

RStatsbook

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Preface

This is a Quarto book.

To learn more about Quarto books visit <https://quarto.org/docs/books>.

...

1 Introduction

This booklet is meant as companion to my R / statistics seminars. It is NOT a complete guide to either R or statistical data analysis.

There are plenty of books available, check out e.g.

[R for Data Science](#)

[Modern Statistics for Modern Biology](#)

[Modern R with the tidyverse](#)

[ggplot2: Elegant Graphics for Data Analysis](#)

Chapters will follow my usual schedule, starting from R basics, introducing ggplot, data import, data preparation and cleaning, descriptive statistics, simple test statistics, then progression to linear models (regression/ANOVA), generalized linear models with logistic regression as example, linear mixed effect models, and machine learning.

2 Syntax rules / basic things to know about R

2.1 Script preparation / basic setup

At the beginning of (almost) every script we define packages to be used. This could be done by either

- checking if packages needed are installed and otherwise do so, followed by function
`library(packagename)`

OR

- simplifying this using function `p_load()` from package pacman; if you want to create fool-proof scripts, check for pacman and install if needed.

```
Sys.setenv(LANG="en_EN.UTF-8") # to get errors/warnings in English
if(!requireNamespace("pacman", quietly = TRUE)){
  install.packages('pacman')
}
pacman::p_load(
  tidyverse, # metapackage
  wrappedtools, # my own tools package
  randomNames # used to create pseudo names
)
```

2.2 Numeric operations

```
### simple calculations ####
2+5
```

[1] 7

```
3*5
```

```
[1] 15
```

```
15/3 #not 15:3!!, would create vector 15,14,13 ... 3
```

```
[1] 5
```

```
3^2
```

```
[1] 9
```

```
9^0.5
```

```
[1] 3
```

```
10%%3 #modulo
```

```
[1] 1
```

2.3 Variables

2.3.1 Variable names

Naming things is harder than you may expect. Try to be verbose and consistent in language and style. Commonly used are snake_case_style and CamelCaseStyle.

Decide about computer-friendly (syntactical) or human-friendly names, illegal names can be used inside backticks: ‘measure [unit]’. My preference is syntactical for script variables and humane for data variables, e.g. column names, print labels etc.

There are rules for valid syntactical names:

- UPPERCASE and lowercase are distinguished
- start with letter or symbols as . __ , but not with a number
- no mathematical symbols or brackets allowed

To store some value into a variable, use the assignment operator `<-` ; while it possible to use `=` or `->` , this is rather unusual. Assignments are silent, so either a call of the variable, or `print()` / `cat()` function are needed to inspect. Alternatively, put brackets around assignment: (varname `<-` content).

```

#### Variable names ####
test <- 1
test1 <- 1
# i test <- 2 # wrong, would result in error
`1test` <- 2 # this would be possible
test_1<- 5
test.1 <- 2
`test-1` <- 6
`test(1)` <- 5
Test <- 'bla'
HereAreFilteredData <- '' #CamelCase
here_are_filtered_data <- "test" #snake_case
`Gewicht [kg]` <- 67

```

2.3.2 Basic classes of data

R is ‘guessing’ the suitable type of data from input. This should be checked after e.g. importing data! If elements of different classes are found, the more inclusive is used. There are functions to change / force a type if needed.

The **class()** function returns the class of an object, which determines how it behaves with respect to functions like **print()**. The class of an object can be changed by using generic functions and methods.

The **typeof()** function returns the basic data type of an object, which determines how it is stored in memory. The basic data type of an object cannot be changed.

The **str()** function shows class and examples of an object.

2.3.2.1 Guessed classes

```

float_num <- 123.456
class(float_num)

```

[1] "numeric"

```

typeof(float_num)

```

[1] "double"

```
int_num <- 123L # L specifies integer, guessing requires more values  
class(int_num)
```

```
[1] "integer"
```

```
typeof(int_num)
```

```
[1] "integer"
```

```
result<-9^(1/2)  
result
```

```
[1] 3
```

```
print(result)
```

```
[1] 3
```

```
cat(result)
```

```
3
```

```
char_var <- ' some words'  
class(char_var)
```

```
[1] "character"
```

```
typeof(char_var)
```

```
[1] "character"
```

```
logical_var <- TRUE  
class(logical_var)
```

```
[1] "logical"
```

```
typeof(logical_var)
```

```
[1] "logical"
```

```
logical(length = 3)
```

```
[1] FALSE FALSE FALSE
```

```
# logicals usually are defined by conditions:  
int_num < float_num
```

```
[1] TRUE
```

```
# all numbers are true but 0  
as.logical(c(0,1,5,-7.45678)) # c() combines values into a vector
```

```
[1] FALSE TRUE TRUE TRUE
```

Factor: categorical variables with limited set of distinct values, internally stored as integers.
Everything intended to group subjects or representing categories should be stored as factor.
Package forcats provides nice tools for factors!

```
factor_var <- factor(c("m","m","f","m","f","f","?"))  
factor_var
```

```
[1] m m f m f f ?  
Levels: ? f m
```

```
class(factor_var)
```

```
[1] "factor"
```

```
typeof(factor_var) # that is why factors can be called enumerated type
```

```
[1] "integer"
```

```
# factor definition can reorder, rename, and drop levels:  
factor_var2 <- factor(c("m","m","f","m","f","f","?"),  
                        levels=c("m","f"),  
                        labels=c("male","female"))  
factor_var2
```

```
[1] male   male   female male   female female <NA>  
Levels: male female
```

```
(date_var <- Sys.Date())
```

```
[1] "2023-07-10"
```

```
class(date_var)
```

```
[1] "Date"
```

```
typeof(date_var)
```

```
[1] "double"
```

```
# mixed classes  
test2 <- c(1,2,'a','b')  
class(test2)
```

```
[1] "character"
```

2.3.2.2 Forcing / casting classes

Casting functions usually start with `as_`, when creating variables filled with NA, use casting functions or specific variants of NA to force type!

```
(test<-c(1,2,3,'a','b','c'))
```

```
[1] "1" "2" "3" "a" "b" "c"
```

```
(test_n<-as.numeric(test))
```

Warning: NAs introduced by coercion

```
[1] 1 2 3 NA NA NA
```

```
as.numeric(factor_var)
```

```
[1] 3 3 2 3 2 2 1
```

```
as.character(10:19)
```

```
[1] "10" "11" "12" "13" "14" "15" "16" "17" "18" "19"
```

```
# NAs  
class(NA_real_)
```

```
[1] "numeric"
```

```
class(NA_integer_)
```

```
[1] "integer"
```

```
class(NA_character_)
```

```
[1] "character"
```

```
class(NA_Date_)
```

```
[1] "Date"
```

2.3.3 Indexing variables

The most general kind of indexing is by position, starting with 1. Negative numbers result in exclusion of position(s). Position indices are provided within square brackets. The index can (and usually will) be a variable instead of hard coded numbers.

```
(numbers1<-c(5,3,6,8,2,1))
```

```
[1] 5 3 6 8 2 1
```

```
numbers1[1]
```

```
[1] 5
```

```
numbers1[1:3]
```

```
[1] 5 3 6
```

```
numbers1[-1]
```

```
[1] 3 6 8 2 1
```

```
numbers2 <- 1:3  
numbers1[numbers2]
```

```
[1] 5 3 6
```

