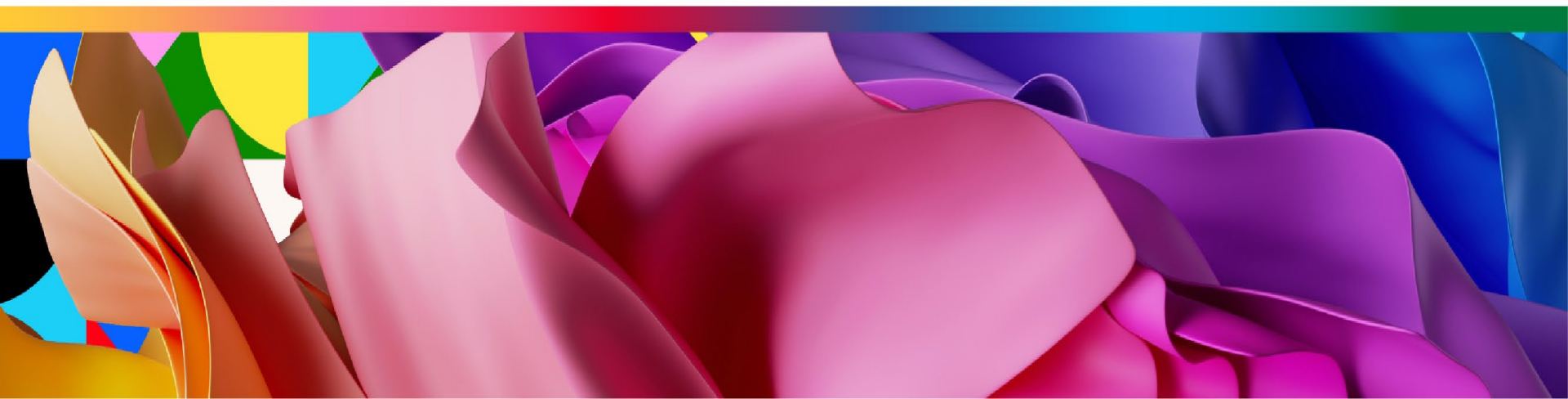


Data Visualisation for Beginners using R

Odile Harrison, Tatum Mortimer & Smritee Dabee

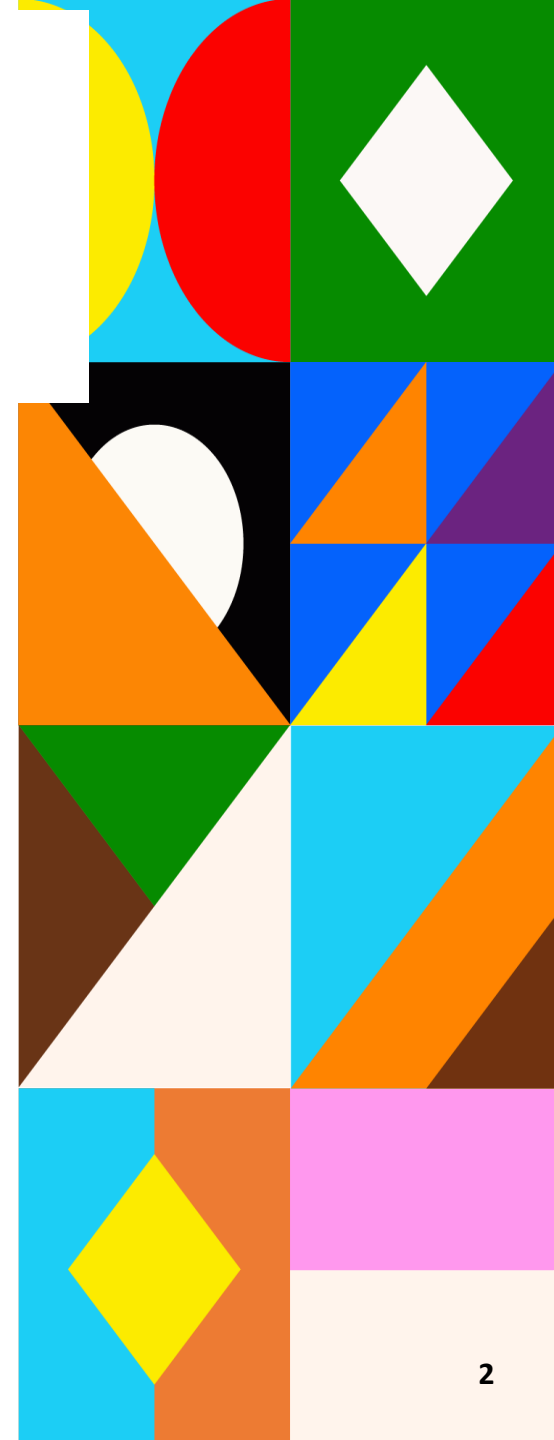
Wednesday 30th July 2025





Workshop Objectives:

- Understand why Data Visualisation is important
- What are good (and bad) visualisation practices
- Gain hands-on experience in generating publication ready figures using R












Data Visualisation: Transforms non-visual big data in a visual form

- Allows information to be rapidly understood
- Detects patterns and relationships within and between data
- Ensures you get your message across



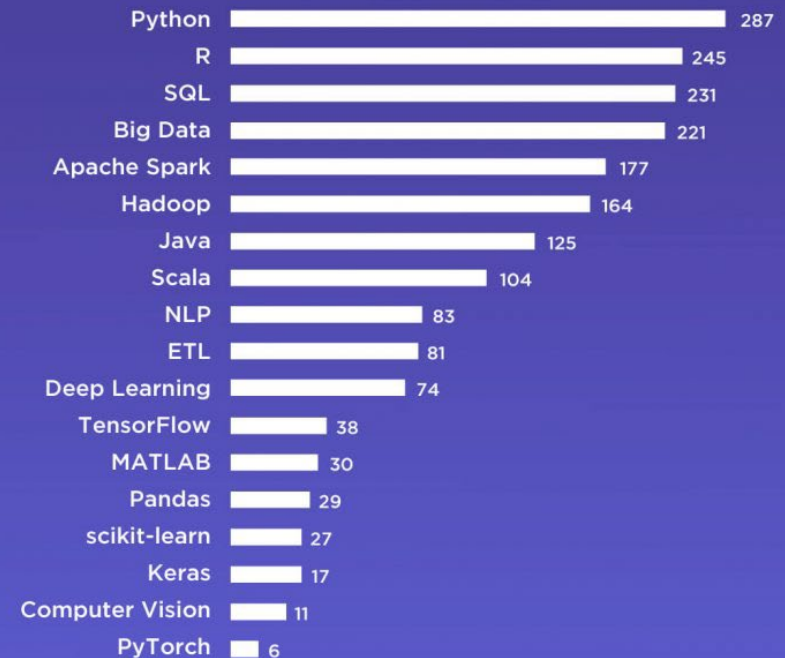
Top 5 Creative Data Visualization Examples for Data Analysis

Data Visualisation tools

Programming Language	Data Science Tasks Each Performs
 python™	<ul style="list-style-type: none"> Conducts data mining Carries out ML algorithms
 R	<ul style="list-style-type: none"> Performs data visualization Conducts Data Analytics
 Scala	<ul style="list-style-type: none"> Eases the performance on high datasets Sculpts data in any given form
 julia	<ul style="list-style-type: none"> Solves mathematical complications at high speed Performs Data Analytics
 Java	<ul style="list-style-type: none"> Wise option for IoT and Big Data Secure enough to work with sensitive data
 SQL	<ul style="list-style-type: none"> Manages large databases Compliant toward Data Science workflow
 MATLAB	<ul style="list-style-type: none"> Performs profound mathematical operations Highly specialized in working with Big Data
JavaScript	<ul style="list-style-type: none"> Sets up data visualizations perfectly Good fit for projects based on web and Big Data technologies
 sas	<ul style="list-style-type: none"> Manipulates and manages data Administers data analysis through statistical models
 C	<ul style="list-style-type: none"> Used in Big Data in collaboration with Java Computes large datasets quickly

The skills Data Scientists need today

(based on 300 job listings from tech companies in June 2019)



Jelvix

Source: CV Compiler

jelvix.com

Online and/or commercial tools

RAWGraphs (<https://www.rawgraphs.io/>)



Tableau



Microsoft 365

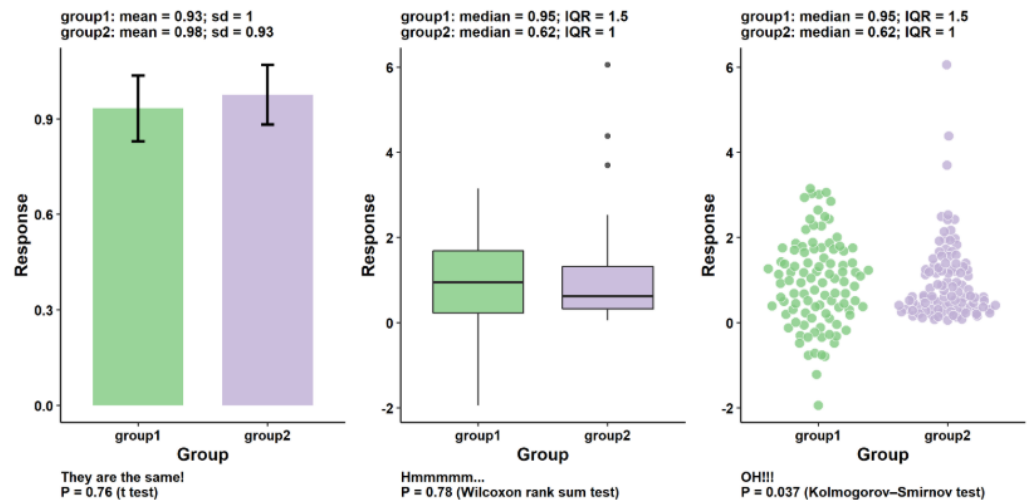
Power BI

Good (and bad) visualisation

Two or more groups with multiple observations. The task of the visualization is to show the means and the spread (dispersion) of the data.

