Analysis and Visualisation of Complex Agro-Environmental Data

Lesson 04

- Testing univariate normality
- Some basics on colour coding
- Visualization of bivariate data
- Working examples and exercise





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1. Graphical methods

Histograms

If the histogram is roughly "bell-shaped", then the data can be assumed to be normally distributed.

Q-Q plots

Graphical tool for assessing whether a set of observed values come from a specific probability distribution – based on **theoretical quantiles**.

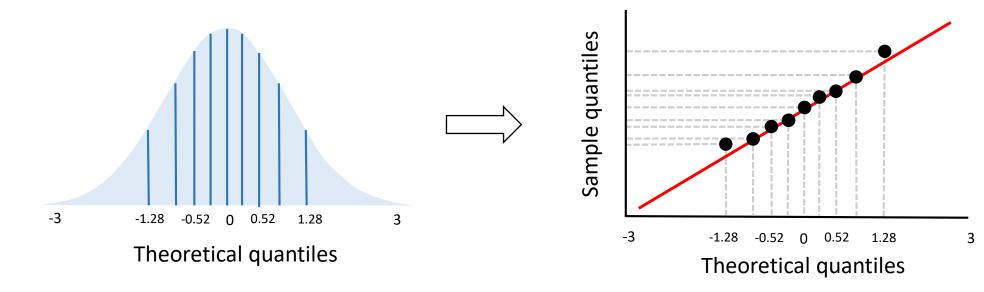
Quantiles - cutpoints dividing the range of a probability distribution into continuous intervals with equal probabilities.

Ex:

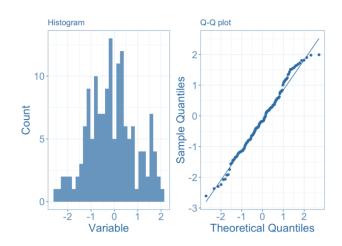
- The 2-quantile is called the median (= mean in normal distributions)
- The 4-quantiles are called quartiles

Steps to run a Q-Q Plot:

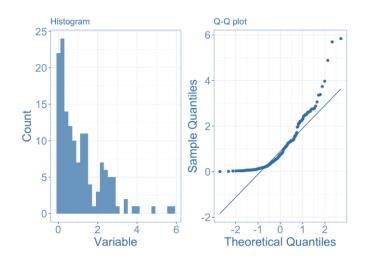
- 1. Order *n* observations from smallest to largest (sample quantiles).
- 2. Get **theoretical quantiles** (software or table) most often of a **Standard Normal Distribution** N(0,1), i.e., mean = 0 and SD = 1.
- 3. Plot observations sorted in ascending order against the theoretical quantiles
- 4. Check if data points lie along the diagonal line



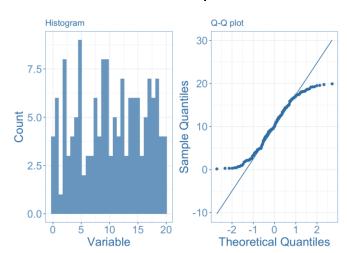
Normal



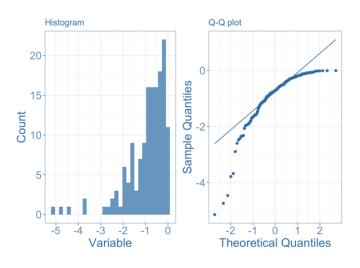
Right skewed



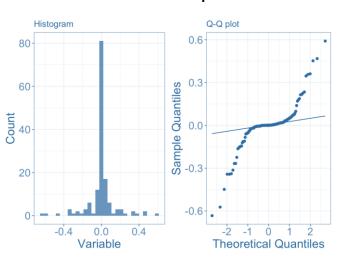
Over dispersed



Left skewed



Under dispersed



2. Normality hypothesis Testing

- Shapiro-Wilk Test
- D'Agostino's K² Test
- Kolmogorov-Smirnov Test
- Anderson-Darling Test

One-sample hypothesis tests - based on estimating the error of rejecting the null hypothesis (H_0) that observations are drawn from a normal distribution

All tests implemented in the SciPy Module for Python



Hypothesis testing – class of statistical methods used to check whether the data is compatible with a given hypothesis (H_0) , by calculating the probability of error when considered as false – it approaches the Karl Popper's concept of falsifiability (science consists in trying to prove the falsity of a hypothesis or theory).