To get first or last entries, head() and tail() can be used. By default 6 entries are returned.

```
tail(x=numbers1, n = 1)
```

```
[1] 1
```

```
head(x = numbers1, n = 3)
```

```
[1] 5 3 6
```

2.3.4 Usage of variables

Variables are like placeholders for their content, so that you don't have to remember where you left things. Operations on variables are operations on their content. Changing the content of a variable does not automatically save those changes back to the variable, this needs to be done explicitly!

```
numbers1+100 # not stored anywhere, just printed
```

```
[1] 105 103 106 108 102 101
```

```
numbers1+numbers2 # why does this even work?
```

```
[1] 6 5 9 9 4 4
```

When combining variables of different length, the short one is recycled, so the numbers2 is added to the first 3 elements of numbers2, then is reused and added to the remaining 3 elements. If the length of the longer is not a multiple of the shorter, there will be a warning.

```
c(2,4,6,8)+1
```

```
[1] 3 5 7 9
```

```
c(2,4,6,8)+c(1,2)
```

```
[1] 3 6 7 10
```

```
c(2,4,6,8)+c(1,2,3)
```

```
Warning in c(2, 4, 6, 8) + c(1, 2, 3): longer object length is not a multiple  
of shorter object length
```

```
[1] 3 6 9 9
```

2.4 Functions

2.4.1 Function usage

Functions have the same naming rules as variables, but the name is always followed by opening/closing round brackets, within those brackets function parameters/arguments can be specified to provide input or control behavior:

```
FunctionName(parameter1=x1,parameter2=x2,x3,...)
```

Most functions have named arguments, those argument names may be omitted as long as parameter values are supplied in the defined order. Arguments may have predefined default values, see help! Some functions like `c()` use unnamed arguments.

```
c('my','name') # unnamed
```

```
[1] "my"    "name"
```

```
# ?mean  
mean(x = c(3,5,7,NA)) #using default parameters
```

```
[1] NA
```

```
mean(x = c(3,5,7,NA),na.rm = TRUE) #overriding default parameter
```

```
[1] 5
```

```
mean(na.rm = TRUE, x=c(3,5,7,NA)) # changed order of arguments
```

```
[1] 5
```

```
mean(c(3,5,7,NA), na.rm = TRUE) # name of 1st argument omitted
```

```
[1] 5
```

```
sd(c(3,5,7,NA), na.rm = TRUE)
```

```
[1] 2
```

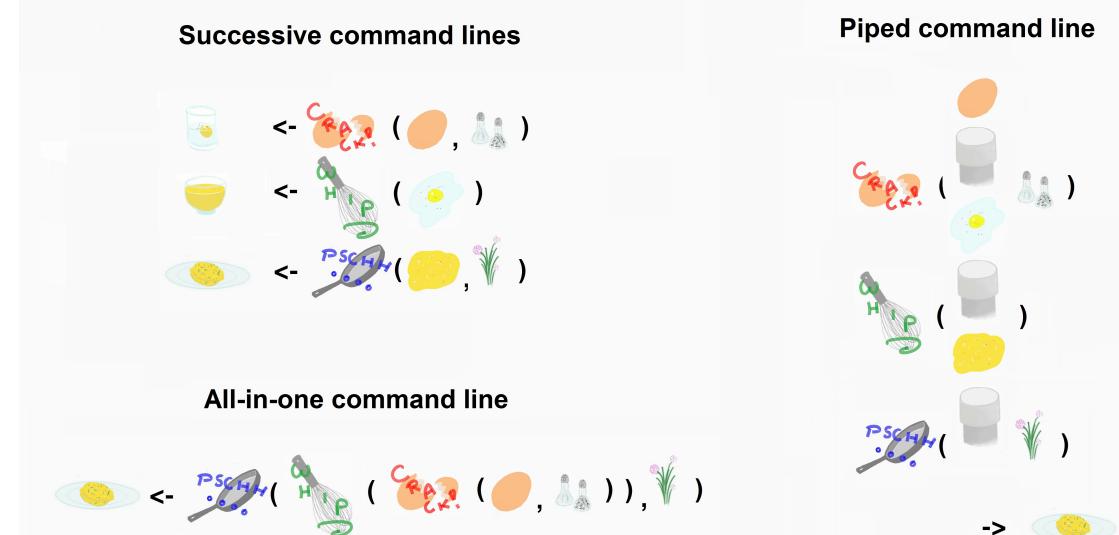
```
# same logic as mean, partially the same arguments
median(1:100, TRUE)
```

[1] 50.5

```
# omitting arguments influences readability of a function, careful!
```

2.4.2 Functions combined

Functions often just solve one problem or task, so usually we need to combine them. This can be done by nesting or piping. Piping makes reading/understanding scripts easier, as it shows



order of functions:

pos='h', alt="piping functions"}
}

@LVaudoo

```
# functions may be nested:
floor(
  as.numeric(
    Sys.Date() -
      as.Date('1985/12/10'))/
  365.25)
```

[1] 37

```
# or (usually better) piped:
mtcars |>
  mutate(am=factor(am)) |>
  filter(vs==1) |>
  group_by(am) |>
  summarize(across(.cols = c(wt, mpg, qsec, disp),
                  .fns = mean)) |>
  pivot_longer(cols = -am, names_to = 'Measure') |>
  pivot_wider(id_cols = Measure, names_from = am,
              values_from = value)
```

```
# A tibble: 4 x 3
  Measure    `0`    `1`
  <chr>     <dbl> <dbl>
1 wt        3.19   2.03
2 mpg       20.7   28.4
3 qsec      20.0   18.7
4 disp      175.   89.8
```

If a sequence of functions is used often, combining them into a new function is advisable, e.g. this combination of descriptive and test statistics:

```
# can be combined into higher order functions:
compare2numvars(data = mtcars,
                  dep_vars = c('mpg', 'wt', 'qsec'),
                  indep_var = 'am',
                  add_n = TRUE,
                  gaussian = TRUE)
```

```
# A tibble: 3 x 5
  Variable desc_all          `am 0`          `am 1`          p
  <fct>    <chr>            <chr>            <chr>            <chr>
1 mpg      20 ± 6 [n=32]    17 ± 4 [n=19]    24 ± 6 [n=13]  0.001
2 wt       3.2 ± 1.0 [n=32] 3.8 ± 0.8 [n=19] 2.4 ± 0.6 [n=13] 0.001
3 qsec     18 ± 2 [n=32]   18 ± 2 [n=19]   17 ± 2 [n=13]  0.206
```

2.4.3 Writing functions

```
#FunctionName<-function(parameters...){definition}
markSign<-function(SignIn) {
  SignIn <- as.numeric(SignIn)
  if(is.na(SignIn)){
```

```

SignOut<-'wrong input, stupido!'
} else {
# if (!is.na(SignIn)) {
SignOut<-'n.s.'
if (SignIn<=0.1) {SignOut<-'+'}
if (SignIn<=0.05) {SignOut<-'*' }
if (SignIn<=0.01) {SignOut<-'**'}
if (SignIn<=0.001) {SignOut<-'***'}
}
return(SignOut)
}

markSign(SignIn=0.035)

```

[1] "*"

```
markSign(SignIn="0.35")
```

[1] "n.s."

```
markSign(SignIn = 'p=3,5%')    #wrong parameter
```

Warning in markSign(SignIn = "p=3,5%"): NAs introduced by coercion

[1] "wrong input, stupido!"

```

Mymean<-function(werte)
{
  return(base::mean(werte,na.rm=T))
}
# source('myfunctions.R')
```

2.5 More complex data types, created by functions

2.5.1 Matrix

A matrix is a 2-dimensional data structure, where all elements are of the same class.