Good visualisation should be:

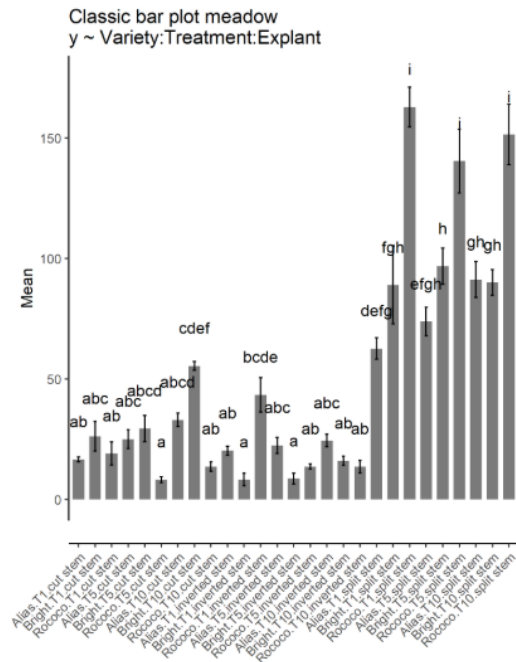
- Easy to interpret and read
- Highlight hidden insights to support your data
- Appeal to your audience
- Display massive insights using limited space



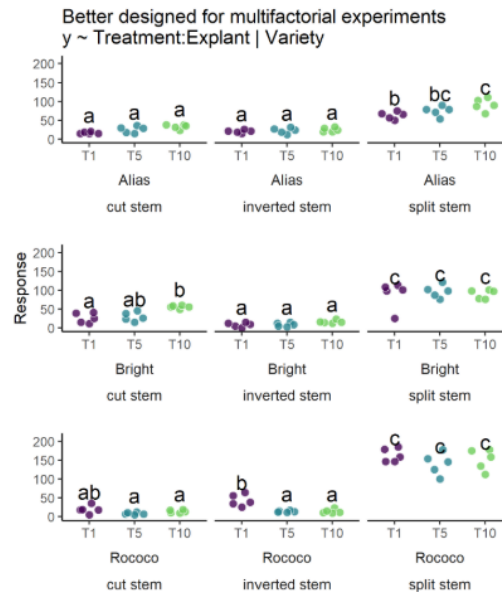
[Weissgerber et al., 2015, PLOS Biology](#). Paper describes limitations of bar charts

Check this resource: [GitHub - cxli233/FriendsDontLetFriends: Friends don't let friends make certain types of data visualization - What are they and why are they bad.](#)

Good (and bad) visualisation



This is horrendous.
What am I looking at?

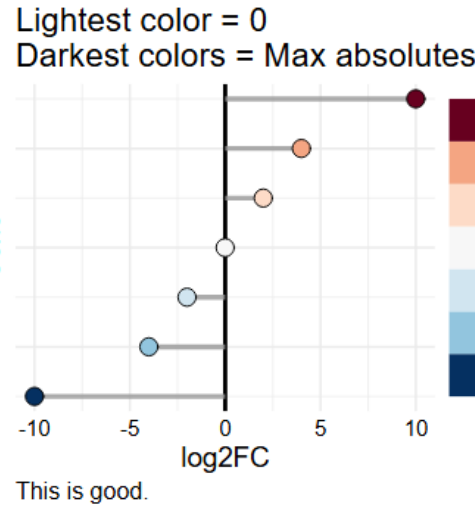
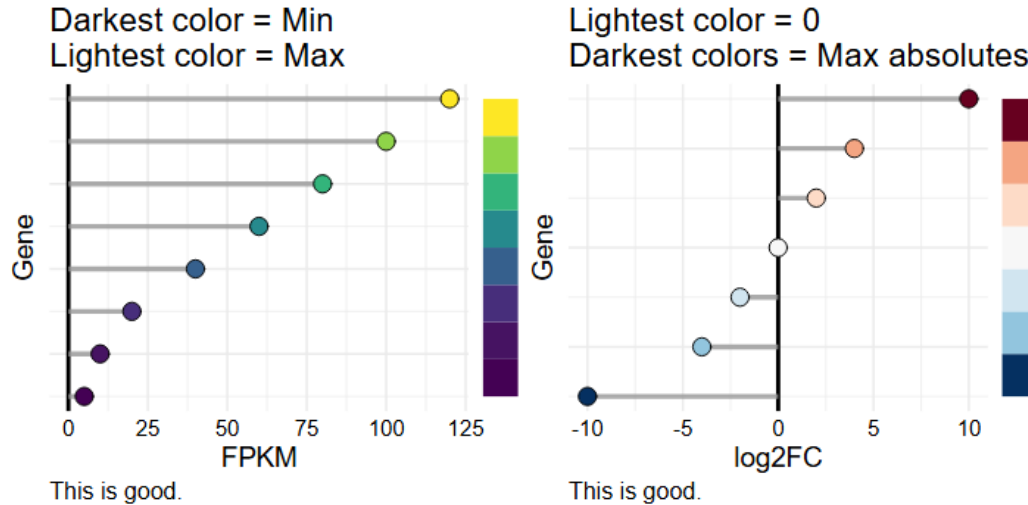


That's better.
Reader's attention is more focused.

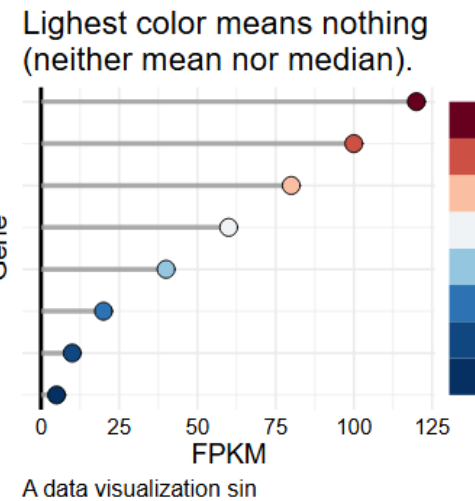
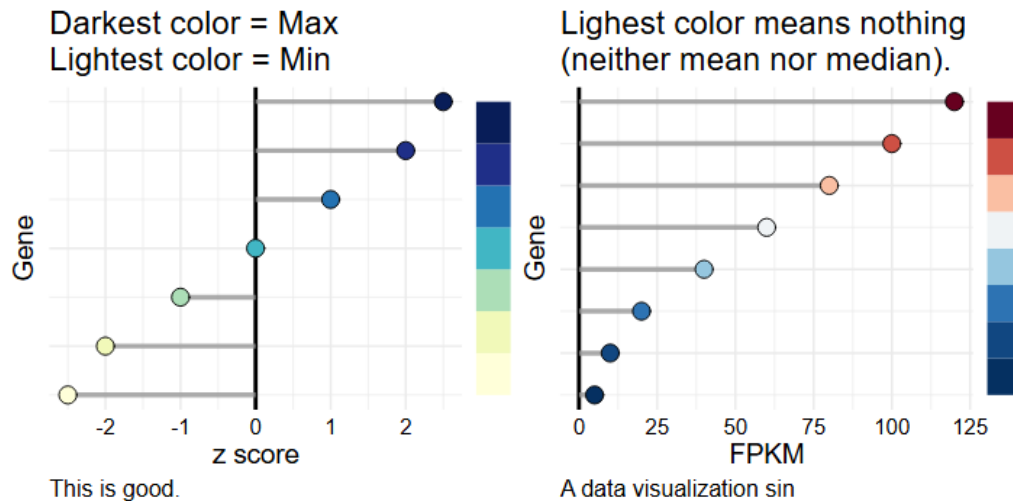
Bar plot meadows are common for multi-factorial experiments. However, a bar plot meadow is poorly designed for its purpose. To communicate results of a multi-factorial experiment, it requires thoughtful designs regarding grouping/faceting by factors of interest.