Involves the computation of a **Statistics**, which is compared with critical values from the distribution of the test statistics, and the associated *p-level*, which is often the probability of error when rejecting H_0 . If the p-level is below a threshold (alpha), then we may reject the H_0 .

Null hypothesis

H_o: Data follows the normal distribution

Alternative hypothesis

H₁: Data do not follow the normal distribution

Test statistic



P-value

Probability of error when rejecting the null hypothesis H₀



p-value $\geq \alpha$ Rejecting H0 has an error probability $> \alpha$

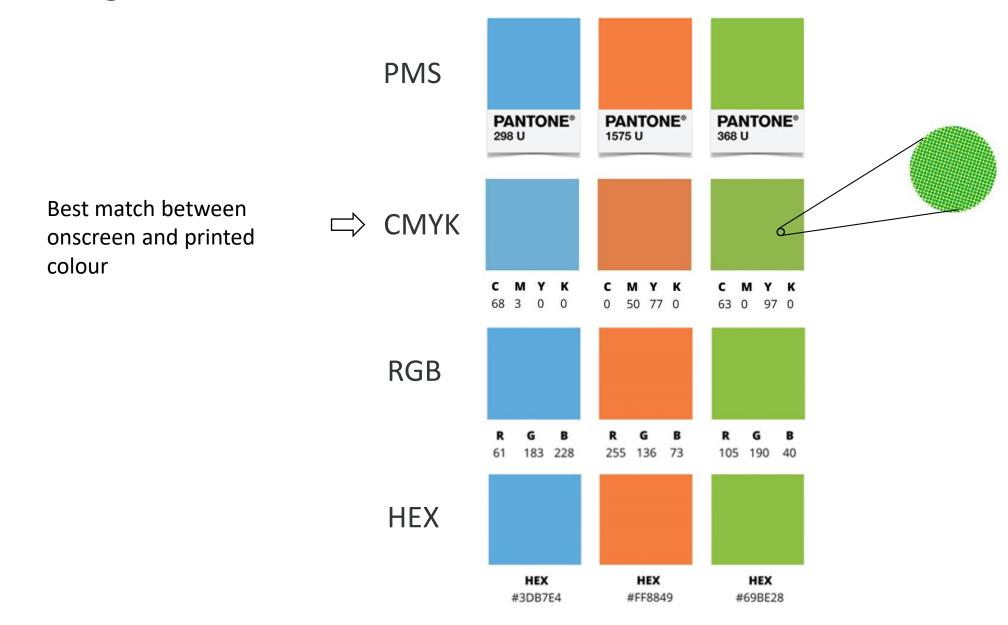
p-value $< \alpha$ Rejecting H0 has an error probability $< \alpha$

Go to: https://github.com/isa-ulisboa/greends-avcad-2024/tree/main/examples

Normality_tests.ipynb

- 1. Univariate normality tests in python
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Colour coding types	Purpose
PMS (Pantone® Matching System) Picker: https://www.pantone-colours.com/	
CMYK (cyan, magenta, yellow, black) Picker: https://www.w3schools.com/colors/colors cmyk.asp	Print
RGB/RGBA (Red, Green, Blue and Alpha) Picker: https://rgbacolorpicker.com/	
HEX (hexadecimal colour) Picker: https://www.hexcolortool.com/	Onscreen
HSL (Hue, Saturation, Lightness) Picker: https://www.w3schools.com/colors/colors-hsl.asp	



HEX coding

(Hexadecimal scale -16 as the base value):

