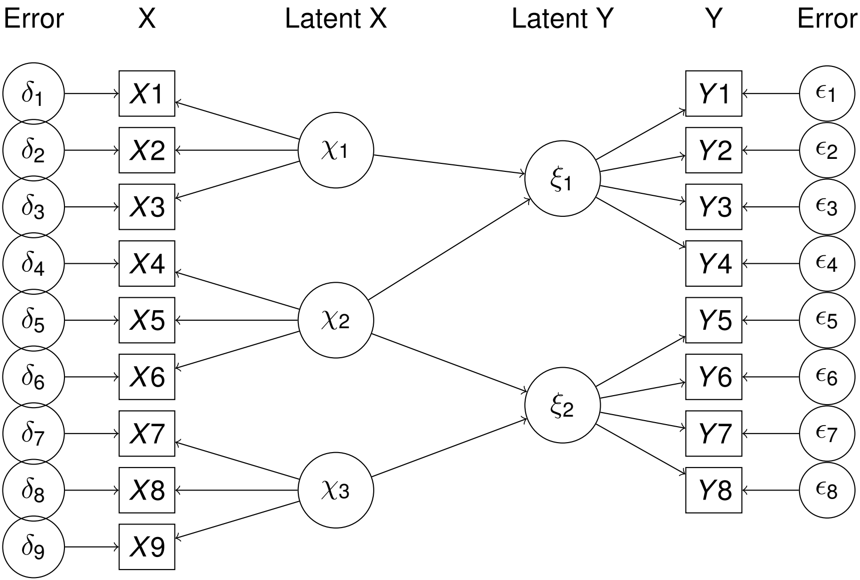
Reliability: How well does a test reflect one latent trait?



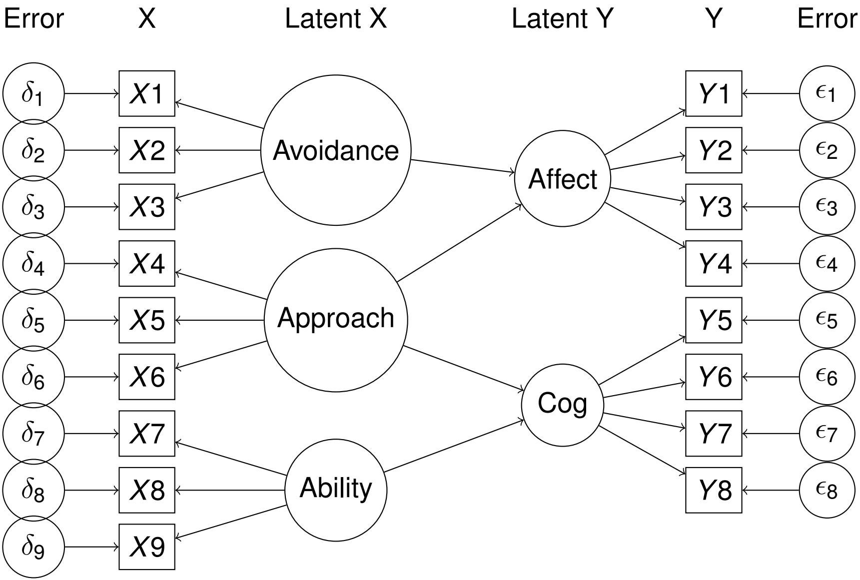
Face, Concurrent, Predictive, Construct



Psychometric Theory: Data, Measurement, Theory



Psychometric Theory: Data, Measurement, Theory



Overview

1. Overview: An introduction to Psychometric Theory
   - What is Psychometrics?
   - What is R?
2. Weeks 1-2: Theory of Data, Issues in Scaling.
3. Weeks 2-3: More than you ever wanted to know about correlation.
   - A review (?) of linear algebra.
4. Weeks 4-5 Dimension reduction through factor analysis, principal components analyze and cluster analysis.
5. Week 6-7 Classical Test Theory and Item Response Theory.
6. Week 8-9 Structural Equation Modeling and applied scale construction.

The process of science

Prologue: two broad themes to be discussed and interwoven

1. The two disciplines of scientific psychology
   1.1 Two broad cultures of intellectual activity (Snow, 1959)
   1.2 Two broad cultures of psychology (Kimble, 1984)
   1.3 Two disciplines within scientific psychology (Cronbach, 1957, 1975) and (Eysenck, 1966, 1987a, 1997).
2. The process of theory construction and validation
   2.1 Science from hunch to law (Eysenck, 1976, 1985)
   2.2 Good theories as alive and generative: the example of theories of Extraversion.

I will emphasize the power of integrating psychometric and experimental techniques in a programmatic study of personality and individual differences. This is mainly a shameless advertisement for interactive personality research.

The two cultures of intellectual inquiry

C.P. Snow (1959) considered two cultures of intellectual inquiry:

> *"I believe the intellectual life of the whole of western society is increasingly being split into two polar groups."* ..
> *"I felt I was moving among two groups–comparable in intelligence, identical in race, not grossly different in social origin, earning about the same incomes, who had almost ceased to communicate at all, who in intellectual, moral and psychological climate had so little in common ... one might have crossed an ocean."*

Kimble and the two cultures of psychology

Just as Snow considered the scientific versus humanistic cultures of English and American society, so did Kimble (1984) consider two cultures of psychology: the scientific and the humanistic.

> *"The remaining points of disagreement involve the items asking about most important values (scientific vs. human), source of basic knowledge (objectivism vs. intuitionism), and generality of laws (nomothetic vs. idiographic).*

Two competing tribes/paradigms within scientific psychology

1. But even within the culture of scientific psychology, we have two competing tribes who differ in their basic paradigmatic view of how to do science: the correlational vs. experimental paradigms discussed by Cronbach (1957, 1975) and Eysenck (1966, 1987a, 1997). Both pleaded for an integration of the two tribes. Neither was overly successful.
2. Others who have tried to reconcile these differences included Vale and Vale (1969), and Underwood (1975).
3. Revelle and Oehlberg (2008) and Garner and Revelle (2025) reported that this dichotomy still continues.
4. We need to go beyond this dichotomy by realizing that theory development and theory testing require a mixture of the inductive power of correlations with the deductive power of experimental techniques.
5. For we as individual differences psychologists are most able to unify the two disciplines.

The conventional dichotomy of research paradigms in psychology ala Cronbach (1957, 1975) and Eysenck (1966, 1987a, 1997)

Correlational

1. Influential founders
   1.1 Galton (1886)
   1.2 Pearson (1896)
   1.3 Spearman (1904)
2. Measurement of variances and covariances
   2.1 bivariate r, ϕ, $Yule_Q$
   2.2 multivariate R, factor analysis, principal components
   2.3 General Linear Model and its extension to multi-level modeling
3. Addresses threats to validity by statistical "control"

Experimental

1. Influential founders
   1.1 Wundt (1904)
   1.2 Gossett (Student, 1908)
   1.3 Fisher (1925)
2. Measurement of central tendencies
   2.1 bivariate t and F
   2.2 multivariate MANOVA
   2.3 General Linear Model and its extension to multi-level modeling
3. Addresses threats to validity by randomization

Two disciplines: two viewpoints

Table: The naive perspective from both sides–the other side is easy, why don't they just do it right? Our variables are complicated, well articulated, theirs are simple, just use any one.