2.5.1.1 Creation

```
my1.Matrix<-  
  matrix(data=1:12,  
         # nrow=4, # this is not needed, can be derived from data  
         ncol=3,  
         byrow=T, # date are put into row 1 first  
         dimnames=list(paste0('row',1:4),  
                       paste0('col',1:3)))  
print(my1.Matrix)
```

```
  col1 col2 col3  
row1    1    2    3  
row2    4    5    6  
row3    7    8    9  
row4   10   11   12
```

```
data <- 1:100  
nrow <- 20  
matrix(data=data,  
       nrow=nrow,  
       byrow=F, # data are put into column 1 first  
       dimnames=list(paste0('row',1:nrow),  
                     paste0('col',1:(length(data)/nrow)))) |>  
head()
```

```
  col1 col2 col3 col4 col5  
row1    1    21   41   61   81  
row2    2    22   42   62   82  
row3    3    23   43   63   83  
row4    4    24   44   64   84  
row5    5    25   45   65   85  
row6    6    26   46   66   86
```

```
mdat <- matrix(c(1,2,3, 11,12,13),  
                nrow = 2, ncol=3) #byrow=FALSE, specified but default  
mdat
```

```
[,1] [,2] [,3]  
[1,]    1     3    12  
[2,]    2    11    13
```

2.5.1.2 Indexing

Addressing a matrix is done with [row_index, column_index]

```
my1.Matrix[2,3] # Index: [row, column]
```

```
[1] 6
```

```
my1.Matrix[2,] # all columns
```

| col1 | col2 | col3 |
|------|------|------|
| 4 | 5 | 6 |

```
my1.Matrix[,2] # all rows
```

| row1 | row2 | row3 | row4 |
|------|------|------|------|
| 2 | 5 | 8 | 11 |

```
my1.Matrix[c(1,3),-2] # exclude column 2
```

| | col1 | col3 |
|------|------|------|
| row1 | 1 | 3 |
| row3 | 7 | 9 |

```
my1.Matrix[1,1] <- NA # Index can be used for writing as well
```

2.5.2 Data frame

A data frame has 2 dimensions, it can handle various data types (1 per columns). This structure is rather superseded by tibbles (see below).

2.5.2.1 Creation

Data frames are defined by creating and filling columns, functions can be used (and piped) to create content.

```

patientN<-15
(myTable<-data.frame(
  patientCode=paste0('pat',1:patientN),
  Var1=1, # gets recycled
  Var2=NA_Date_)) |> head()

```

```

patientCode Var1 Var2
1      pat1     1 <NA>
2      pat2     1 <NA>
3      pat3     1 <NA>
4      pat4     1 <NA>
5      pat5     1 <NA>
6      pat6     1 <NA>

```

```
str(myTable)
```

```

'data.frame': 15 obs. of 3 variables:
$ patientCode: chr "pat1" "pat2" "pat3" "pat4" ...
$ Var1        : num 1 1 1 1 1 1 1 1 1 1 ...
$ Var2        : Date, format: NA NA ...

```

```

set.seed(101)
myTable<-data.frame(
  patientCode=paste0('pat',1:patientN),
  Age=runif(n=patientN,min=18,max=65) |> floor(),
  Sex=factor(rep(x=NA,times=patientN),
             levels=c('m','f')),
  sysRR=round(rnorm(n=patientN,mean=140,sd=10)))
head(myTable)

```

```

patientCode Age  Sex sysRR
1      pat1  35 <NA>   142
2      pat2  20 <NA>   132
3      pat3  51 <NA>   122
4      pat4  48 <NA>   157
5      pat5  29 <NA>   144
6      pat6  32 <NA>   148

```

2.5.2.2 Indexing

Beside the numeric index, columns can be addressed by name. This can be done by either `dfname$colname` (for the content of a single column) or `dfname[, "colname"]` for 1 or more columns.

```
myTable[1:5,1]
```

```
[1] "pat1" "pat2" "pat3" "pat4" "pat5"
```

```
myTable$patientCode[1:5]
```

```
[1] "pat1" "pat2" "pat3" "pat4" "pat5"
```

```
myTable[1:5,"patientCode"]
```

```
[1] "pat1" "pat2" "pat3" "pat4" "pat5"
```

```
# returns vector of values for a single column, df otherwise  
myTable["patientCode"] # returns df
```

```
patientCode  
1      pat1  
2      pat2  
3      pat3  
4      pat4  
5      pat5  
6      pat6  
7      pat7  
8      pat8  
9      pat9  
10     pat10  
11     pat11  
12     pat12  
13     pat13  
14     pat14  
15     pat15
```

```
spalten<-c('Sex',"Age")
myTable[1:5,spalten]
```

```
  Sex Age
1 <NA> 35
2 <NA> 20
3 <NA> 51
4 <NA> 48
5 <NA> 29
```

```
myTable[1:5,c('patientCode','Age')]
```

```
 patientCode Age
1      pat1 35
2      pat2 20
3      pat3 51
4      pat4 48
5      pat5 29
```

```
myTable[,1]<-paste0('Code',1:patientN)
```

2.5.3 Tibble

Tibbles are a modern and efficient data structure that extend data frames, providing enhanced features and performance for data manipulation and analysis.