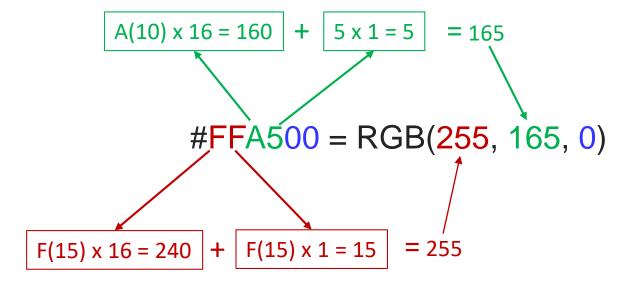
The code usually starts with a # followed by:

Value	Code
1-9:	1-9
>9:	A=10
	B=11
	C=12
	D=13
	E=14
	F=15

Converting HEX to RGB

(Hexadecimal to decimal scale)

Ex: Orange - #FFA500



HSL coding – the most perceptive way of decomposing colour

Hue palletes – *colour* component – adequate to represent **nominal categorical variables**



Saturation palletes – *colourfulness* component – adequate to represent **variable importance**



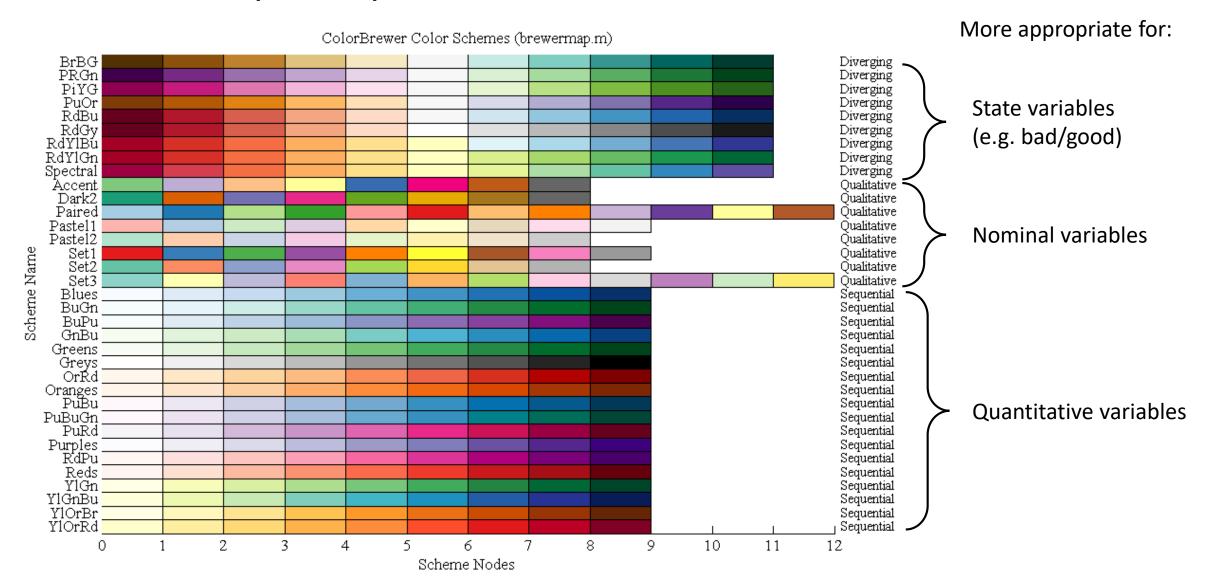
Lightness palletes – *light* component – adequate to represent **intensity** - **quantitative variables**



Colour names



Palete names (Seaborn)



Check more info here:

Colours Tutorial

https://www.w3schools.com/colors/default.asp

Colours in matplotlib

https://matplotlib.org/stable/tutorials/colors/colors.html

https://matplotlib.org/stable/tutorials/colors/colormaps.html

Understanding HEX coding scheme

https://www.pluralsight.com/blog/tutorials/understanding-hexadecimal-colors-simple