Individual Differences	Experimental
Personality Ability	Task Performance

The experimentalist's challenge: what to measure

Measures

1. Giant 3
   - EPI
   - EPQ
2. Big 5
   - NEO-PI-R
   - IPIP B5
   - IPIP NEO
   - BFI
   - TIPI
3. Beyond the Big 5
   - HEXACO
   - IPIP HEXACO
   - BFAS
   - SAPA 3-6-12-27
   - ICAR-IQ
   - ...

Constructs

1. Extraversion
   - but which one? Costa vs. Goldberg
2. Neuroticism
3. Agreeableness
4. Conscientiousness
5. Openness-Intellect
   - but is it openness or is it intellect?
6. Honesty/Humility
7. Impulsivity
8. Sociability
9. Trust
10. ...

The challenge for individual difference researchers: what constructs to measure

Memory

1. Working memory
2. Iconic memory
3. Short Term memory
4. Long Term memory
5. Semantic memory
6. Episodic memory
7. Procedural memory
8. Autobiographical memory
9. False memory
10. Recall
11. Recognition

Attention

1. Sustained Attention
2. Allocation of Attention
3. Capturing Attention
4. Breadth of Attention
5. Local/Global Attention
6. Paying Attention

System I or System II

1. Fast, automatic
2. Slow, controlled, but lazy

The experimentalist's challenge: how to analyze, what to report

Analysis

1. Dimension Reduction
   - Principal Components
   - EFA
   - CFA
2. Structure
   - Path Analysis
   - SEM
   - Latent Growth Curves
3. Reliability analysis
   - Internal Consistency
   - Alternate Form
   - Test-Retest
4. Item Response Theory

Statistics

1. Measures of association
   - Pearson r, Spearman ρ
   - ϕ or $Yule_Q$
   - $r_{tetrachoric}$, $r_{polychoric}$
2. Goodness of fit
   - χ^2 or χ^2 difference
   - RMSEA or RMSR
   - Tucker-Lewis
   - BIC or AIC
3. Reliability
   - α
   - β
   - ω_h
   - ω_t

The challenge for individual difference researchers: which paradigm to use

Memory

1. Reaction time
   - Sternberg Memory Scanning
   - Ratcliff choice
   - Jacoby identification
2. Accuracy
3. Serial anticipation
4. Free recall
5. Cued recognition

Attention

1. Posner letter search
2. Erickson flanker task
3. Vigilance
4. dot probe
5. emotional “Stroop”
6. Eye tracking
7. Reaction Time

The extra subtleties of design

Personality

1. Item wording
2. Response alternatives
3. Appropriate sample size
4. Subject selection
   - restriction of range
5. Generalization of subject characteristics

Experimental

1. Number of practice trials
2. Inter Stimulus Interval
3. Stimulus Onset Asynchrony
4. Type of randomization/counterbalancing
   - block randomization
   - complete randomization
   - counterbalancing
5. Data trimming procedures
6. Power/p-hacking

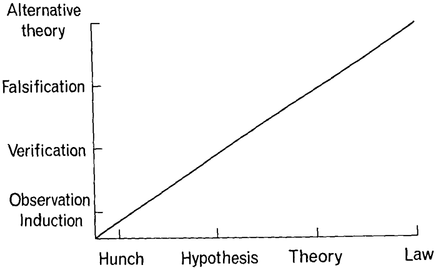
Theory testing is hard work

1. Confirmatory bias
2. Theory induced blindness
3. Seductive power of hindsite
4. Illusion of control
    - Under appreciation of chance
5. See *Thinking, Fast and Slow* Kahneman (2011)
6. An old but important classic Meehl (1992)

Scientific progress and levels of theory

Eysenck (1976, 1985); Eysenck and Eysenck (1985)

1. Hunch
   - observations
   - deduction
2. Hypothesis
   - hypothesis development
   - hypothesis verification
3. Theory
   - Weak theory – confirmation studies
   - Strong theory –disconfirmation studies
4. Law



Eysenck, Lakatos, Popper and Kuhn

Eysenck (1983, 1985, 1987b, 1988); Eysenck and Eysenck (1985) followed Lakatos (1968) in suggesting that disconfirmation studies did not lead to theory rejection until a better theory was supplied.

> *"Purely negative, destructive criticism, like 'refutation' or demonstration of an inconsistency does not eliminate a programme. Criticism of a programme is a long and often frustrating process and one must treat budding programmes leniently. One can, of course, undermine a research-programme but only with dogged patience. It is usually only constructive criticism which, with the help of rival research programmes can achieve major successes; but even so, dramatic, spectacular results become visible only with hindsight and rational reconstruction." (Lakatos, 1968, p 183)*

Eysenck's theory as an adaptive and changing theory of personality

Eysenck (1983) thought that the building of paradigmatic personality research required critical analysis of theory and welcomed the publications of some of his strongest critics (e.g., Gray, 1981).

> *"the existence of anomalies should be no bar to the acceptance of the paradigm; the existence of such anomalies should merely act as a spur for the puzzle-solving capacities of ordinary science."*

Indeed, in his presidential address to the International Society for the Study of Individual Differences Eysenck (1983) spent much of the time discussing Gray's criticisms and then cheerfully announced that Gray was going to replace him at the Maudsley!

Use R

R: Statistics for all of us

1. What is it?
2. Why use it?
3. Common (mis)perceptions of R
4. Examples for psychologists
   - graphical displays
   - basic statistics
   - advanced statistics
   - Although programming is easy in R, that is beyond the scope of this course.

R: What is it?

1. R: An international collaboration
2. R: The open source - public domain version of S+
3. R: Written by statistician (and all of us) for statisticians (and the rest of us)
4. R: Not just a statistics system, also an extensible language.
    - This means that as new statistics are developed they tend to appear in R far sooner than elsewhere.
    - R facilitates asking questions that have not already been asked.
5. R: encourages publications of "Reproducible Research"
    - integrate data, code, text into one document
    - Sweave and knitr
6. Many journals and chapters include R code appendices to allow for open science.

Statistical Programs for Psychologists

- General purpose programs
  - R
  - S+
  - SAS
  - SPSS
  - STATA
  - Systat
- Specialized programs
  - Mx
  - EQS
  - AMOS
  - LISREL
  - MPlus
  - Your favorite program

Statistical Programs for Psychologists

- General purpose programs
    - R
    - $+
    - A
    - $P$$
    - $TATA
    - $y$tat
- Specialized programs
    - Mx (OpenMx is part of R)
    - EQ$
    - AMO$
    - LI$REL
    - MPlu$
    - Your favorite program

R: A way of thinking (from the fortunes package)

- “R is the lingua franca of statistical research. Work in all other languages should be discouraged.” (Jan de Leeuw , 2003)(Mizumoto and Plonsky, 2015)
- “Evelyn Hall: I would like to know how (if) I can extract some of the information from the summary of my nlme. Simon Blomberg: This is R. There is no if. Only how. – Evelyn Hall and Simon ’Yoda’ Blomberg R-help (April 2005)
- “Overall, SAS is about 11 years behind R and S-Plus in statistical capabilities (last year it was about 10 years behind) in my estimation.” (Frank Harrell, 2003)
- "I quit using SAS in 1991 because my productivity jumped at least 20% within one month of using S-Plus." (Frank Harrell, 2003)
- Actually, I see it as part of my job to inflict R on people who are perfectly happy to have never heard of it. Happiness doesn’t equal proficient and efficient. In some cases the proficiency of a person serves a greater good than their momentary happiness. – Patrick Burns R-help (April 2005)

Taken from the R.-fortunes (selections from the R.-help list serve)

More fortunes

“You must realize that R is written by experts in statistics and statistical computing who, despite popular opinion, do not believe that everything in SAS and SPSS is worth copying. Some things done in such packages, which trace their roots back to the days of punched cards and magnetic tape when fitting a single linear model may take several days because your first 5 attempts failed due to syntax errors in the JCL or the SAS code, still reflect the approach of “give me every possible statistic that could be calculated from this model, whether or not it makes sense". The approach taken in R is different. The underlying assumption is that the useR is thinking about the analysis while doing it. " (Douglas Bates, 2007)

R is open source, how can you trust it?