2.5.3.1 Creation

```
patientN <- 25
rawdata <- tibble(
  PatID=paste('P',1:patientN), # as in data.frame
  Sex=sample(x = c('male','female'), # random generator
             size = patientN,replace = T,
             prob = c(.7,.3)),
  Ethnicity=sample(1:6,patientN,T,c(.01,.01,.05,.03,.75,.15)),
  # random assignments
  `Given name`=randomNames(n = patientN,
                            gender = Sex,
                            # this is a reference to column Sex
```

```

            ethnicity = Ethnicity,
            which.names = 'first'),
`Family name`=randomNames(n = patientN,
                           ethnicity = Ethnicity,
                           which.names = 'last'),
Treatment=sample(c('Placebo','Verum'),patientN,T),
`sysRR (mmHg)`=round(rnorm(n=patientN,mean=140,sd=10))-
(Treatment=='Verum')*15,
`diaRR (mmHg)`=round(rnorm(n=patientN,mean=80,sd=10))-
(Treatment=='Verum')*10,
HR=round(rnorm(n=patientN,mean=90,sd=7)))
rawdata

```

```

# A tibble: 25 x 9
# ... with 9 variables:
#   PatID     Sex    Ethnicity `Given name` `Family name` Treatment `sysRR (mmHg)` `diaRR (mmHg)` HR
#   <chr>    <chr>   <int>      <chr>       <chr>        <chr>      <dbl>      <dbl>   <dbl>
1 P 1     male      5 Ian        Roy        Placebo      128
2 P 2     male      3 Dametrious Martin     Placebo      116
3 P 3     female    5 Alyxandra Fisher     Verum       120
4 P 4     female    6 Musfira    el-Karimi   Verum       130
5 P 5     male      6 Saleel     al-Bey     Placebo      135
6 P 6     male      5 Kahner    Melott     Verum       148
7 P 7     male      5 Skylar    Burgess    Verum       137
8 P 8     male      5 Michael   Harper    Placebo      139
9 P 9     female    5 Julia     Tovrea    Placebo      154
10 P 10    male     4 Eric      Barreras  Verum       113
# i 15 more rows
# i 2 more variables: `diaRR (mmHg)` <dbl>, HR <dbl>

```

```
colnames(rawdata)
```

```
[1] "PatID"          "Sex"           "Ethnicity"       "Given name"     "Family name"
[6] "Treatment"      "sysRR (mmHg)"  "diaRR (mmHg)"  "HR"
```

```
cn() # shortcut from wrappedtools
```

```
[1] "PatID"          "Sex"           "Ethnicity"       "Given name"     "Family name"
[6] "Treatment"      "sysRR (mmHg)"  "diaRR (mmHg)"  "HR"
```

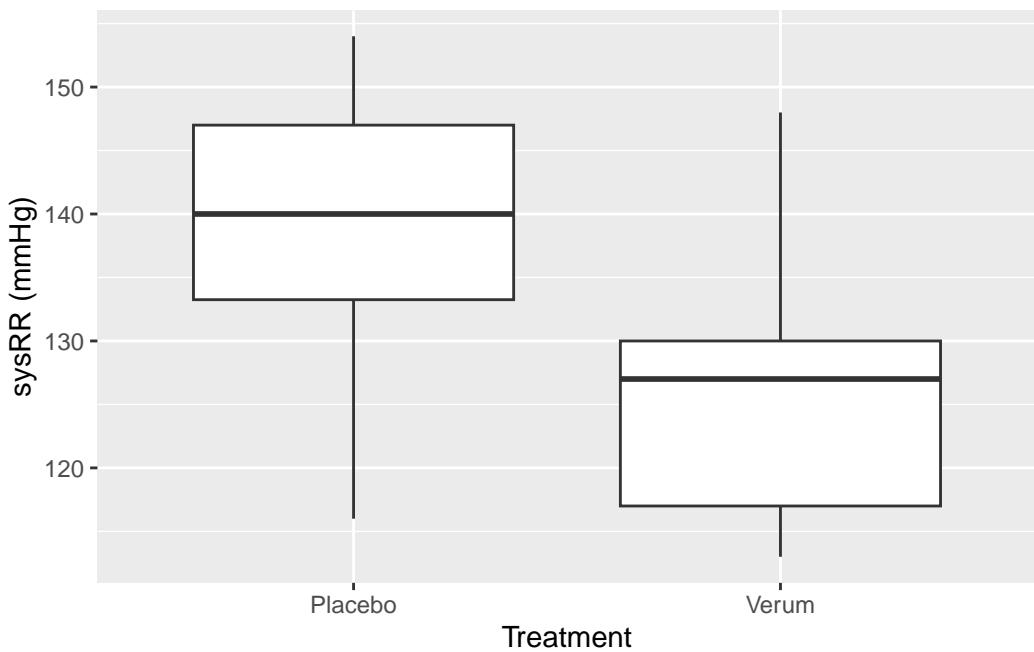
```

# example of data management for a tibble, recoding ethnicity:
rawdata <- rawdata |>
  mutate(Ethnicity=factor(
    Ethnicity, levels = 1:6,
    labels= c(
      'American Indian or Native Alaskan',
      'Asian or Pacific Islander',
      'Black (not Hispanic)',
      'Hispanic',
      'White (not Hispanic)',
      'Middle-Eastern, Arabic')))

# quick visual inspection
ggplot(rawdata,aes(x = Treatment,y = `sysRR (mmHg)`))+  

  geom_boxplot()

```



2.5.3.2 Indexing

The same rules as for the data frame, but more consistent behavior.

```
rawdata[1:5,1:2]
```

```
# A tibble: 5 x 2
  PatID Sex
```

```
<chr> <chr>
1 P 1    male
2 P 2    male
3 P 3    female
4 P 4    female
5 P 5    male
```

```
rawdata[,6]
```

```
# A tibble: 25 x 1
  Treatment
  <chr>
 1 Placebo
 2 Placebo
 3 Verum
 4 Verum
 5 Placebo
 6 Verum
 7 Verum
 8 Placebo
 9 Placebo
10 Verum
# i 15 more rows
```

```
rawdata[6]
```

```
# A tibble: 25 x 1
  Treatment
  <chr>
 1 Placebo
 2 Placebo
 3 Verum
 4 Verum
 5 Placebo
 6 Verum
 7 Verum
 8 Placebo
 9 Placebo
10 Verum
# i 15 more rows
```

```
rawdata[[6]]
```

```
[1] "Placebo" "Placebo" "Verum"    "Verum"    "Placebo" "Verum"    "Verum"
[8] "Placebo" "Placebo" "Verum"    "Verum"    "Verum"    "Verum"    "Placebo"
[15] "Verum"   "Verum"   "Verum"    "Placebo"  "Placebo"  "Verum"   "Placebo"
[22] "Placebo" "Placebo" "Placebo"  "Verum"
```

```
rawdata$`Family name`
```

```
[1] "Roy"          "Martin"        "Fisher"        "el-Karimi"
[5] "al-Bey"       "Melott"        "Burgess"       "Harper"
[9] "Tovrea"       "Barreras"      "Klamerus"     "al-Satter"
[13] "al-Sultana"   "Yi"            "Helm"          "Molina-Peinado"
[17] "Spilsted"     "Egan"          "Thompson"     "Schauss"
[21] "Owens"         "Vick"          "Reeves"        "Chesney"
[25] "Minnillo"
```

Differences in addressing data frames and tibbles:

- tibble and [always returns tibble
- tibble and [[always returns vector
- data.frame and [may return data.frame (if >1 column) or vector
- data.frame and [[always returns vector

```
rawdata_df <- as.data.frame(rawdata)
rawdata[2] #returns Tibble with 1 column
```

```
# A tibble: 25 x 1
  Sex
  <chr>
1 male
2 male
3 female
4 female
5 male
6 male
7 male
8 male
9 female
10 male
# i 15 more rows
```

```
rawdata[[2]] #returns vector
```

```
[1] "male"   "male"   "female" "female" "male"   "male"   "male"   "male"  
[9] "female" "male"   "female" "male"   "male"   "male"   "male"   "female"  
[17] "female" "male"   "female" "female" "female" "male"   "male"   "female"  
[25] "female"
```

```
rawdata[,2] #returns Tibble with 1 column
```

```
# A tibble: 25 x 1  
  Sex  
  <chr>  
1 male  
2 male  
3 female  
4 female  
5 male  
6 male  
7 male  
8 male  
9 female  
10 male  
# i 15 more rows
```

```
rawdata[,2:3] #returns tibble with 2 columns
```

```
# A tibble: 25 x 2  
  Sex     Ethnicity  
  <chr>   <fct>  
1 male    White (not Hispanic)  
2 male    Black (not Hispanic)  
3 female  White (not Hispanic)  
4 female  Middle-Eastern, Arabic  
5 male    Middle-Eastern, Arabic  
6 male    White (not Hispanic)  
7 male    White (not Hispanic)  
8 male    White (not Hispanic)  
9 female  White (not Hispanic)  
10 male   Hispanic  
# i 15 more rows
```

```
rawdata_df[2] #returns DF with 1 column
```

```
Sex  
1 male  
2 male  
3 female  
4 female  
5 male  
6 male  
7 male  
8 male  
9 female  
10 male  
11 female  
12 male  
13 male  
14 male  
15 male  
16 female  
17 female  
18 male  
19 female  
20 female  
21 female  
22 male  
23 male  
24 female  
25 female
```

```
rawdata_df[[2]] #returns vector
```

```
[1] "male"    "male"    "female"   "female"   "male"    "male"    "male"    "male"  
[9] "female"   "male"    "female"   "male"     "male"    "male"    "male"    "female"  
[17] "female"   "male"    "female"   "female"   "female"   "male"    "male"    "female"  
[25] "female"
```

```
rawdata_df[,2] #returns vector
```

```
[1] "male"    "male"    "female"   "female"   "male"    "male"    "male"    "male"  
[9] "female"   "male"    "female"   "male"     "male"    "male"    "male"    "female"  
[17] "female"   "male"    "female"   "female"   "female"   "male"    "male"    "female"  
[25] "female"
```

```
rawdata_df[,2:3] #returns DF with 2 columns
```

| | Sex | Ethnicity |
|----|--------|---------------------------|
| 1 | male | White (not Hispanic) |
| 2 | male | Black (not Hispanic) |
| 3 | female | White (not Hispanic) |
| 4 | female | Middle-Eastern, Arabic |
| 5 | male | Middle-Eastern, Arabic |
| 6 | male | White (not Hispanic) |
| 7 | male | White (not Hispanic) |
| 8 | male | White (not Hispanic) |
| 9 | female | White (not Hispanic) |
| 10 | male | Hispanic |
| 11 | female | White (not Hispanic) |
| 12 | male | Middle-Eastern, Arabic |
| 13 | male | Middle-Eastern, Arabic |
| 14 | male | Asian or Pacific Islander |
| 15 | male | White (not Hispanic) |
| 16 | female | Hispanic |
| 17 | female | White (not Hispanic) |
| 18 | male | White (not Hispanic) |
| 19 | female | White (not Hispanic) |
| 20 | female | White (not Hispanic) |
| 21 | female | White (not Hispanic) |
| 22 | male | Black (not Hispanic) |
| 23 | male | White (not Hispanic) |
| 24 | female | White (not Hispanic) |
| 25 | female | White (not Hispanic) |

There are specific functions for picking columns or rows, especially useful in pipes.

```
rawdata %>% select(PatID:Ethnicity, `sysRR (mmHg)` :HR)
```

| # A tibble: 25 x 6 | PatID | Sex | Ethnicity | `sysRR (mmHg)` | `diaRR (mmHg)` | HR |
|--------------------|-------|--------|------------------------|----------------|----------------|-------|
| | <chr> | <chr> | <fct> | <dbl> | <dbl> | <dbl> |
| 1 | P 1 | male | White (not Hispanic) | 128 | 87 | 88 |
| 2 | P 2 | male | Black (not Hispanic) | 116 | 72 | 82 |
| 3 | P 3 | female | White (not Hispanic) | 120 | 60 | 93 |
| 4 | P 4 | female | Middle-Eastern, Arabic | 130 | 76 | 82 |
| 5 | P 5 | male | Middle-Eastern, Arabic | 135 | 60 | 100 |
| 6 | P 6 | male | White (not Hispanic) | 148 | 85 | 85 |
| 7 | P 7 | male | White (not Hispanic) | 137 | 54 | 98 |

```

8 P 8   male   White (not Hispanic)           139      95      94
9 P 9   female  White (not Hispanic)          154      71      83
10 P 10  male   Hispanic                      113      74      82
# i 15 more rows

```

```
rawdata %>% select(PatID:Ethnicity, `sysRR (mmHg)` :HR) %>% slice(1:5)
```

```
# A tibble: 5 x 6
  PatID Sex    Ethnicity           `sysRR (mmHg)` `diaRR (mmHg)`   HR
  <chr> <chr>  <fct>                <dbl>        <dbl> <dbl>
1 P 1   male   White (not Hispanic)       128         87     88
2 P 2   male   Black (not Hispanic)      116         72     82
3 P 3   female  White (not Hispanic)     120         60     93
4 P 4   female  Middle-Eastern, Arabic  130         76     82
5 P 5   male   Middle-Eastern, Arabic   135         60    100
```

```
rawdata %>% select(contains('RR', ignore.case = F))
```

```
# A tibble: 25 x 2
  `sysRR (mmHg)` `diaRR (mmHg)`
  <dbl>        <dbl>
1 128          87
2 116          72
3 120          60
4 130          76
5 135          60
6 148          85
7 137          54
8 139          95
9 154          71
10 113         74
# i 15 more rows
```

```
rawdata %>% select(ends_with('r'))
```

```
# A tibble: 25 x 1
  HR
  <dbl>
1 88
2 82
```

```

3    93
4    82
5   100
6    85
7    98
8    94
9    83
10   82
# i 15 more rows

```

```
rawdata %>% select(-contains('name'))
```

```
# A tibble: 25 x 7
  PatID Sex   Ethnicity Treatment `sysRR (mmHg)` `diaRR (mmHg)`   HR
  <chr> <chr> <fct>      <chr>          <dbl>          <dbl> <dbl>
1 P 1   male  White (not Hispan~ Placebo        128           87   88
2 P 2   male  Black (not Hispan~ Placebo        116           72   82
3 P 3   female White (not Hispan~ Verum         120           60   93
4 P 4   female Middle-Eastern, A~ Verum         130           76   82
5 P 5   male  Middle-Eastern, A~ Placebo        135           60  100
6 P 6   male  White (not Hispan~ Verum         148           85   85
7 P 7   male  White (not Hispan~ Verum         137           54   98
8 P 8   male  White (not Hispan~ Placebo        139           95   94
9 P 9   female White (not Hispan~ Placebo        154           71   83
10 P 10  male  Hispanic          Verum         113           74   82
# i 15 more rows
```

```
rawdata %>% select(`sysRR (mmHg)`)
```

```
# A tibble: 25 x 1
`sysRR (mmHg)`
<dbl>
1     128
2     116
3     120
4     130
5     135
6     148
7     137
8     139
9     154
10    113
# i 15 more rows
```

```
rawdata %>% select(contains('r'), -contains('rr'))
```

```
# A tibble: 25 x 2
  Treatment    HR
  <chr>      <dbl>
1 Placebo     88
2 Placebo     82
3 Verum       93
4 Verum       82
5 Placebo    100
6 Verum       85
7 Verum       98
8 Placebo     94
9 Placebo     83
10 Verum      82
# i 15 more rows
```

```
rawdata %>% pull(`sysRR (mmHg)`)
```

```
[1] 128 116 120 130 135 148 137 139 154 113 118 117 127 143 117 135 117 147 127
[20] 130 136 141 150 147 130
```