Matand et al., 2020, BMC Plant Biology

Good (and bad) visualisation



Think carefully about colour scales in figures. They should represent something meaningful.



Common applications of R

- I have two datasets, and I want to merge them
- I have a very large file (Excel can't open) how do I select a few columns to work with?
- Data transformations
- Data cleaning
- Statistical analysis
- Visualizations: how to I generate publication ready plots?
- Spatial analysis: creating maps
- Dashboards and interactive interfaces

How to get started

Step 1: Downloading & Install R (<https://cran.r-project.org/>)

The Comprehensive R Archive Network

Download and Install R

Precompiled binary distributions of the base system and contributed packages, **Windows and Mac** users most likely want one of these versions of R:

- [Download R for Linux](#) ([Debian](#), [Fedora/Redhat](#), [Ubuntu](#))
- [Download R for macOS](#)
- [Download R for Windows](#)

Step 2: Download and install R studio (user interface) (<https://posit.co/download/rstudio-desktop/>)

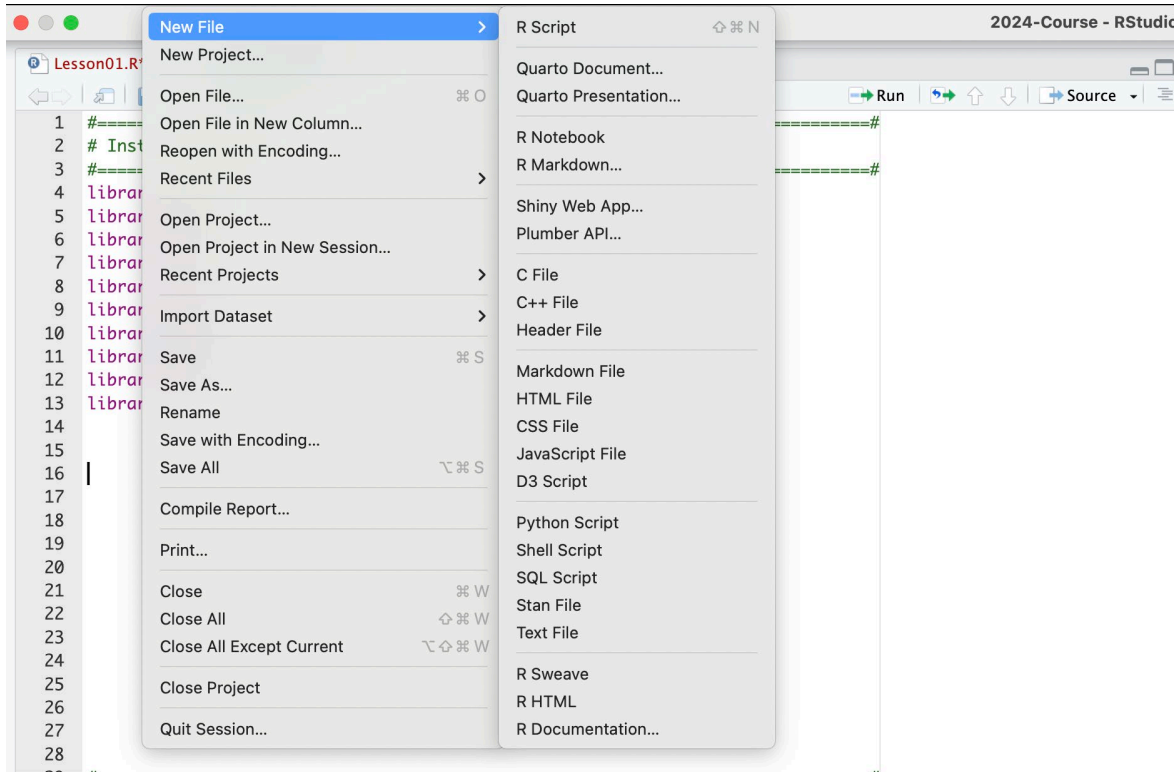
OS	Download	Size
Windows 10/11	RSTUDIO-2025.05.1-513.EXE ↕	281.24 MB
macOS 13+	RSTUDIO-2025.05.1-513.DMG ↕	607.30 MB
Ubuntu 22/Debian 12	RSTUDIO-2025.05.1-513-AMD64.DEB ↕	209.78 MB
Ubuntu 24	RSTUDIO-2025.05.1-513-AMD64.DEB ↕	209.78 MB
Fedora 41	RSTUDIO-2025.05.1-513-X86_64.RPM ↕	224.98 MB

Navigating the R console

The screenshot shows the RStudio interface with four main panels. Annotations are placed over these panels to identify their functions:

- Console:** A box labeled "Console: script output panel" is placed over the top-left panel, which displays the output of R commands.
- Data, Objects:** A box labeled "Data, Objects" is placed over the top-right panel, which shows the Environment pane listing loaded objects and their types.
- Editor:** A box labeled "Editor" is placed over the bottom-left panel, which contains the R script code.
- Files, Plots, Package help:** A box labeled "Files, Plots, Package help" is placed over the bottom-right panel, which contains the Files, Plots, Packages, and Help panes.

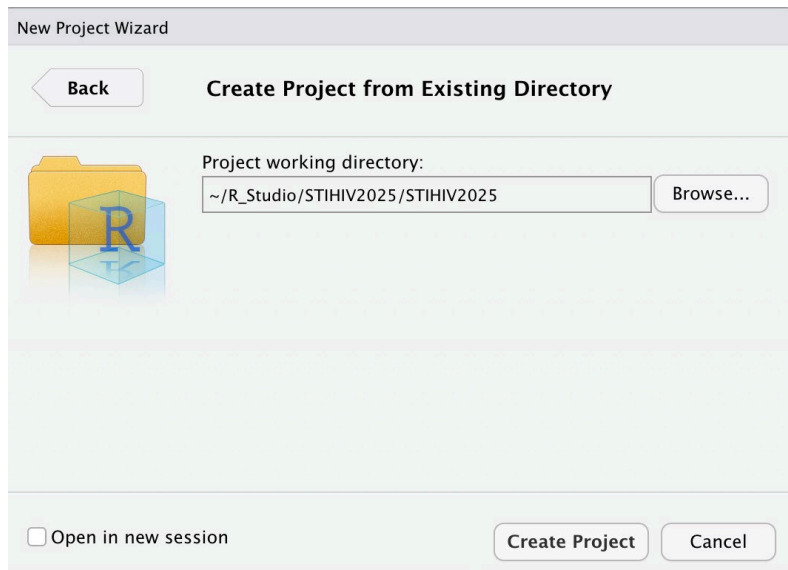
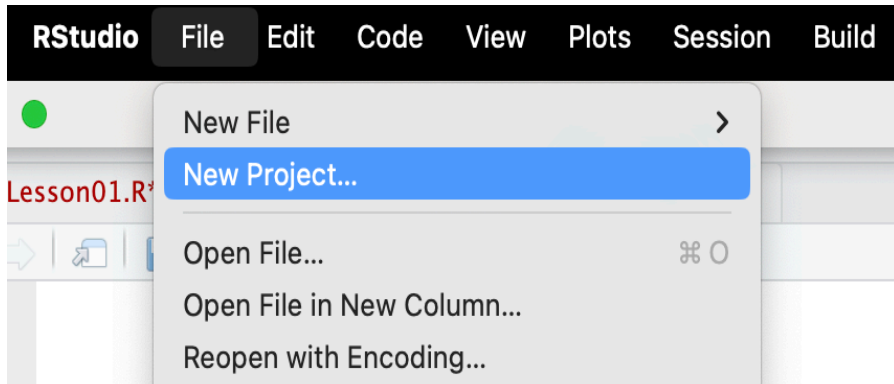
R studio



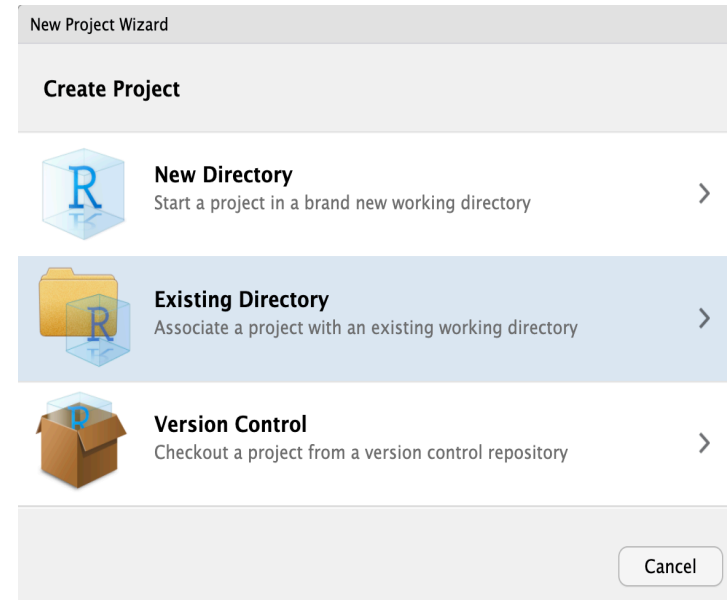
R studio: User interface, Customizable interface, Code autocompletion, write code in other languages