- Q: “When you use it [R], since it is written by so many authors, how do you know that the results are trustable?”
- A: “The R engine [...] is pretty well uniformly excellent code but you have to take my word for that. Actually, you don’t. The whole engine is open source so, if you wish, you can check every line of it. If people were out to push dodgy software, this is not the way they’d go about it.” (Bill Venables, 2004)
- “It’s interesting that SAS Institute feels that non-peer-reviewed software with hidden implementations of analytic methods that cannot be reproduced by others should be trusted when building aircraft engines." – Frank Harrell (in response to the statement of the SAS director of technology product marketing: "We have customers who build engines for aircraft. I am happy they are not using freeware when I get on a jet.") R-help (January 2009)

What is R?: Technically

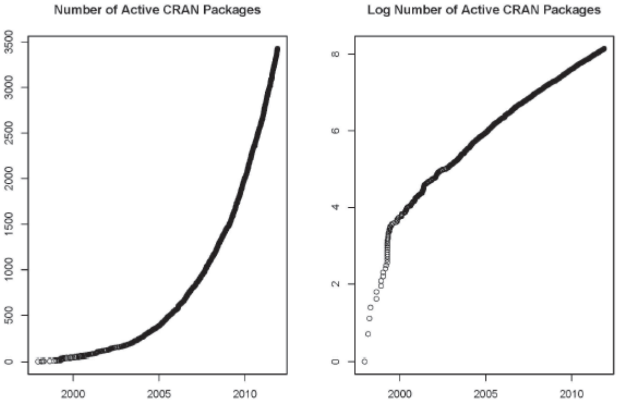
- R is an open source implementation of S (S-Plus is a commercial implementation)
- R is available under GNU Copy-left
- R1.0.0 was released on February 29, 2000
- The current version of R is 4.4.3.
- R is a group project run by a core group of developers (with new releases $\approx$ semiannually)
- R 4.4.5 is to be released sometime in late April or May, 2025

(Adapted from Robert Gentleman)

R: A brief history

- 1991-93: Ross Dhaka and Robert Gentleman begin work on R project for Macs at U. Auckland (S for Macs).
- 1995: R available by ftp under the General Public License.
- 96-97: mailing list and R core group is formed.
- 2000: John Chambers, designer of S joins the Rcore (wins a prize for best software from ACM for S)
- 2001-2019: Core team continues to improve base package with a new release every 6 months (now more like yearly).
- Many others contribute "packages" to supplement the functionality for particular problems.
    - 2003-04-01: 250 packages
    - 2004-10-01: 500 packages
    - 2007-04-12: 1,000 packages
    - 2009-10-04: 2,000 packages
    - 2011-05-12: 3,000 packages
    - 2012-08-27: 4,000 packages
    - 2014-05-16: 5,547 packages (on CRAN) + 824 bioinformatic packages on BioConductor
    - 2016-03-21 8,120 packages (on CRAN) + 1,104 bioinformatic packages + ?,000s on GitHub/R-Forge
    - 2020-04-04 15,514 packages (CRAN) + 1,823 on BioConductor + ?,000s on GitHub
    - 2022-03-25 19,017 packages (CRAN) + 1,974 on BioConductor > 70,000 on GitHub
    - 2025-04-01 22,253 packages (CRAN) + 2,266 on BioConductor > 70,000 on GitHub

Has R grown too much? Exponential growth rate continues



See also http://r4stats.com/articles/popularity/

Misconception: R is hard to use

1. R doesn't have a GUI (Graphical User Interface)
   - Partly true, many use syntax
   - Partly not true, GUIs exist (e.g., R Commander, R-Studio)
   - Quasi GUIs for Mac and PCs make syntax writing easier
2. R syntax is hard to use
   - Not really, unless you think an iPhone is hard to use
   - Easier to give instructions of 1-4 lines of syntax rather than pictures of what menu to pull down.
   - Keep a copy of your syntax, modify it for the next analysis.
3. R is not user friendly: A personological description of R
   - R is introverted: it will tell you what you want to know if you ask, but not if you don't ask.
   - R is conscientious: it wants commands to be correct.
   - R is not agreeable: its error messages are at best cryptic.
   - R is stable: it does not break down under stress.
   - R is open: new ideas about statistics are easily developed.

Misconceptions: R is hard to learn

1. With a brief web based tutorial http://personality-project.org/r, 2nd and 3rd year undergraduates in psychological methods and personality research courses are using R for descriptive and inferential statistics and producing publication quality graphics.
2. More and more psychology departments are using it for graduate and undergraduate instruction.
3. R is easy to learn, hard to master
   - R-help newsgroup is very supportive
   - Multiple web based and pdf tutorials see (e.g., http://www.r-project.org/)
   - Short courses using R for many applications
   - Longer Tutorials (e.g., I think therefore I R)
4. Books and websites for SPSS and SAS users trying to learn R.

Ok, how do I get it: Getting started with R

1. Download from R Cran (http://cran.r-project.org/)
    - Choose appropriate operating system and download compiled R
2. Install R (current version is 4.4.3 with 4.4.5 coming next month spring
3. Start R
4. Add useful packages (just need to do this once)
    - install.packages("ctv") #this downloads the task view package
    - library(ctv) #this activates the ctv package
    - install.views("Psychometrics") #among others
    - Take a 5 minute break
5. Activate the package(s) you want to use (e.g., *psych*)
    - library(psych) #necessary for most of this course
    - library(lavaan) #will be used for a few examples
6. Use R
7. (See detailed tutorial at https://personality-project.org/r/r.guide.html#gettingstarted

Start up R and get ready to play (Mac version)

```
R version 4.4.3 (2025-02-28) -- "Trophy Case"
Copyright (C) 2025 The R Foundation for Statistical Computing
Platform: aarch64-apple-darwin20

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

  Natural language support but running in an English locale

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

[R.app GUI 1.81 (8497) aarch64-apple-darwin20]

[Workspace restored from /Users/WR/.RData]
[History restored from /Users/WR/.Rapp.history]

Good evening Bill.
```

Annotated installation guide: don't type the >

```
#To install all the psychometric
                                   task views:
> install.packages("ctv")

> library(ctv)

> install.views("Psychometrics")

#or just install a few packages
> install.packages("psych")
 >install.packages("psychTools")
> install.packages("GPArotation")
> install.packages("mnormt")
```

- Install the task view installer package. You might have to choose a "mirror" site.
- Make it active
- Install all the packages in the "Psychometrics" task view. This will take a few minutes.
- Or, just install two package (e.g., psych, psychTools)
- as well as a few suggested packages that add functionality for factor rotation, multivariate normal distributions, etc.