Exercise: Think of a cruet_stand / Gewürzmenage - define n_elements <- 5*10^3 - create a tibble “menage” with columns saltshaker, peppercaster and n_elements each for saltgrain and pepperflake - print saltshaker - print salt - print 100 saltgrains

2.5.4 List

While matrix, data.frames, and tibbles always have the same number of rows for each column, sometimes different lengths are required. A list can handle all kinds of data with different number of elements for each sublist. This is a typical output format for statistical functions and is useful for collecting e.g. result tables or figures. Package rlist provides useful tools.

2.5.4.1 Creation

```
shopping<-list(beverages=c('beer','water',
                             'gin(not Gordons!!)', 'tonic'),
                 snacks=c('chips','pretzels'),
                 nonfood=c('DVDs','Akku'),
```

```

mengen=1:10,
volumen=rnorm(50,100,2))
shopping

```

```

$beverages
[1] "beer"           "water"          "gin(not Gordons!!)"
[4] "tonic"

$snacks
[1] "chips"         "pretzels"

$nonfood
[1] "DVDs"          "Akku"

$mengen
[1] 1 2 3 4 5 6 7 8 9 10

$volumen
[1] 101.98092 99.72118 101.25978 99.50115 99.88413 103.65050 100.35412
[8] 103.72203 97.45847 98.51527 98.86176 100.25617 99.18075 101.11364
[15] 99.49699 99.67630 99.17729 100.27251 100.64437 98.00664 99.25581
[22] 100.43009 100.20727 100.25817 98.48912 96.71237 96.46227 101.04724
[29] 96.47107 100.85070 97.64126 100.82651 102.66924 98.58853 99.72314
[36] 100.51849 98.90033 101.05662 100.26360 97.92360 100.89800 98.84879
[43] 101.56033 98.08456 100.80067 101.36969 94.41230 100.80553 99.60254
[50] 100.62478

```

```

shopping$snacks

```

```

[1] "chips"        "pretzels"

```

2.5.4.2 Indexing

```

shopping[1]      #returns a list

```

```

$beverages
[1] "beer"           "water"          "gin(not Gordons!!)"
[4] "tonic"

```

```
shopping[[1]] #returns a vector
```

```
[1] "beer"           "water"          "gin(not Gordons!!)"  
[4] "tonic"
```

```
str(shopping[1])
```

```
List of 1  
$ beverages: chr [1:4] "beer" "water" "gin(not Gordons!!)" "tonic"
```

```
str(shopping[[1]])
```

```
chr [1:4] "beer" "water" "gin(not Gordons!!)" "tonic"
```

```
str(shopping$beverages)
```

```
chr [1:4] "beer" "water" "gin(not Gordons!!)" "tonic"
```

```
shopping[1][2]
```

```
$<NA>  
NULL
```

```
shopping[[1]][2]
```

```
[1] "water"
```

```
shopping$beverages[2]
```

```
[1] "water"
```

```
t_out <- t.test(x = rnorm(n = 20, mean = 10, sd = 1),
                 y = rnorm(20, 12, 1))
str(t_out)
```

```
List of 10
$ statistic : Named num -5.74
..- attr(*, "names")= chr "t"
$ parameter : Named num 36.1
..- attr(*, "names")= chr "df"
$ p.value   : num 1.52e-06
$ conf.int  : num [1:2] -2.35 -1.12
..- attr(*, "conf.level")= num 0.95
$ estimate  : Named num [1:2] 10.2 11.9
..- attr(*, "names")= chr [1:2] "mean of x" "mean of y"
$ null.value: Named num 0
..- attr(*, "names")= chr "difference in means"
$ stderr    : num 0.302
$ alternative: chr "two.sided"
$ method    : chr "Welch Two Sample t-test"
$ data.name  : chr "rnorm(n = 20, mean = 10, sd = 1) and rnorm(20, 12, 1)"
- attr(*, "class")= chr "htest"
```

```
t_out$p.value
```

```
[1] 1.523729e-06
```

2.6 Control structures

2.6.1 Loops

Repetitive tasks like computation of descriptive statistics over many variables or repeated simulations of data can be declared inside of a loop. There are functions (like summarize(across(...))) that create those repetitions internally, but often doing this explicitly improves readability or helps solving various tasks like describing AND plotting data.

for-loop In a for-loop, we can define the number of runs in advance, e.g. by the number of variables to describe. There are 2 ways/styles, how to define this number: 1. by creating an index variable with an integer vector 1,2,3, ... #runs/variables 2. by creating an index containing e.g. colnames

```
# integer index
print('### Game of Loops ###')
```

```
[1] "### Game of Loops ###"
```

```
for(season_i in 1:3) {  
  cat(paste('GoL Season',season_i,'\n'))  
  for(episode_i in 1:5) {  
    cat(paste0('  GoL S.',season_i,  
              ' Episode ',episode_i,'\n'))  
  }  
  cat('\n')  
}
```

```
GoL Season 1  
  GoL S.1 Episode 1  
  GoL S.1 Episode 2  
  GoL S.1 Episode 3  
  GoL S.1 Episode 4  
  GoL S.1 Episode 5  
  
GoL Season 2  
  GoL S.2 Episode 1  
  GoL S.2 Episode 2  
  GoL S.2 Episode 3  
  GoL S.2 Episode 4  
  GoL S.2 Episode 5  
  
GoL Season 3  
  GoL S.3 Episode 1  
  GoL S.3 Episode 2  
  GoL S.3 Episode 3  
  GoL S.3 Episode 4  
  GoL S.3 Episode 5
```

```
# content index  
## names of elements  
for(col_i in colnames(rawdata)){  
  print(col_i)  
}
```

```
[1] "PatID"  
[1] "Sex"  
[1] "Ethnicity"  
[1] "Given name"
```

```
[1] "Family name"  
[1] "Treatment"  
[1] "sysRR (mmHg)"  
[1] "diaRR (mmHg)"  
[1] "HR"
```

```
## content of elements  
for(col_i in shopping){  
  print(col_i)  
}
```

```
[1] "beer"           "water"          "gin(not Gordons!!)"  
[4] "tonic"  
[1] "chips"         "pretzels"  
[1] "DVDs"          "Akku"  
[1] 1 2 3 4 5 6 7 8 9 10  
[1] 101.98092 99.72118 101.25978 99.50115 99.88413 103.65050 100.35412  
[8] 103.72203 97.45847 98.51527 98.86176 100.25617 99.18075 101.11364  
[15] 99.49699 99.67630 99.17729 100.27251 100.64437 98.00664 99.25581  
[22] 100.43009 100.20727 100.25817 98.48912 96.71237 96.46227 101.04724  
[29] 96.47107 100.85070 97.64126 100.82651 102.66924 98.58853 99.72314  
[36] 100.51849 98.90033 101.05662 100.26360 97.92360 100.89800 98.84879  
[43] 101.56033 98.08456 100.80067 101.36969 94.41230 100.80553 99.60254  
[50] 100.62478
```

```
# automatic creation of integer index from elements  
for(col_i in seq_along(colnames(rawdata))){  
  print(colnames(rawdata)[col_i])  
}
```

```
[1] "PatID"  
[1] "Sex"  
[1] "Ethnicity"  
[1] "Given name"  
[1] "Family name"  
[1] "Treatment"  
[1] "sysRR (mmHg)"  
[1] "diaRR (mmHg)"  
[1] "HR"
```

```
# edge-case of 0 elements -> 0 runs
for(col_i in seq_len(0)){
  print(colnames(rawdata)[col_i])
}
```