Creating an R project and/or saving your work

Step 1



Step 2



Basic but Important Commands

1. **#** - not a command, but used for commenting code

2. Installing and loading packages:

install.packages("name_of_package") then **library(name_of_package)**

```
# Installing the required packages  
install.packages("") # all required packages have been pre-installed
```

```
# Loading required libraries  
library(data.table)  
library(dplyr)
```


3. Use the function **search()** to know which packages have been loaded

4. Use **setwd()** & **getwd()** to set working directory etc

Files used in the course

[GitHub - mortimer-lab/STIHIV2025 ECR DataViz: Resources for the Data Visualization Workshop at STI HIV 2025](#)

Download Course_data

[STIHIV2025_ECR_DataViz](#) / [data](#) / [CDC_STI_Surveillance_2023.csv](#) 



 **tatumdmortimer** changed encoding from windows to UTF-8

c0a0724 • last month  History

Preview

Code

Blame

84 lines (84 loc) • 9.18 KB

Raw



Exploring Data using R

[GitHub - mortimer-lab/STIHIV2025 ECR DataViz: Resources for the Data Visualization Workshop at STI HIV 2025](https://github.com/mortimer-lab/STIHIV2025_ECR_DataViz)

1. Download Course_data: African_meningococci.csv
2. Load the dataset in R:

```
data_01_africa <- read.csv("data/African_meningococci.csv")
```


View and understand your data

```
#=====
# 1. to know the structure of your data
str(data_01_Africa)
```

OR

```
glimpse(data_01_Africa)
```

```
#=====
# 2. view the column names
names(data_01_Africa)
```

OR

```
colnames(data_01_Africa)
```

..

```
#=====
# 3. tidy up the column names.
data_02_Africa <- clean_names(data_01_Africa)

# confirm that the names of the columns have changed
names(data_01_Africa)
names(data_02_Africa)
```

```
#=====
# 4. To view the first top rows - by default will view 6
data_03_Africa <- head(data_01_Africa)
```

```
#=====
# 5. To view the bottom rows - by default will view the last 6
data_04_Africa <- tail(data_01_Africa)
```

```
#=====
# 6. Selecting columns
data_01_subset <- select(data_01_Africa, id, isolate, country)
```

OR (remove certain columns)

```
data_02_subset <- select(data_01_Africa, -id, -isolate)
```

```
#=====
# 7. Filtering rows
```

```
Nigeria <- filter(data_01_Africa, country == "Nigeria")
```

```
#=====
# 8. Number of samples in each country
table(data_01_Africa$country)
```

Can you answer these?

1. The number of samples in each year? [hint: table]
2. The number of samples in each serogroup?
3. The number of samples collected in each year only in Togo?
[hint: filter then table]

Answers

1. The number of samples in each year? [hint: table]

```
> Table(data_01_Africa$year
```

2011	2012	2013	2014	2015	2016
115	272	60	26	158	85

2. The number of samples in each serogroup?

```
> Table(data_01_Africa$serogroup
```

A	C	NG	W	X	Y
90	124	8	431	61	2

3. The number of samples collected in each year only in Togo?
[hint: filter then table]

```
> TOGO <- filter(data_01_Africa, country == "Togo")
> Table(TOGO$year)
```

2014	2015	2016
16	12	42

Too many variables

- Pipe operator to link commands: %>%
- Can I clean col names, select, filter all in one variable and run once?

```
#=====#  
# remove all the data frames loaded except the data_01_Africa  
rm(data_02_Africa, data_03_Africa, data_04_Africa, Nigeria, data_01_subset, data_02_subset)
```

9. clean names

```
data_02_Africa <- data_01_Africa %>%  
  clean_names()
```

10. clean names | selecting columns

```
data_02_Africa <- data_01_Africa %>%  
  clean_names() %>%  
  select(id, isolate, year, country)
```

11. clean names | selecting columns | Filter only "Burkina Faso"

```
data_02_Africa <- data_01_Africa %>%  
  clean_names() %>%  
  select(id, isolate, year, country) %>%  
  filter(country == "Burkina Faso")
```

Grouping and summarizing data

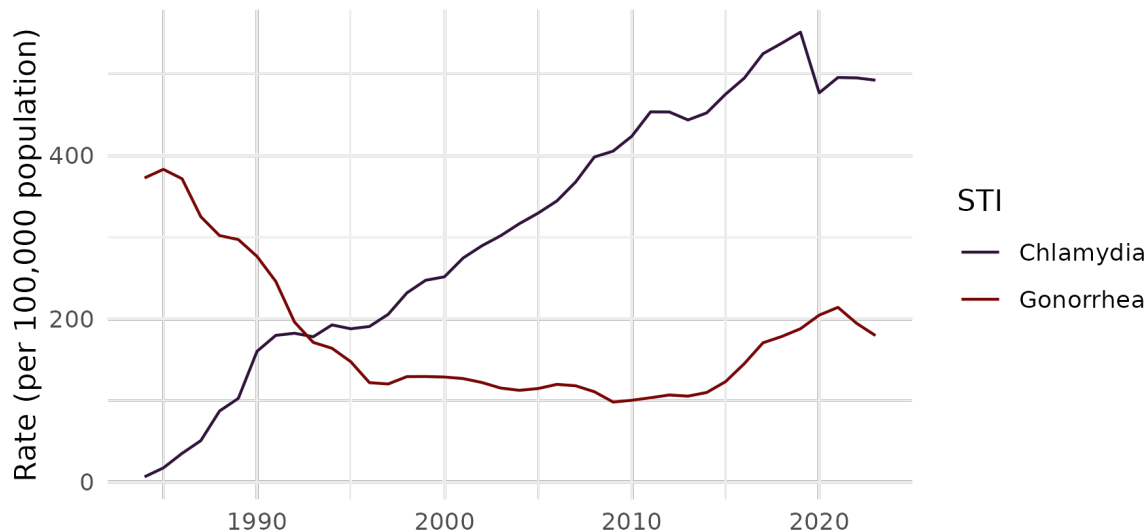
- **group_by** and **summarise** function

```
#=====
# 12. Number of samples identified per year per country
data_03_Africa <- data_01_Africa %>%
  clean_names() %>%
  group_by(country, year) %>%
  summarise(n())
```

country	year	count
Benin	2012	41
Burkina Faso	2012	167
Burkina Faso	2011	41
Burkina Faso	2013	20
Burkina Faso	2015	11
Burkina Faso	2016	5
Burkina Faso	2014	4
Cameroon	2012	4
Central African Republic	2016	23
Central African Republic	2015	7

```
# 13. Number of samples identified by country and clonal complex proportions
data_04_Africa <- data_01_Africa %>%
  clean_names() %>%
  group_by(country, clonal_complex_mlst) %>%
  summarise(count = n()) %>%
  mutate(prop = count/sum(count) *100)
```

STI Surveillance: Line Plot



Packages used

- tidyverse: collection of packages includes dplyr and ggplot2
- janitor: cleaning
- viridis: colorblind-friendly color palettes



Input Data

Table 1. Sexually Transmitted Infections — Reported Cases and Rates of Reported Cases*, United States

DATA TABLES FROM STI SURVEILLANCE, 2023 | PAGE 1 OF 37 | ALL PAGES ↓

 For Everyone
NOVEMBER 12, 2024

ABOUT

The table below is from *Sexually Transmitted Infections Surveillance, 2023*.