The *psych* package is under constant development

1. The most recent “official version" is on CRAN
2. The development version is on the pmc server and may be installed from there:
   - `install.packages("psych", repos="http://personality-project.org/r", type="source")`
3. This will give you the “bleeding edge" version.
   - Bug fixes have been added.
   - New features have been added.
4. Read the news to find out what has changed.
   - `news(Version >="2.5.3", package="psych")`

Check the version number for R (should be $\geq$ 4.4.3 and for psych ($\geq$2.5.3)

```
> library(psych)
> sessionInfo()

R version 4.4.3 (2025-02-28)     #the 25th anniversary of R
Platform: aarch64-apple-darwin20 (64-bit)
Running under: macOS Sonoma 14.2.1

Matrix products: default
BLAS:   /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/lib/l
LAPACK: /Library/Frameworks/R.framework/Versions/4.3-arm64/Resources/lib/l
LAPACK version 3.11.0

Random number generation:
 RNG:     Mersenne-Twister
 Normal:  Inversion
 Sample:  Rounding

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

time zone: America/Chicago
tzcode source: internal
```

R is extensible: The use of "packages"

- More than 22,253 packages are available for R (and growing daily)
- Can search all packages that do a particular operation by using the sos package
  - `install.packages("sos")` #if you haven't already
  - library(sos) # make it active once you have it
    - `findFn`("X") #will search a web data base for all packages/functions that have "X"
    - `findFn`("principal components analysis ") #will return 2,554 matches and reports the top 400 and download 385 links to 174 packages
    - `findFn`("Item Response Theory") # will return 503 matches with 326 links in 76 packages
    - `findFn`("INDSCAL ") # will return 20 matches in 5 packages.
- install.packages("X") will install a particular package (add it to your R library – you need to do this just once)
- library(X) #will make the package X available to use if it has been installed (and thus in your library)

A small subset of very useful packages

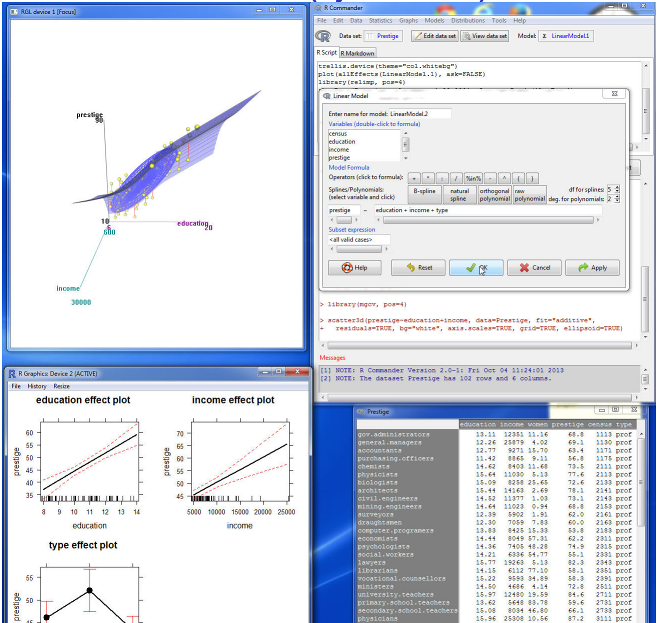
- General use
  - core R
  - MASS
  - lattice (core)
  - lme4 (core)
  - psych
- Special use
  - ltm
  - sem
  - lavaan
  - OpenMx
  - GPArotation
  - mnormt
  - >21,356 known
  - + ?

- General applications
  - most descriptive and inferential stats
  - Modern Applied Statistics with S
  - Lattice or Trellis graphics
  - Linear mixed-effects models
  - Personality and psychometrics
- More specialized packages
  - Latent Trait Model (IRT)
  - SEM and CFA (multiple groups)
  - SEM and CFA (multiple groups)
  - SEM and CFA (multiple groups +)
  - Jennrich + Browne rotations
  - Multivariate distributions
  - Thousands of more packages on CRAN
  - Code on webpages/journal articles

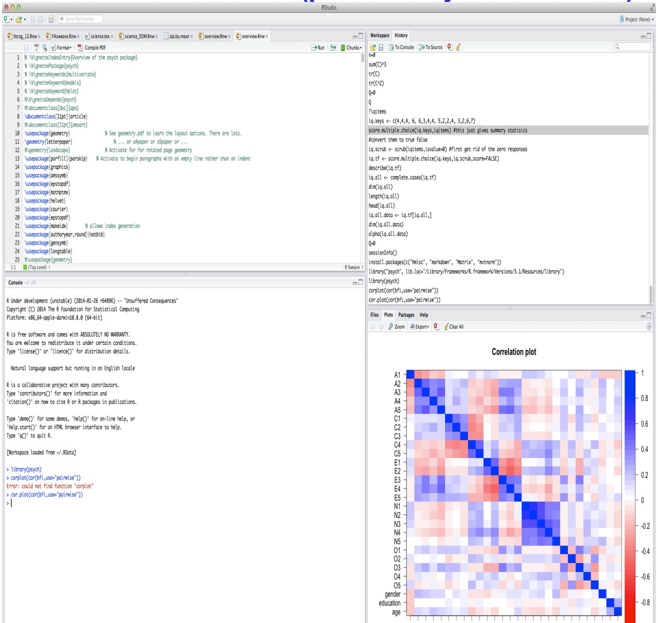
Implementations

1. Base R in the Unix/Linux/Mac X11 framework
2. Base R on the Mac/PC
   - Mac has prompts at bottom of window
3. Graphical User Interfaces
   - R Commander
   - R studio as a convenient shell
4. R studio integrates with *Rmarkdown* to allow easy note taking /annotation while writing scripts
5. Documenting scripts allows for more open science (and helps you remember what you have done)

R Commander (by John Fox) has a basic GUI



RStudio (particularly nice for PCs)



Using R

1. Install the relevant packages (just once!)
   - Either one at a time, or by using a "task view"
2. Make the packages you want to use "active" by library(package name) e.g., library(psych), library(psychTools).
   - You need to do this for each session or it
   - Can be automatized at startup with

```
.First() <- function() {library(psych); library(psychTools)}
```

3. Use the functions in a package
   - To see all functions in a package go to the index of the package or use the objects function: e.g., objects(package:psych)
   - Apply a function to data
   - All functions require an object to act upon. Most require this in parentheses. All functions return an object. This may be saved for later.
     - function(object) #apply the function to the object, show it
     - sqrt(2)
     - result <- function(object) #apply the function to object, save it
     - answer <- alpha(ability) #lots and lots of output is saved

What makes R useful?

1. The basic philosophy of open source allows one to see the code and modify it.
2. Object oriented meaning that all functions return objects that can be acted upon by other functions.
   - e.g., output of `mean` and `sd` is included in `describe` or `describeBy`
   - Output of `cor` is used in `fa`, `alpha`, etc.
   - Can add other functions (e.g.`tetrachoric` to do correlations instead of `cor`
3. This is perhaps the most powerful feature of R!
4. R is vectorized, so that if it works for X, it will work for ***X***

Basic R commands – remember don't enter the >

R is just a fancy calculator. Add, subtract, sum, products, group

```
> 2 + 2
[1] 4
> 3^4
[1] 81
> sum(1:10)
[1] 55
> prod(c(1, 2, 3, 5, 7))
[1] 210
```

It is also a statistics table (the normal distribution, the t distribution, F, χ^2, ...)