A colour picker (copy paste to the python code)

https://coolors.co/palettes/trending

Choosing colour palettes

https://seaborn.pydata.org/tutorial/color_palettes.html

Colours – some basics

Check github: https://github.com/isa-ulisboa/greends-avcad-2024/tree/main/examples

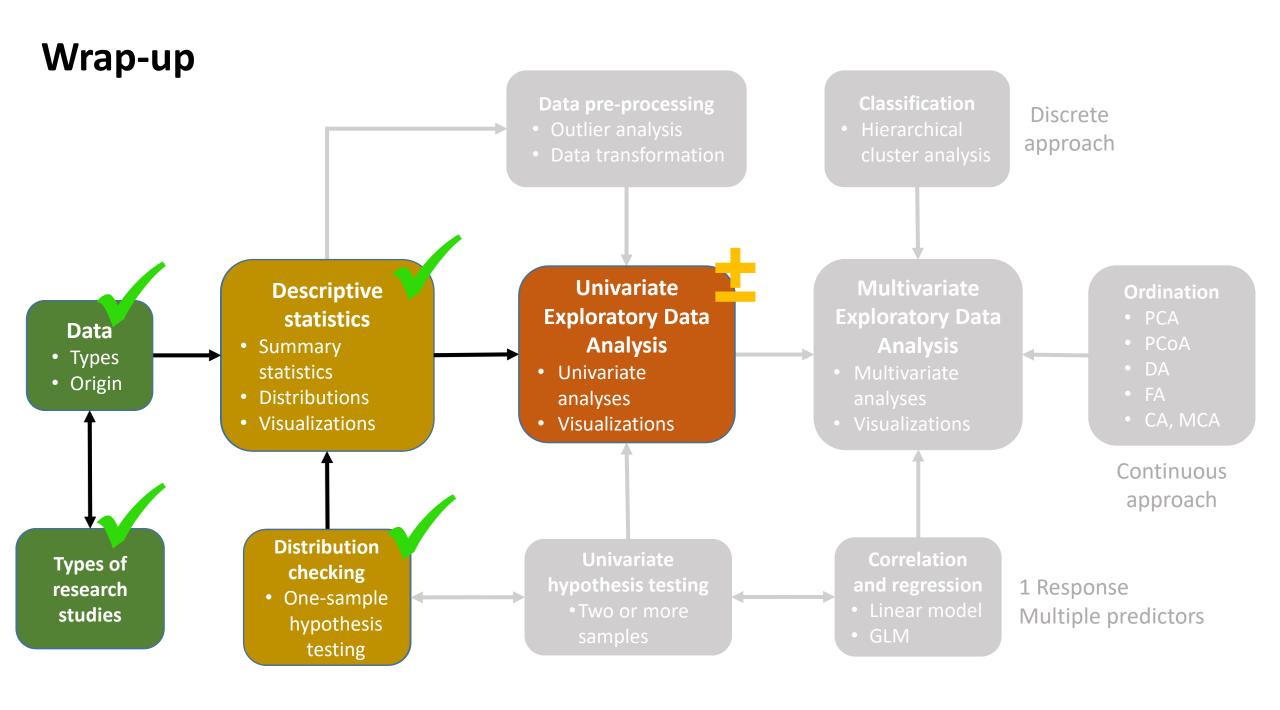
Colors.ipynb

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Bivariate analysis and visualization

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Bivariate_visuals.ipynb



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Exercise 4

In this exercise you will use the dataset in EFIplus_medit.zip to:

- 1. Using an appropriate visualization, explore how Mean Annual Temperature (Temp_ann) may affect the presence of *Salmo trutta fario* (Brown Trout).
- 2. Check the same effect but now separately for Minho and in the Tagus catchments and comparing the "effect sizes".
- 3. Test, using both visualization and hypothesis testing methods, if the actual_river_slope is drawn from a normal distribution.
- 4. Take 100 samples of 2000 observations with replacement, compute the mean for each sample and plot the resulting histogram of means. Test if these 100 mean values are drawn from a normal distribution.