1941–2023

Year†	Syphilis										Gonorrhea		Chlamydia		Chancroid¶	
	Total Syphilis‡		Congenital		Primary and Secondary		Early Non-Primary Non-Secondary§		Unknown Duration or Late§							
	Cases	Rate	Cases	Rate	Cases	Rate	Cases	Rate	Cases	Rate	Cases	Rate	Cases	Rate	Cases	Rate
1941	485,560	368.2	17,600	651.1	68,231	51.7	109,018	82.6	202,984	153.9	193,468	146.7	NR	—	3,384	2.5
1942	479,601	363.4	16,918	566.0	75,312	57.0	116,245	88.0	202,064	153.1	212,403	160.9	NR	—	5,477	4.1
1943	575,593	447.0	16,164	520.7	82,204	63.8	149,390	116.0	251,958	195.7	275,070	213.6	NR	—	8,354	6.4

Reading and Cleaning Input Data

```
# read input data
# Table 1 from CDC's Sexually Transmitted Surveillance, 2023. Found here: https://www.cdc.gov/std/surveillance/
# na = c("NR", "-") converts not reported designations from the table to NA
sti_surveillance <- read_csv("data/CDC_STI_Surveillance_2023.csv", na = c("NR", "-"))
```

```
# clean up column names with janitor package
sti_surveillance_clean <- sti_surveillance %>% clean_names()
```

```
# Compare the column names before and after using the command clean_names
colnames(sti_surveillance)
colnames(sti_surveillance_clean)
```

```
> colnames(sti_surveillance)
[1] "Year"
[4] "Congenital Syphilis Cases"
[7] "Primary and Secondary Syphilis Rate"
[10] "Unknown Duration or Late Syphilis Cases"
[13] "Gonorrhea Rate"
[16] "Chancroid Cases"
> colnames(sti_surveillance_clean)
[1] "year"
[4] "congenital_syphilis_cases"
[7] "primary_and_secondary_syphilis_rate"
[10] "unknown_duration_or_late_syphilis_cases"
[13] "gonorrhea_rate"
[16] "chancroid_cases"

"Total Syphilis Cases"
"Congenital Syphilis Rate"
"Early Non-Primary Non-Secondary Syphilis Cases"
"Unknown Duration or Late Syphilis Rate"
"Chlamydia Cases"
"Chancroid Rate"

"Total Syphilis Rate"
"Primary and Secondary Syphilis Cases"
"Early Non-Primary Non-Secondary Syphilis Rate"
"Gonorrhea Cases"
"Chlamydia Rate"

"total_syphilis_cases"
"congenital_syphilis_rate"
"early_non_primary_non_secondary_syphilis_cases"
"unknown_duration_or_late_syphilis_rate"
"chlamydia_cases"
"chancroid_rate"

"total_syphilis_rate"
"primary_and_secondary_syphilis_cases"
"early_non_primary_non_secondary_syphilis_rate"
"gonorrhea_cases"
"chlamydia_rate"
```

Reformatting Clean Data

```
# select columns we are interested in
gc_ct_surveillance <- sti_surveillance %>% select(year, gonorrhea_rate, chlamydia_rate)

# filter to years with both gonorrhea and chlamydia rates
gc_ct_surveillance <- gc_ct_surveillance %>% drop_na()

# some figures require the data to be in the `long` format (rather than the `wide` format)
gc_ct_surveillance_long <- gc_ct_surveillance %>%
  rename(Gonorrhea = gonorrhea_rate, Chlamydia = chlamydia_rate) %>%
  pivot_longer(-year, names_to = "STI", values_to = "rate")
```

```
> gc_ct_surveillance
```

```
# A tibble: 40 × 3
```

	year <dbl>	gonorrhea_rate <dbl>	chlamydia_rate <dbl>
1	1984	372.	6.5
2	1985	383	17.4
3	1986	372.	35.2
4	1987	325	50.8
5	1988	302.	87.1
6	1989	297.	102.
7	1990	276.	160.
8	1991	246.	180.
9	1992	196	182.
10	1993	171.	178

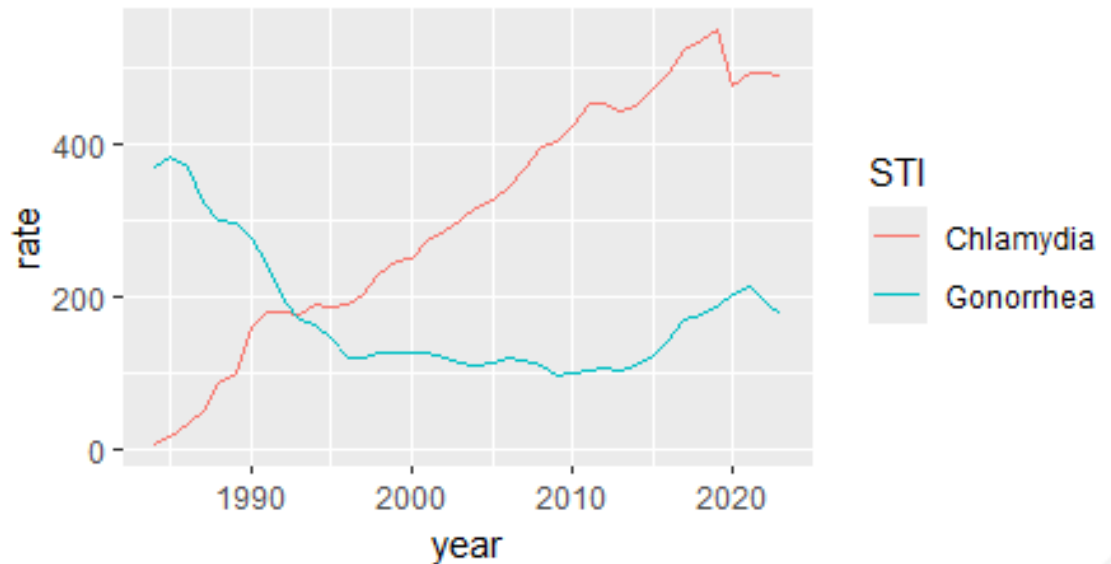
```
> gc_ct_surveillance_long
```

```
# A tibble: 80 × 3
```

	year <dbl>	STI <chr>	rate <dbl>
1	1984	Gonorrhea	372.
2	1984	Chlamydia	6.5
3	1985	Gonorrhea	383
4	1985	Chlamydia	17.4
5	1986	Gonorrhea	372.
6	1986	Chlamydia	35.2
7	1987	Gonorrhea	325
8	1987	Chlamydia	50.8
9	1988	Gonorrhea	302.
10	1988	Chlamydia	87.1

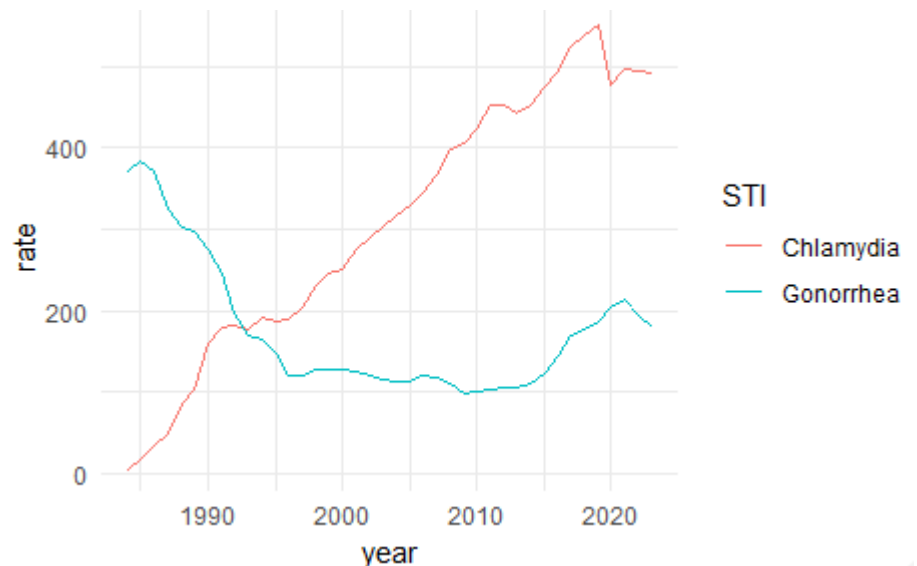
Minimal Plot

```
plot <- gc_ct_surveillance_long %>%  
  ggplot(aes(x=year, y=rate, color=STI)) +  
  geom_line()
```



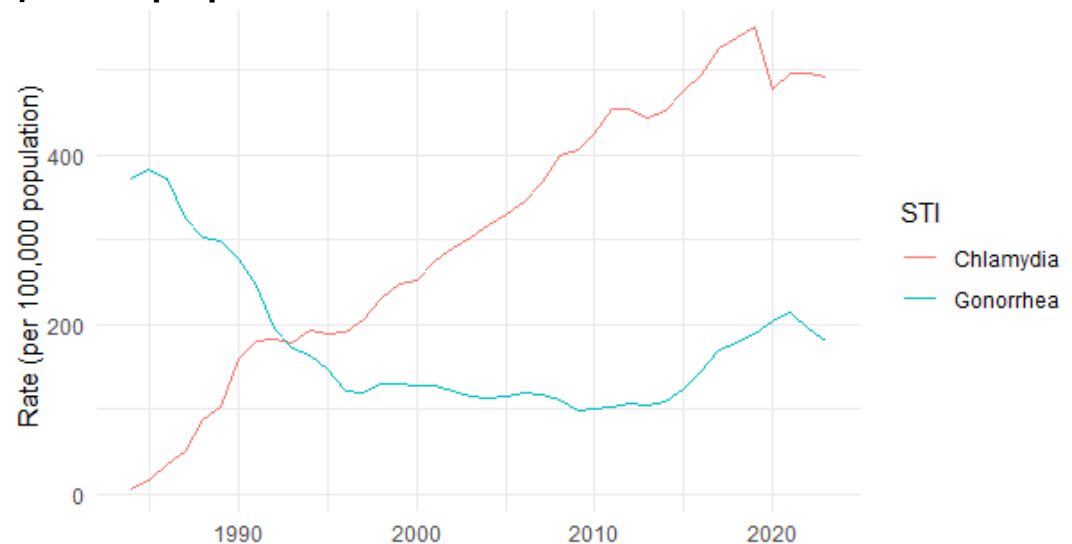
Adjusting Theme

```
plot <- gc_ct_surveillance_long %>%  
  ggplot(aes(x=year, y=rate, color=STI)) +  
  geom_line() + theme_minimal()
```