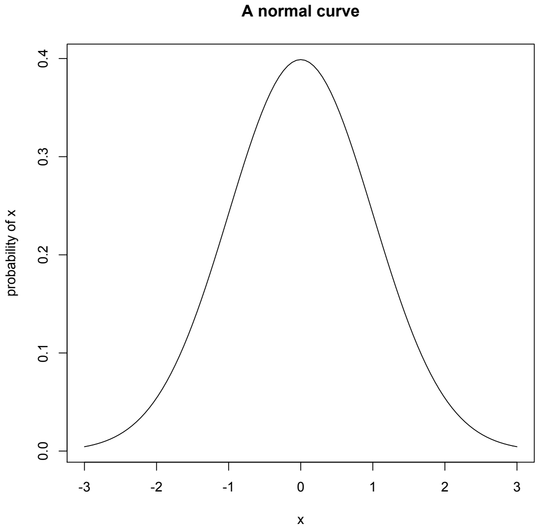
```
> pnorm(q = 1)    #probability of normal value > 1
[1] 0.8413447
> pt(q = 2, df = 20) #probability of t > 2 with 20 df
[1] 0.9703672
```

R is a set of distributions. Don't buy a stats book with tables!

Table: To obtain the density, prefix with *d*, probability with *p*, quantiles with *q* and to generate random values with *r*. (e.g., the normal distribution may be chosen by using dnorm, pnorm, qnorm, or rnorm.)

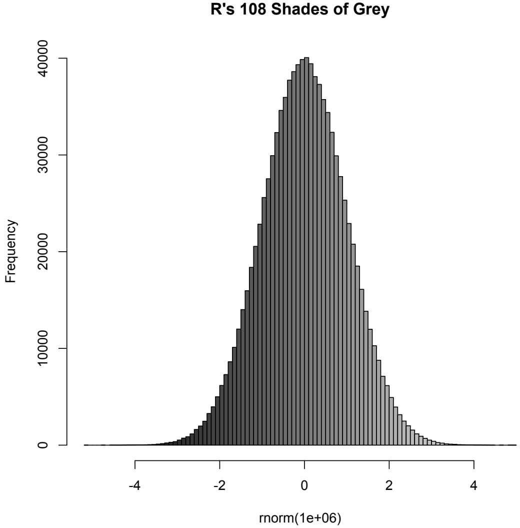
Distribution	base name	P 1	P 2	P 3	example application
Normal	norm	mean	sigma		Most data
Multivariate normal	mvnorm	mean	r	sigma	Most data
Log Normal	lnorm	log mean	log sigma		income or reaction time
Uniform	unif	min	max		rectangular distributions
Binomial	binom	size	prob		Bernuilli trials (e.g. coin flips)
Student's t	t	df		nc	Finding significance of a t-test
Multivariate t	mvt	df	corr	nc	Multivariate applications
Fisher's F	f	df1	df2	nc	Testing for significance of F test
χ^2	chisq	df		nc	Testing for significance of χ^2
Exponential	exp	rate			Exponential decay
Gamma	gamma	shape	rate	scale	distribution theoryh
Hypergeometric	hyper	m	n	k	
Logistic	logis	location	scale		Item Response Theory
Poisson	pois	lambda			Count data
Weibull	weibull	shape	scale		Reaction time distributions
Cauchy	cauchy	location	scale	log	infinite variance!

R can draw distributions




```
curve(dnorm(x),-3,3,ylab="probability of x",main="A normal curve")
```

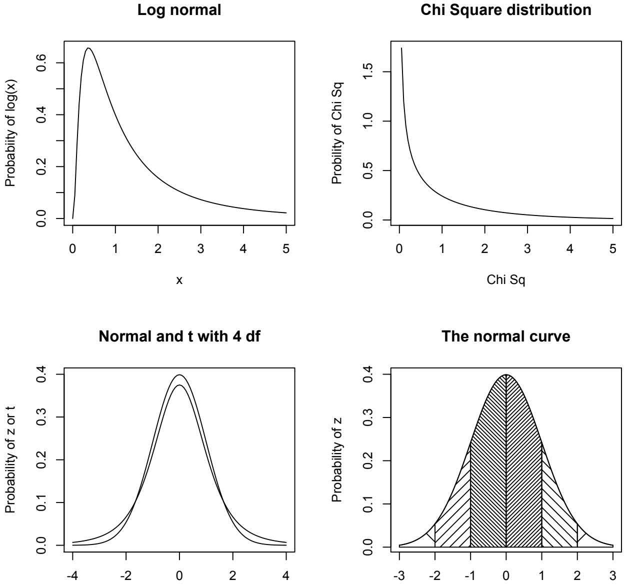
R (authors) can make jokes (from R fortunes)




```
hist(rnorm(1e6),
col = col-
ors()[grep("grey",
colors())],
nclass = 108,
main = "R's 108
Shades of Grey")
```

– Fritz Scholz
(proving R has
more than 50
Shades of Grey)

R can draw more interesting distributions



R is also a graphics calculator

The first line draws the normal curve, the second prints the title, the next lines draw the cross hatching.

```
op <- par(mfrow=c(2,2))          #set up a 2 x 2 graph
curve(dnorm(x),-3,3,xlab="",ylab="Probability of z")
title(main="The normal curve",outer=FALSE)
xvals <-  seq(-3,-2,length=100)
dvals <- dnorm(xvals)
polygon(c(xvals,rev(xvals)),c(rep(0,100),rev(dvals)),density=2,angle=-45)
xvals <-  seq(-2,-1,length=100)
dvals <- dnorm(xvals)
polygon(c(xvals,rev(xvals)),c(rep(0,100),rev(dvals)),density=14,angle=45)
xvals <-  seq(-1,-0,length=100)
dvals <- dnorm(xvals)
polygon(c(xvals,rev(xvals)),c(rep(0,100),rev(dvals)),density=34,angle=-45)
xvals <-  seq(2,3,length=100)
dvals <- dnorm(xvals)
polygon(c(xvals,rev(xvals)),c(rep(0,100),rev(dvals)),density=2,angle=45)
xvals <-  seq(1,2,length=100)
dvals <- dnorm(xvals)
polygon(c(xvals,rev(xvals)),c(rep(0,100),rev(dvals)),density=14,angle=-45)
xvals <-  seq(0,1,length=100)
dvals <- dnorm(xvals)
polygon(c(xvals,rev(xvals)),c(rep(0,100),rev(dvals)),density=34,angle=45)
curve(dlnorm(x),0,5,ylab='Probabiity of log(x)',main='Log normal')
curve(dchisq(x,1),0,5,ylab='Probility of Chi Sq',xlab='Chi Sq',main='Chi Square distribution')
curve(dnorm(x),-4,4,ylab='Probability of z or t',xlab='z or t',main='Normal and t with 4 df')
curve(dt(x,4),add=TRUE)
op <- par(mfrow=c(1,1))
```