2.6.1.1 while-loops

If not number of repetitions is known, but a condition.

```
test <- 0
while(test<10){
  print(test)
  test  <- test + 1 #test <- test+1
}
```

```
[1] 0
[1] 1
[1] 2
[1] 3
[1] 4
[1] 5
[1] 6
[1] 7
[1] 8
[1] 9
```

2.6.2 Conditions

2.6.2.1 if else

We can run code if condition(s) are true:

```
sex<-'male'
if (sex=='male')  {
  print('Male')
} else {
  print('Female')
}
```

```
[1] "Male"
```

```
if (sex=='male') {  
  print('Male')  
}
```

```
[1] "Male"
```

```
if (sex!='male'){  
  print('Female')  
}  
TRUE&FALSE
```

```
[1] FALSE
```

```
(1>10)&(1<5)
```

```
[1] FALSE
```

```
TRUE|FALSE
```

```
[1] TRUE
```

```
(1>10) | (1<5)
```

```
[1] TRUE
```

2.6.2.2 ifelse

We can get text conditionally:

```
print(ifelse(test = sex=='male',  
            yes = 'is male',  
            no = 'is female'))
```

```
[1] "is male"
```

```

p <- .0012
paste0('That is ',
       ifelse(test = p<=.05, yes = '', no = 'not '),
       'significant')

```

```
[1] "That is significant"
```

```

testvar <- 3
if(testvar %in% c(1,3,5)){
  print('uneven')
}

```

```
[1] "uneven"
```

2.6.2.3 case_when / case_match

When there are many tests to do, case_when or case_match are nice replacements for ifelse.

```

mutate(rawdata,
       Hypertension=case_when(
         `sysRR (mmHg)`<120 & `diaRR (mmHg)`<70 ~ "normotensive",
         `sysRR (mmHg)`<160 & `diaRR (mmHg)`<=80 ~ "borderline",
         .default = "hypertensive")) |>
       select(contains("RR"),Hypertension)

```

```

# A tibble: 25 x 3
`sysRR (mmHg)` `diaRR (mmHg)` Hypertension
      <dbl>        <dbl> <chr>
1        128          87 hypertensive
2        116          72 borderline
3        120          60 borderline
4        130          76 borderline
5        135          60 borderline
6        148          85 hypertensive
7        137          54 borderline
8        139          95 hypertensive
9        154          71 borderline
10       113          74 borderline
# i 15 more rows

```

3 Importing data

```
pacman::p_load(tidyverse, wrappedtools, readxl)
```

3.1 Import from text files (.txt, .csv)

3.2 Import from Excel

3.2.1 Tidy Excel files

```
rawdata <- read_excel('data/Medtest_e.xlsx')
rawdata <- rename(rawdata,
  `Size (cm)` = size,
  `Weight (kg)` = weight) |>
  select(-Sex_m)
saveRDS(rawdata, file = "data/rawdata.rds")
```

3.2.2 Dirty Excel files

3.3 Import from SPSS

3.4 Import from SAS

4 Grouping of variables by type / distribution / use

```
pacman::p_load(wrappedtools)
```

4.1 Test for normal distribution

4.2 Picking column names and positions

```
rawdata <- readRDS('data/rawdata.rds')
quantvars <- ColSeeker(data = rawdata,
                        varclass = "numeric",
                        exclude = "code")
gaussvars <- ColSeeker(namepattern = c("si","we","BMI","BP","mri"))

ordvars <- ColSeeker(namepattern = c("age","lab"))

factvars <- ColSeeker(namepattern = c("sex","med","NYHA"),
                      returnclass = TRUE)
save(rawdata,list = ls(pattern = "vars"),file = "data/bookdata1.RData")
```

5 Visualize data with ggplot

```
pacman::p_load(tidyverse,#plotrix,
  grid,gridExtra,car,
  ggsci,ggsignif, ggthemes, ggridges,
  gganimate,ggforce,
  # survival, survminer,
  ggdendro, ggbeeswarm,
  rpart,rpart.plot,
  gapminder,
  wrappedtools)

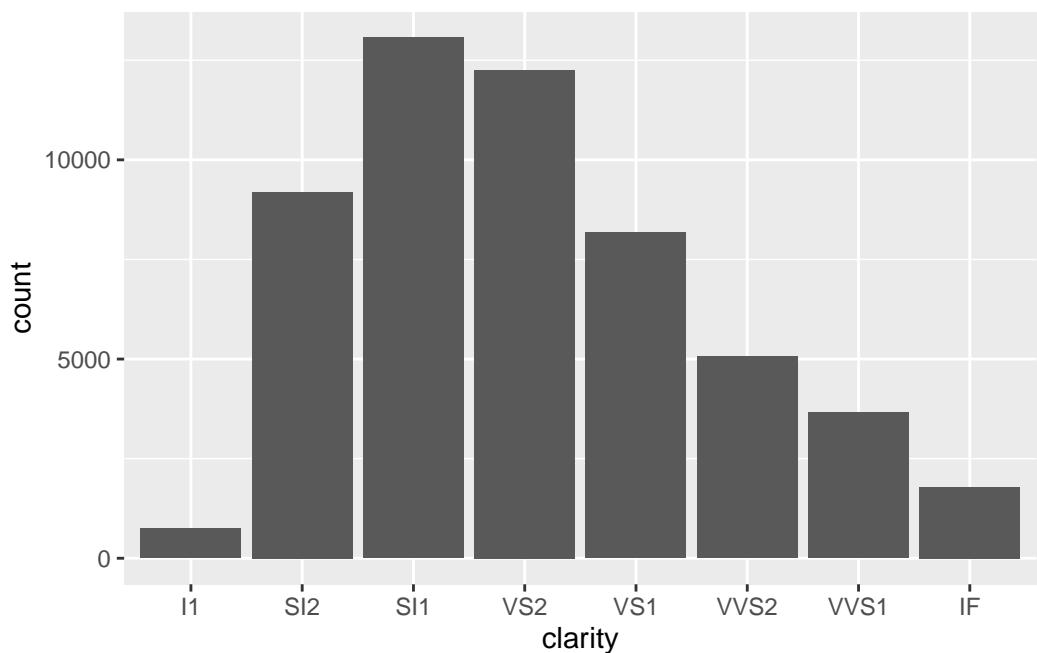
#sample data
head(diamonds)
```

```
# A tibble: 6 x 10
  carat cut      color clarity depth table price     x     y     z
  <dbl> <ord>    <ord> <ord>   <dbl> <dbl> <int> <dbl> <dbl> <dbl>
1 0.23 Ideal    E      SI2      61.5   55    326  3.95  3.98  2.43
2 0.21 Premium  E      SI1      59.8   61    326  3.89  3.84  2.31
3 0.23 Good     E      VS1      56.9   65    327  4.05  4.07  2.31
4 0.29 Premium  I      VS2      62.4   58    334  4.2   4.23  2.63
5 0.31 Good     J      SI2      63.3   58    335  4.34  4.35  2.75
6 0.24 Very Good J      VVS2     62.8   57    336  3.94  3.96  2.48
```