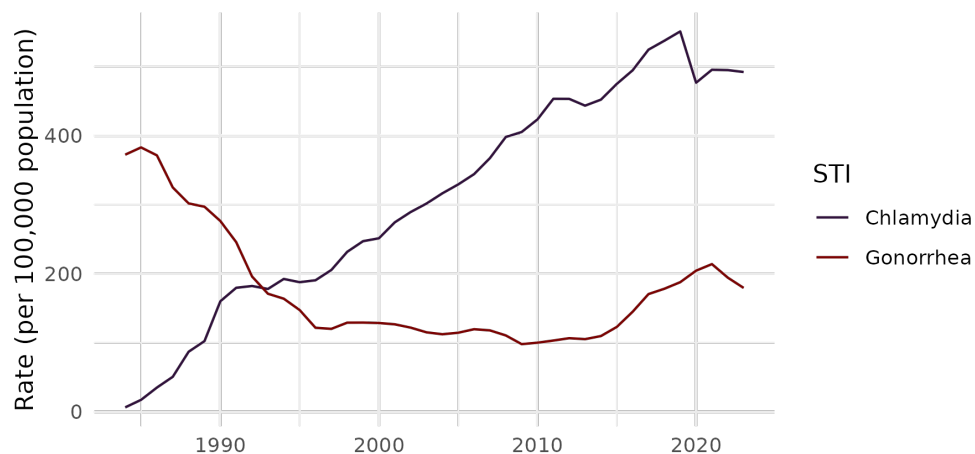
Changing Axis Labels

```
plot <- gc_ct_surveillance_long %>%  
  ggplot(aes(x=year, y=rate, color=STI)) +  
  geom_line() +  
  theme_minimal() +  
  ylab("Rate (per 100,000 population)") +  
  xlab("")
```

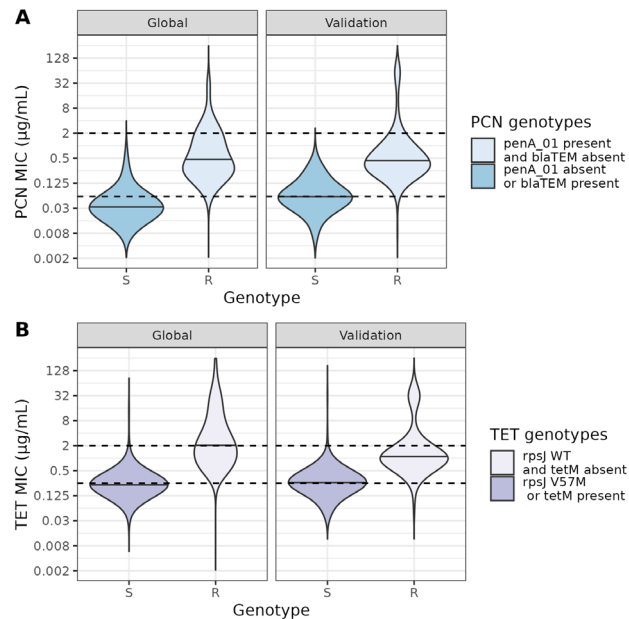


Changing Color Scheme

```
plot <- gc_ct_surveillance_long %>%  
  ggplot(aes(x=year, y=rate, color=STI)) +  
  geom_line() +  
  theme_minimal() +  
  ylab("Rate (per 100,000 population)") +  
  xlab("") +  
  scale_color_viridis(discrete = "T", option = "turbo")
```

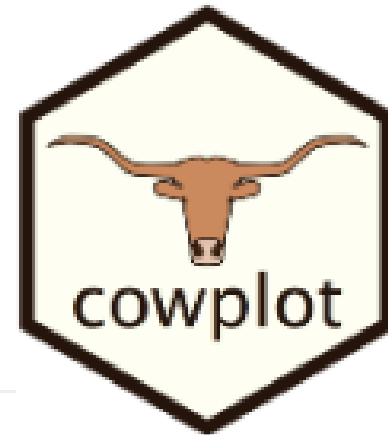


Antimicrobial Susceptibility: Violin Plot



New Packages

- cowplot: plot annotation



Input Data

Loci for prediction of penicillin and tetracycline susceptibility
in *Neisseria gonorrhoeae*: a genome-wide association study

Tatum D Mortimer, Jessica J Zhang*, Kevin C Ma, Yonatan H Grad*

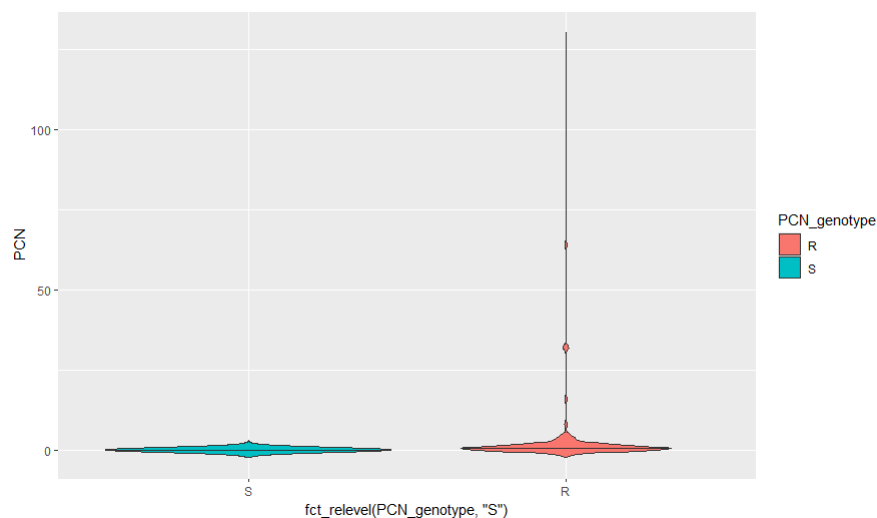
Reading and Cleaning Input Data

```
metadata_pcn <- read_csv("data/MortimerZhang2022_penicillin_genotypes_phenotypes.csv")
metadata_tet <- read_csv("data/MortimerZhang2022_tetracycline_genotypes_phenotypes.csv")
view(metadata_pcn)
glimpse(metadata_pcn)
```

```
> glimpse(metadata_pcn) # Basic information about the data structure
Rows: 8,345
Columns: 10
$ wgs_id          <chr> "SRR1661153", "SRR1661154", "SRR1661155", "SRR1661156", "SRR1661157", "SRR1661158", "SRR1...
$ reference       <chr> "Demczuk2015", "Demczuk2015", "Demczuk2015", "Demczuk2015", "Demczuk2015", "Demczuk2015", ...
$ penA_01        <dbl> 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
$ blaTEM         <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ...
$ penA_id        <dbl> 4, 13, 9, 17, 4, 10, 100, 10, 40, 4, 10, 4, 10, 9, 1, 22, 34, 12, 43, 22, 27, 27, 12, 5, ...
$ penA_description <chr> "penA Type IV NonMosaic; A517G, G543S", "penA Type XIII NonMosaic; A501V, A517G", "penA T...
$ PCN_genotype   <chr> "R", "R", "R", "R", "R", "R", "S", "R", "R", "R", "R", "R", "R", "R", "R", "R", "R", "R", "R", "R", ...
$ PCN            <dbl> 4.000, 2.000, 2.000, 2.000, 4.000, 4.000, 0.008, 4.000, 0.063, 4.000, 4.000, 2.000, 4.000...
$ PCN_interpretation <chr> "R", "R", "R", "R", "R", "R", "S", "R", "S", "R", "R", "R", "R", "R", "I", "I", "R", "I", ...
$ dataset        <chr> "Global", "Global", "Global", "Global", "Global", "Global", "Global", "Global", "Global", "Global", ...
```

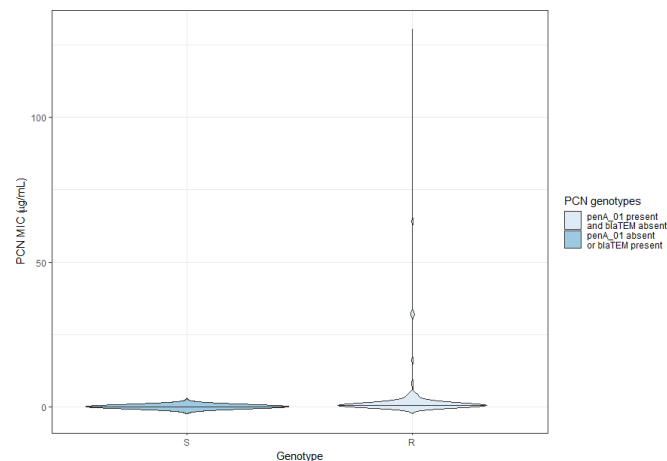
Minimal Plot

```
pcn_plot <- metadata_pcn %>%  
  ggplot(aes(x = fct_relevel(PCN_genotype, "S"),  
             y = PCN,  
             fill = PCN_genotype)) +  
  geom_violin(bw=0.8, draw_quantiles=c(0.5), trim=FALSE)
```