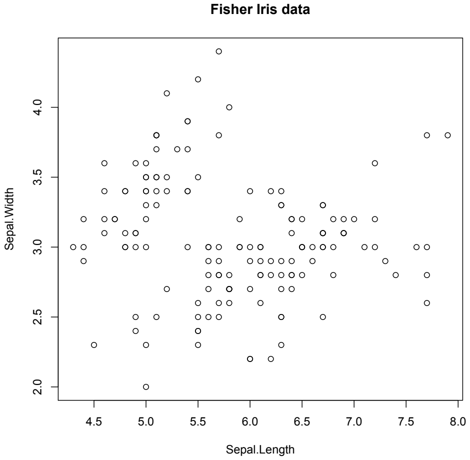
Example data sets built into many packages

Table: Some of the 50 data sets in the psych or psychTools packages

Name	Content description
veg	Thurstone's Vegetables
cities	Airplane distances for 11 US cities
galton	Francis Galton's original data set of heights
cushny	The original t-test data from "student" (Gossett)
ability	16 ability items from SAPA
bfi	25 Big Five items + gender, age, education from SAPA
sat.act	Test scores, gender, age and education
Thurstone	9 ability variables from Thurstone
msq	75 mood items from the PMC lab
neo	Correlation matrix of the 30 NEO-PI-R facets

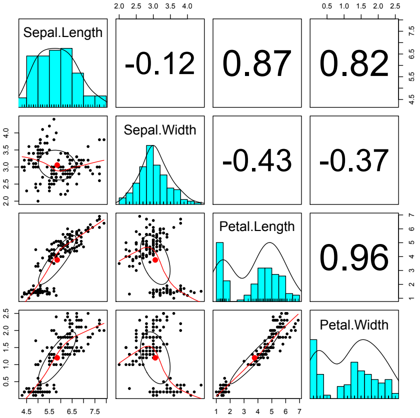
```
data()   #to see all available
data(package=c("psych","psychTools"))   # to see all psych data sets
```

A simple scatter plot using `plot` shows Fisher's Iris data set




```
plot(iris[1:2],xlab="Sepal.Length",ylab="Sepal.Width"
,main="Fisher Iris data")
```

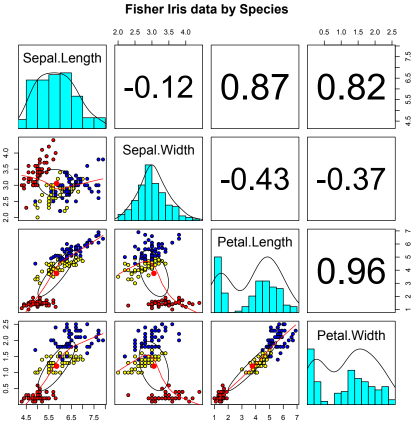
A scatter plot matrix with loess regression using `pairs.panels` shows more information than a simple scatter plot



`pairs.panels(iris[1:4])`

1. Correlations above the diagonal
2. Diagonal shows histograms and densities
3. scatter plots below the diagonal with correlation ellipse
4. locally smoothed (loess) regressions for each pair

A better SPLOM with colors for groups using `pairs.panels`



1. Correlations above the diagonal
2. Diagonal shows histograms and densities
3. scatter plots below the diagonal with correlation ellipse
4. locally smoothed (loess) regressions for each pair
5. optional color coding of grouping variables.

```
pairs.panels(iris[1:4],bg=c("red","yellow","blue")
[iris$Species],pch=21,main="Fisher Iris data by
Species")
```

Using R for psychological statistics: Basic statistics

1. Writing syntax
   - For a single line, just type it
   - Mistakes can be redone by using the up arrow key
   - For longer code, use a text editor (built into some GUIs)
2. Data entry
   - Using built in data sets for examples
   - Copying from another program (using the "clipboard")
   - Reading a text or csv file
   - Importing from SPSS or SAS
   - Simulate it (using various simulation routines)
3. Descriptives
   - Graphical displays
   - Descriptive statistics
   - Correlation
4. Inferential
   - the t test
   - the F test
   - the linear model

Data entry overview

1. Using built in data sets for examples
    - `data()` will list $>$ 100 data sets in the `datasets` package as well as all sets in loaded packages.
    - Most packages have associated data sets used as examples
    - *psych* and *psychTools* have $>$ 50 example data sets
2. Copying from another program
    - use copy and paste into R using `read.clipboard` and its variations
3. Reading a text or csv file
    - read a local or remote file using the `read.file` function
4. Importing from SPSS or SAS
5. Simulate it (using various simulation routines)

Examples of built in data sets from the *psych* package

```
> data(package="psych")

Bechtoldt                      Seven data sets showing a bifactor solution
Dwyer                          8 cognitive variables used by Dwyer for an
Reise                          Seven data sets showing a bifactor solution
all.income (income)            US family income from US census 2008
bfi                            25 Personality items representing 5 factors
blot                           Bond's␣Logical␣Operations␣Test␣-␣BLOT
burt␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣11␣emotional␣variables␣from␣Burt␣(1915)
cities␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣Distances␣between␣11␣US␣cities
epi.bfi␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣13␣personality␣scales␣from␣the␣Eysenck␣Pers
␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣and␣Big␣5␣inventory
affect␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣Two␣data␣sets␣of␣affect␣and␣arousal␣scores␣
␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣personality␣and␣movie␣conditions.
galton␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣␣Galton's Mid parent child height data
income                         US family income from US census 2008
iqitems                        16 multiple choice IQ items
msq                            75 mood items from the Motivational State Q
                               for N = 3896
neo                            NEO correlation matrix from the NEO_PI_R ma
sat.act                        3 Measures of ability: SATV, SATQ, ACT
Thurstone                      The classic Thurstone 9 variable problem
veg (vegetables)               Paired comparison of preferences for 9 vege
```

Reading data from another program –using the clipboard

1. Read the data in your favorite spreadsheet or text editor
2. Copy to the clipboard
3. Execute the appropriate `read.clipboard` function with or without various options specified

```
my.data <- read.clipboard()      #assumes headers and tab or space delimited
my.data <- read.clipboard.csv()      #assumes headers and comma delimited
my.data <- read.clipboard.tab()      #assumes headers and tab delimited
                                        (e.g., from Excel)
my.data <- read.clipboard.lower()   #read in a matrix given the lower
my.data <- read.clipboard.upper() # or upper off diagonal
my.data <- read.clipboard.fwf()   #read in data using a fixed format width
                                           (see read.fwf for instruct
```

4. `read.clipboard()` has default values for the most common cases and these do not need to be specified. Consult ?read.clipboard for details. (Note, the `read.clipboard` and `read.file` functions require the *psychTools*. Install and make it active. e.g., library(psychTools)).

Reading from a local or remote file

1. Perhaps the standard way of reading in data is using the `read` command.
   - First must specify the location of the file
   - Can either type this in directly or use the `file.choose` function
   - The file name/location can be a remote URL
2. Two examples of reading data

```
file.name <- file.choose() #this opens a window to allow you find the file
my.data <- read.table(file.name)    #read the file
my.data <- read.file()     #opens a search window, reads the file according
to the suffix
datafilename="http://personality-project.org/r/datasets/R.appendix1.c
data.ex1=read.table(datafilename,header=TRUE)     #read the data into
a table

> dim(data.ex1)  #what are the dimensions of what we read?
[1] 18  2
> describe(data.ex1) #do the data look right?
           var  n  mean   sd median trimmed  mad min max range skew ku
se
Dosage*      1 18  1.89 0.76      2    1.88 1.48   1   3     2 0.16
-1.12 0.18
Alertness    2 18 27.67 6.82     27   27.50 8.15  17  41    24 0.25
-0.68 1.61
```

read a "foreign" file e.g., an SPSS sav file

`read.spss` reads a file stored by the SPSS save or export commands. Can be done using the `read.file` command

```
read.spss(file, use.value.labels = TRUE, to.data.frame = FALSE,
          max.value.labels = Inf, trim.factor.names = FALSE,
          trim_values = TRUE, reencode = NA, use.missings = to.data.frame)
```

file	Character string: the name of the file or URL to read.
use.value.labels	Convert variables with value labels into R factors with those levels?
to.data.frame	return a data frame? Defaults to FALSE, probably should be TRUE in most cases.
max.value.labels	Only variables with value labels and at most this many unique values will be converted to factors if use.value.labels $=$ *TRUE*.
trim.factor.names	Logical: trim trailing spaces from factor levels?
trim_values	logical: should values and value labels have trailing spaces ignored when matching for use.value.labels $=$ *TRUE*?
use.missings	logical: should information on user-defined missing values be used to set the corresponding values to NA?

Simulate data

For many demonstration purposes, it is convenient to generate simulated data with a certain defined structure. The *psych* package has a number of built in simulation functions. Here are a few of them.

1. Simulate various item structures
   - **sim.congeneric** A one factor congeneric measure model
   - **sim.items** A two factor structure with either simple structure or a circumplex structure.
   - **sim.rasch** Generate items for a one parameter IRT model.
   - **sim.irt** Generate items for a one-four parameter IRT Model
2. Simulate various factor structures and show observed as well as latent data.
   - **sim** Defaults to four correlated factors with a three time point simplex structure.
   - **sim.hierarchical** Default is 9 variables with three correlated factors.

Get the data and look at it

Read in some data, look at the first and last few cases, and then get basic descriptive statistics. For this example, we will use a built in data set.

```
> my.data <- epi.bfi
> headtail(my.data)
```

	epiE	epiS	epiImp	epilie	epiNeur	bfagree	bfcon	bfext	bfneur	bfopen	bdi	traitanx	stateanx
1	18	10	7	3	9	138	96	141	51	138	1	24	22
2	16	8	5	1	12	101	99	107	116	132	7	41	40
3	6	1	3	2	5	143	118	38	68	90	4	37	44
4	12	6	4	3	15	104	106	64	114	101	8	54	40
...	...	...	...	...	...	...	...	...	...	...	...	...	...
228	12	7	4	3	15	155	129	127	88	110	9	35	34
229	19	10	7	2	11	162	152	163	104	164	1	29	47
230	4	1	1	2	10	95	111	75	123	138	5	39	58
231	8	6	3	2	15	85	62	90	131	96	24	58	58

epi.bfi has 231 cases from two personality measures

Now find the descriptive statistics for this data set

```
> describe(my.data)
```

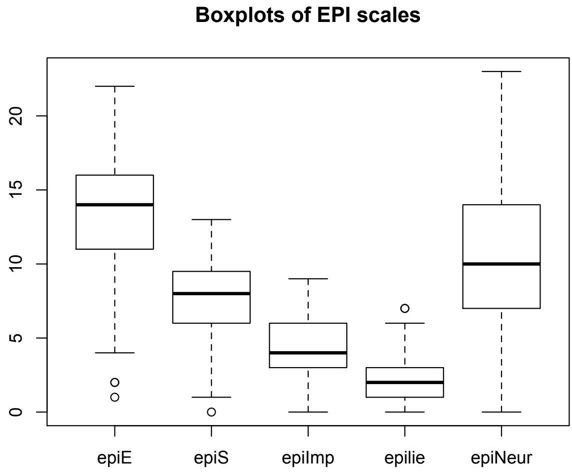
	var	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
epiE	1	231	13.33	4.14	14	13.49	4.45	1	22	21	−0.33	−0.01	0.27
epiS	2	231	7.58	2.69	8	7.77	2.97	0	13	13	−0.57	0.04	0.18
epiImp	3	231	4.37	1.88	4	4.36	1.48	0	9	9	0.06	−0.59	0.12
epilie	4	231	2.38	1.50	2	2.27	1.48	0	7	7	0.66	0.30	0.10
epiNeur	5	231	10.41	4.90	10	10.39	4.45	0	23	23	0.06	−0.46	0.32
bfagree	6	231	125.00	18.14	126	125.26	17.79	74	167	93	−0.21	−0.22	1.19
bfcon	7	231	113.25	21.88	114	113.42	22.24	53	178	125	−0.02	0.29	1.44
bfext	8	231	102.18	26.45	104	102.99	22.24	8	168	160	−0.41	0.58	1.74
bfneur	9	231	87.97	23.34	90	87.70	23.72	34	152	118	0.07	−0.51	1.54
bfopen	10	231	123.43	20.51	125	123.78	20.76	73	173	100	−0.16	−0.11	1.35
bdi	11	231	6.78	5.78	6	5.97	4.45	0	27	27	1.29	1.60	0.38
traitanx	12	231	39.01	9.52	38	38.36	8.90	22	71	49	0.67	0.54	0.63
stateanx	13	231	39.85	11.48	38	38.92	10.38	21	79	58	0.72	0.04	0.76

`describe` is one of the most important functions to use on any new data set. Look at the ranges, the minima, the maxima, the sds.

Boxplots are a convenient descriptive device

Show the Tukey “boxplot” for the Eysenck Personality Inventory

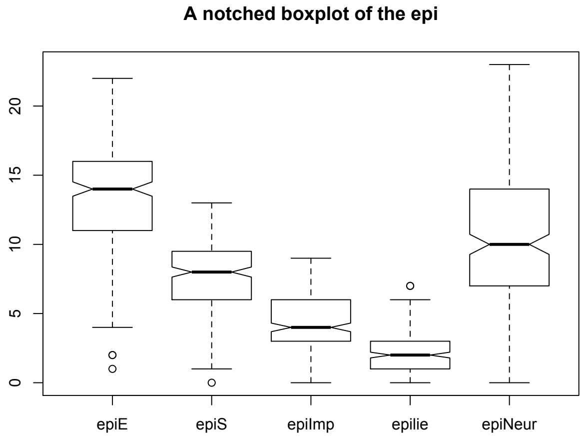
```
boxplot(my.data[1:5]) #just the first 5 variables
```



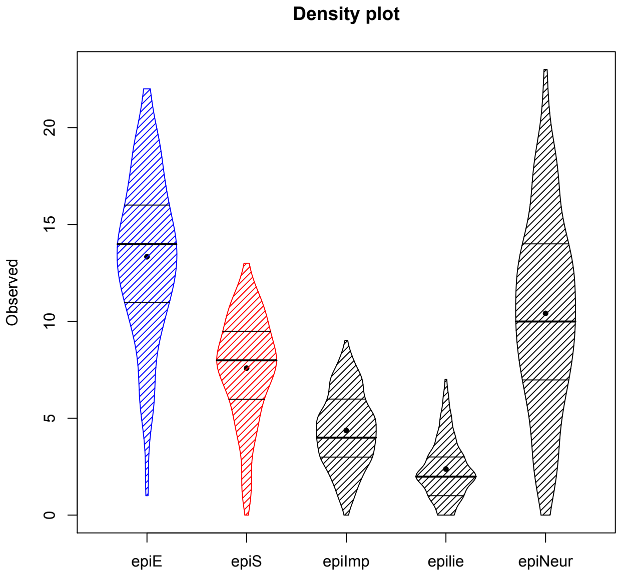
Enhanced box plots are even more convenient descriptive devices