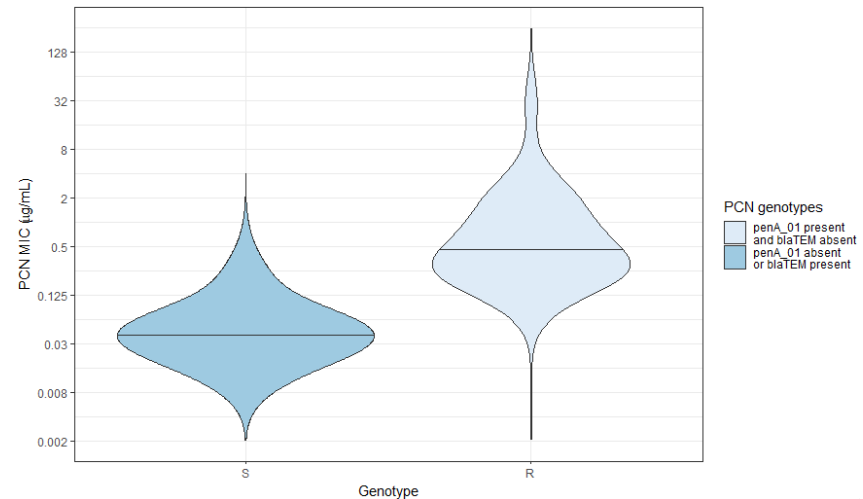


Adjusting Theme, Axis Labels, and Color Palette

```
pcn_plot <- metadata_pcn %>%
  ggplot(aes(x = fct_relevel(PCN_genotype, "S"),
    y = PCN,
    fill = PCN_genotype)) +
  geom_violin(bw=0.8, draw_quantiles=c(0.5), trim=FALSE) +
  theme_bw() +
  xlab("Genotype") +
  ylab(expression(paste("PCN MIC (", mu, "g/mL)", ))) +
  scale_fill_brewer(name = "PCN genotypes",
    labels = c("penA_01 present \nand\nblaTEM absent", "penA_01 absent \nand\nblaTEM present"))
```



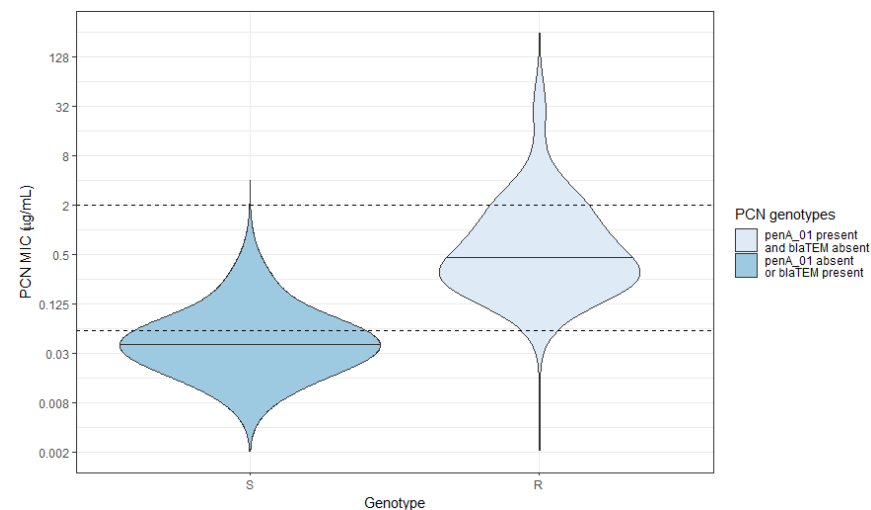
Changing Axis Scale



```
pcn_plot <- metadata_pcn %>%
  ggplot(aes(x = fct_relevel(PCN_genotype, "S"),
    y = PCN,
    fill = PCN_genotype)) +
  geom_violin(bw=0.8, draw_quantiles=c(0.5), trim=FALSE) +
  theme_bw() +
  xlab("Genotype") +
  ylab(expression(paste("PCN MIC (", mu, "g/mL)", ))) +
  scale_fill_brewer(name = "PCN genotypes",
    labels = c("penA_01 present \nand blaTEM absent", "penA_01 absent \nor
blaTEM present")) +
  scale_y_continuous(trans = 'log2',
    limits = c(0.002, 256),
    breaks = c(2^-9, 2^-7, 2^-5, 2^-3, 2^-1, 2^1, 2^3, 2^5, 2^7),
    labels = c(0.002, 0.008, 0.03, 0.125, 0.5, 2, 8, 32, 128))
```

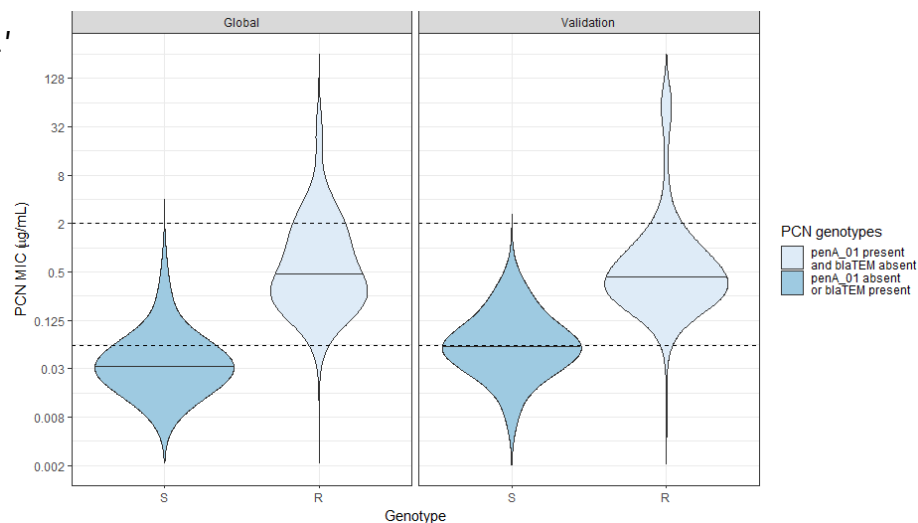
Adding Horizontal Lines

```
pcn_plot <- metadata_pcn %>%
  ggplot(aes(x = fct_relevel(PCN_genotype, "S"),
    y = PCN,
    fill = PCN_genotype)) +
  geom_violin(bw=0.8, draw_quantiles=c(0.5), trim=FALSE) +
  theme_bw() +
  xlab("Genotype") +
  ylab(expression(paste("PCN MIC (", mu, "g/mL)", ))) +
  scale_fill_brewer(name = "PCN genotypes",
    labels = c("penA_01 present \nand blaTEM absent",
      "penA_01 absent \nor blaTEM present")) +
  scale_y_continuous(trans = 'log2',
    limits = c(0.002, 256),
    breaks = c(2^-9, 2^-7, 2^-5, 2^-3, 2^-1, 2^1, 2^3, 2^5, 2^7),
    labels = c(0.002, 0.008, 0.03, 0.125, 0.5, 2, 8, 32, 128)) +
  geom_hline(yintercept = 0.06, linetype = "dashed") +
  geom_hline(yintercept = 2, linetype = "dashed")
```



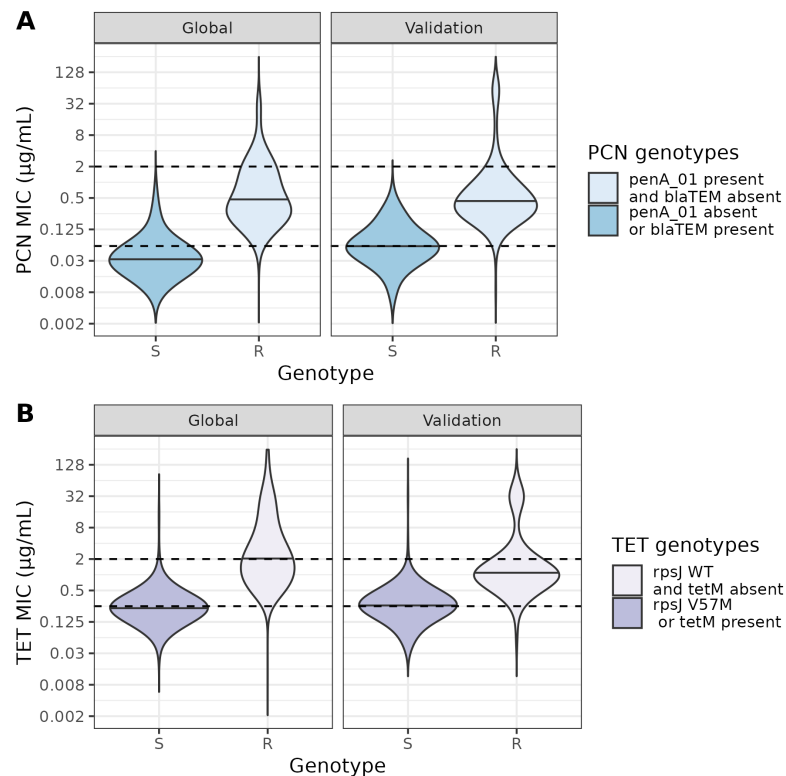
Facet by variable

```
pcn_plot <- metadata_pcn %>%
  ggplot(aes(x = fct_relevel(PCN_genotype, "S"),
    y = PCN,
    fill = PCN_genotype)) +
  geom_violin(bw=0.8, draw_quantiles=c(0.5), trim=FALSE) +
  theme_bw() +
  xlab("Genotype") +
  ylab(expression(paste("PCN MIC (", mu, "g/mL)", ))) +
  scale_fill_brewer(name = "PCN genotypes",
    labels = c("penA_01 present \nand blaTEM absent",
      "penA_01 absent \nor blaTEM present")) +
  scale_y_continuous(trans = 'log2',
    limits = c(0.002, 256),
    breaks = c(2^-9, 2^-7, 2^-5, 2^-3, 2^-1, 2^1, 2^3, 2^5, 2^7),
    labels = c(0.002, 0.008, 0.03, 0.125, 0.5, 2, 8, 32, 128)) +
  geom_hline(yintercept = 0.06, linetype = "dashed") +
  geom_hline(yintercept = 2, linetype = "dashed") +
  facet_wrap(~dataset)
```

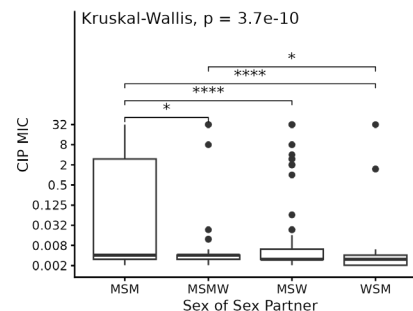
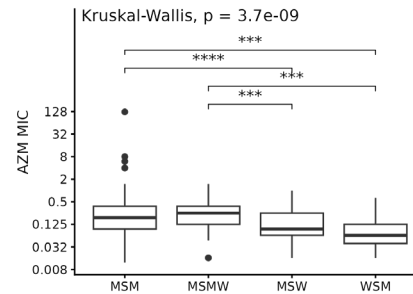
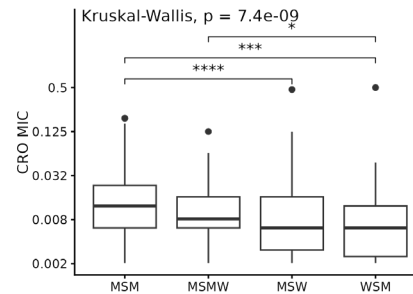


Making a multi-panel plot

```
p <- plot_grid(pcn_plot, tet_plot, labels = c("A","B"), nrow = 2)
```



AMR and Sexual Behavior: Box Plot



New Packages

- `ggpubr`: annotate plot with statistical tests

Input Data

The Distribution and Spread of Susceptible and Resistant *Neisseria gonorrhoeae* Across Demographic Groups in a Major Metropolitan Center

Tatum D. Mortimer,^{1,✉} Preeti Pathela,² Addie Crawley,² Jennifer L. Rakeman,³ Ying Lin,³ Simon R. Harris,⁴ Susan Blank,^{2,5} Julia A. Schillinger,^{2,5,a} and Yonatan H. Grad,^{1,6,a,✉}

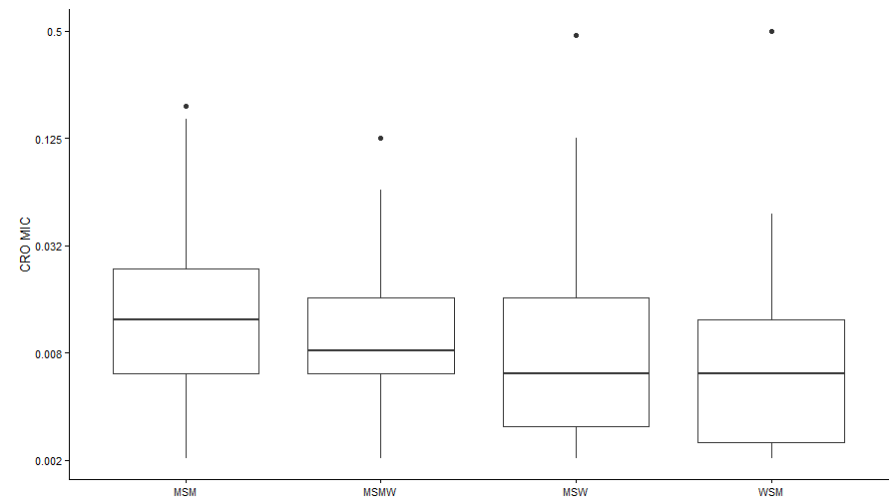
Reading Input Data and Setting Theme

```
theme_set(theme_cowplot(font_size=10))
metadata <- read_csv("data/Mortimer2020_sexualbehavior_AMR.csv")
```

```
> metadata
# A tibble: 874 × 5
  run_accession partner azithromycin ceftriaxone ciprofloxacin
  <chr>          <chr>          <dbl>         <dbl>         <dbl>
1 ERR2632001    MSM             0.19          0.004          0.003
2 ERR3200989    MSM             0.5           0.008          0.002
3 ERR3200897    MSW             0.38          0.004          0.003
4 ERR2631781    MSM             0.5           0.012          0.003
5 ERR3200986    MSM             0.5           0.012          0.003
6 ERR3200988    MSM             0.5           0.008          0.003
7 ERR3201259    MSM             0.25          0.004          0.002
8 ERR3200992    MSM             0.38          0.003          0.002
9 ERR2632019    MSM             0.19          0.008          0.003
10 ERR2631957    MSM             0.25          0.006          0.004
```

Base Plot

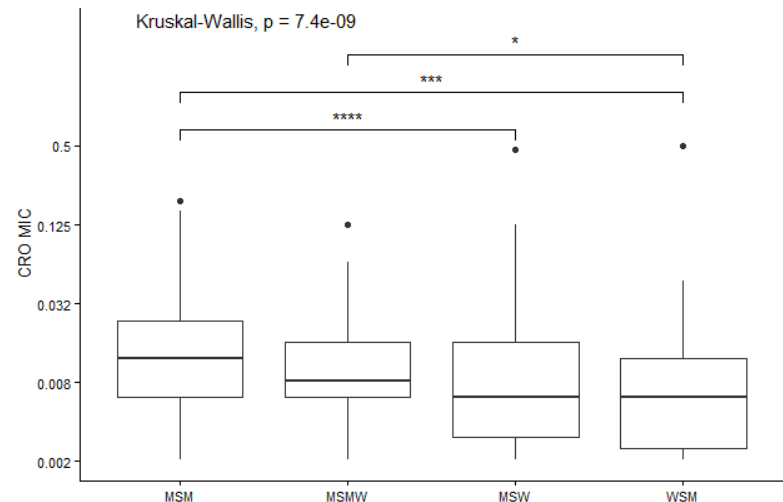
```
partner.cro <- metadata %>% ggplot(aes(x = partner, y = ceftriaxone)) +  
  geom_boxplot() +  
  scale_y_continuous(trans='log2',  
    breaks = c(2^(-9), 2^(-7), 2^(-5), 2^(-3), 2^(-1)),  
    labels = c("0.002", "0.008", "0.032", "0.125", "0.5")) +  
  labs(x = "", y = "CRO MIC")
```



Adding Statistical Comparisons

```
comparisons.cro <- list(c("MSM", "MSW"), c("MSM", "WSM"), c("MSMW", "WSM"))

partner.cro <- metadata %>% ggplot(aes(x = partner, y = ceftriaxone)) +
  geom_boxplot() +
  scale_y_continuous(trans='log2',
    breaks = c(2^(-9), 2^(-7), 2^(-5), 2^(-3), 2^(-1)),
    labels = c("0.002", "0.008", "0.032", "0.125", "0.5")) +
  labs(x = "", y = "CRO MIC") +
  stat_compare_means(comparisons = comparisons.cro, label = "p.signif") +
  stat_compare_means(label.y = 2)
```



Combining Plots into Panels

```

partner.mic <- plot_grid(partner.cro,
                          partner.azi,
                          partner.cip,
                          ncol = 1,
                          align = "v",
                          axis = "tb")
  
```