Show the Tukey “boxplot” for the Eysenck Personality Inventory

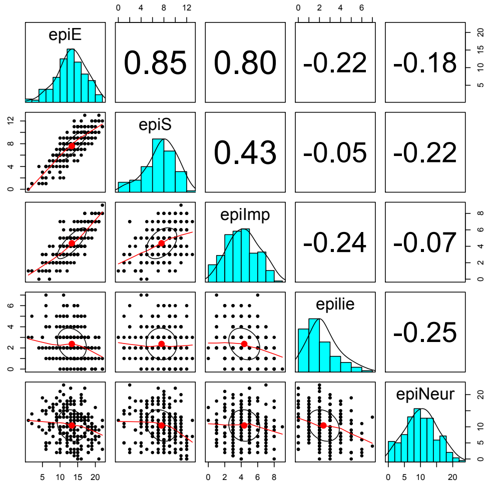
```
boxplot(my.data[1:5]) #just the first 5 variables
```



A violin plot shows the density distribution more graphically



Plot the scatter plot matrix (SPLOM) of the first 5 variables using the `pairs.panels` function



Use the `pairs.panels` function from *psych*

```
pairs.panels(my.data[1:5])
```

```
Note that we specify
 the range of variables.
```

Find the correlations for this data set, round off to 2 decimal places

```
> round(cor(my.data, use = "pairwise"), 2)
```

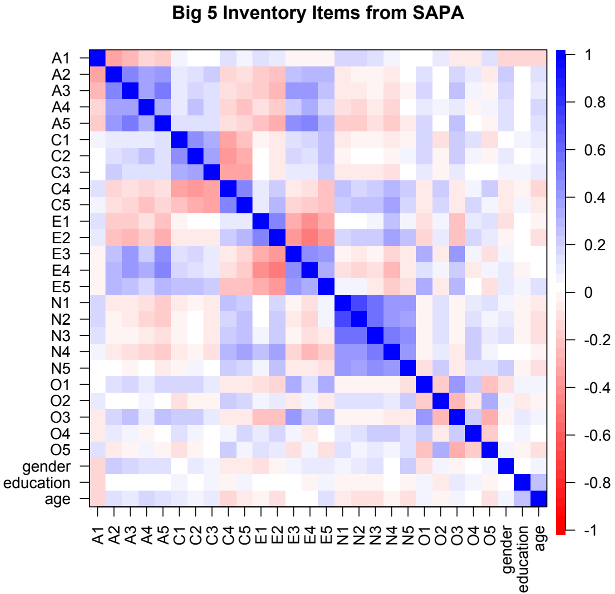
	epiE	epiS	epiImp	epilie	epiNeur	bfagree	bfcon	bfext	bfneur	bfopen	bdi	traitanx	s
epiE	1.00	0.85	0.80	-0.22	-0.18	0.18	-0.11	0.54	-0.09	0.14	-0.16	-0.23	
epiS	0.85	1.00	0.43	-0.05	-0.22	0.20	0.05	0.58	-0.07	0.15	-0.13	-0.26	
epiImp	0.80	0.43	1.00	-0.24	-0.07	0.08	-0.24	0.35	-0.09	0.07	-0.11	-0.12	
epilie	-0.22	-0.05	-0.24	1.00	-0.25	0.17	0.23	-0.04	-0.22	-0.03	-0.20	-0.23	
epiNeur	-0.18	-0.22	-0.07	-0.25	1.00	-0.08	-0.13	-0.17	0.63	0.09	0.58	0.73	
bfagree	0.18	0.20	0.08	0.17	-0.08	1.00	0.45	0.48	-0.04	0.39	-0.14	-0.31	
bfcon	-0.11	0.05	-0.24	0.23	-0.13	0.45	1.00	0.27	0.04	0.31	-0.18	-0.29	
bfext	0.54	0.58	0.35	-0.04	-0.17	0.48	0.27	1.00	0.04	0.46	-0.14	-0.39	
bfneur	-0.09	-0.07	-0.09	-0.22	0.63	-0.04	0.04	0.04	1.00	0.29	0.47	0.59	
bfopen	0.14	0.15	0.07	-0.03	0.09	0.39	0.31	0.46	0.29	1.00	-0.08	-0.11	
bdi	-0.16	-0.13	-0.11	-0.20	0.58	-0.14	-0.18	-0.14	0.47	-0.08	1.00	0.65	
traitanx	-0.23	-0.26	-0.12	-0.23	0.73	-0.31	-0.29	-0.39	0.59	-0.11	0.65	1.00	
stateanx	-0.13	-0.12	-0.09	-0.15	0.49	-0.19	-0.14	-0.15	0.49	-0.04	0.61	0.57	

Find the correlations using `lowerCor`

```
> lowerCor(my.data)
```

```
         epiE  epiS  epImp epili epiNr bfagr bfcon bfext bfner bfopn bdi   trtnx sttnx
epiE      1.00
epiS      0.85  1.00
epiImp    0.80  0.43  1.00
epilie   -0.22 -0.05 -0.24  1.00
epiNeur  -0.18 -0.22 -0.07 -0.25  1.00
bfagree   0.18  0.20  0.08  0.17 -0.08  1.00
bfcon    -0.11  0.05 -0.24  0.23 -0.13  0.45  1.00
bfext     0.54  0.58  0.35 -0.04 -0.17  0.48  0.27  1.00
bfneur   -0.09 -0.07 -0.09 -0.22  0.63 -0.04  0.04  0.04  1.00
bfopen    0.14  0.15  0.07 -0.03  0.09  0.39  0.31  0.46  0.29  1.00
bdi      -0.16 -0.13 -0.11 -0.20  0.58 -0.14 -0.18 -0.14  0.47 -0.08  1.00
traitanx -0.23 -0.26 -0.12 -0.23  0.73 -0.31 -0.29 -0.39  0.59 -0.11  0.65  1.00
stateanx -0.13 -0.12 -0.09 -0.15  0.49 -0.19 -0.14 -0.15  0.49 -0.04  0.61  0.57  1.00
```

A heat map of 25 BFI items using `cor.plot`



R resources

1. Every function in every package as a ? help file
2. Many paclkages have *vignettes* (more examples than a help file, including more text)
3. For Psychometrics, there are a number of “how to" pages
   3.1 `https://personality-project.org/r/psych/intro.pdf` Overview I
   3.2 `http://personality-project.org/r/psych/overview.pdf` Overview II
   3.3 `https://personality-project.org/r/psych/HowTo/factor.pdf` Factor analysis
   3.4 `http://personality-project.org/r/psych/HowTo/omega.pdf` omega
   3.5 `http://personality-project.org/r/psych/HowTo/scoring.pdf` Scoring scales

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