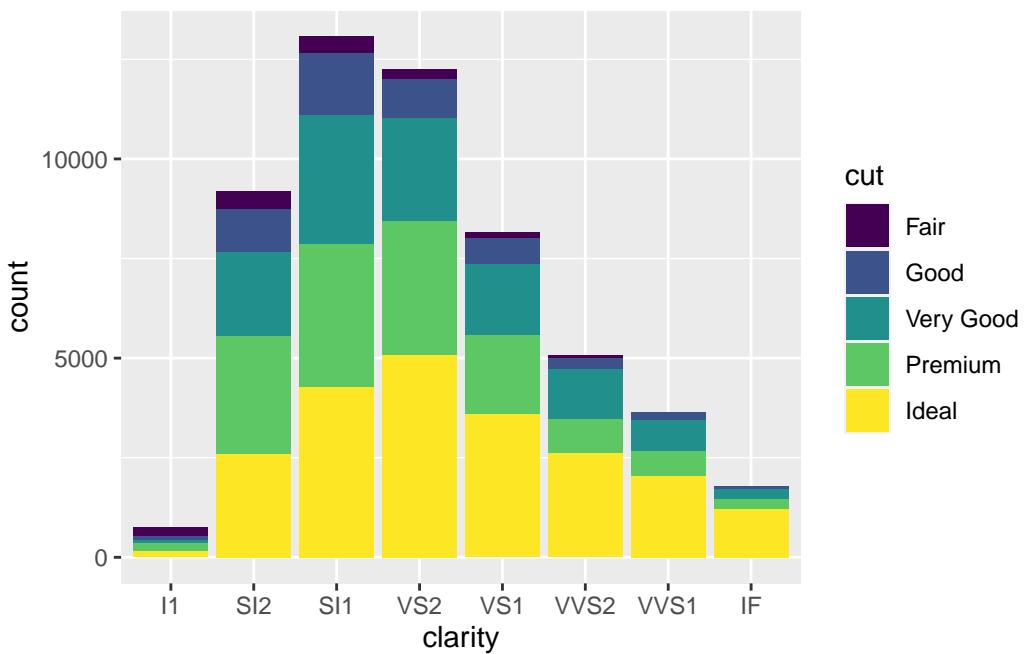
```
head(mtcars)
```

| | mpg | cyl | disp | hp | drat | wt | qsec | vs | am | gear | carb |
|-------------------|------|-----|------|-----|------|-------|-------|----|----|------|------|
| Mazda RX4 | 21.0 | 6 | 160 | 110 | 3.90 | 2.620 | 16.46 | 0 | 1 | 4 | 4 |
| Mazda RX4 Wag | 21.0 | 6 | 160 | 110 | 3.90 | 2.875 | 17.02 | 0 | 1 | 4 | 4 |
| Datsun 710 | 22.8 | 4 | 108 | 93 | 3.85 | 2.320 | 18.61 | 1 | 1 | 4 | 1 |
| Hornet 4 Drive | 21.4 | 6 | 258 | 110 | 3.08 | 3.215 | 19.44 | 1 | 0 | 3 | 1 |
| Hornet Sportabout | 18.7 | 8 | 360 | 175 | 3.15 | 3.440 | 17.02 | 0 | 0 | 3 | 2 |
| Valiant | 18.1 | 6 | 225 | 105 | 2.76 | 3.460 | 20.22 | 1 | 0 | 3 | 1 |

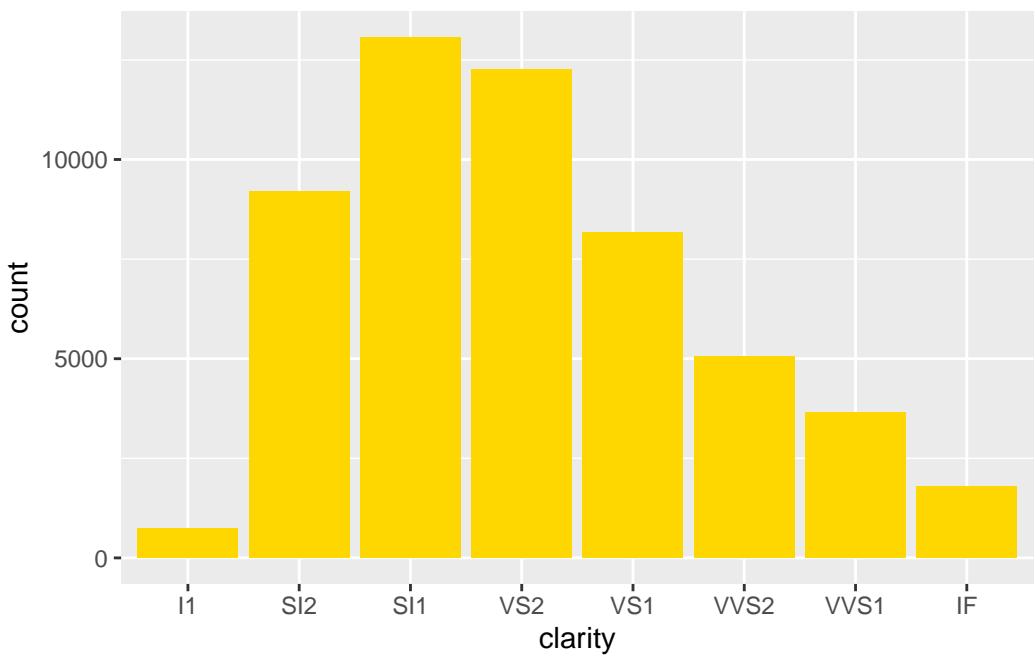
```
ggplot(data=diamonds,mapping = aes(x=clarity))+  
  geom_bar()
```



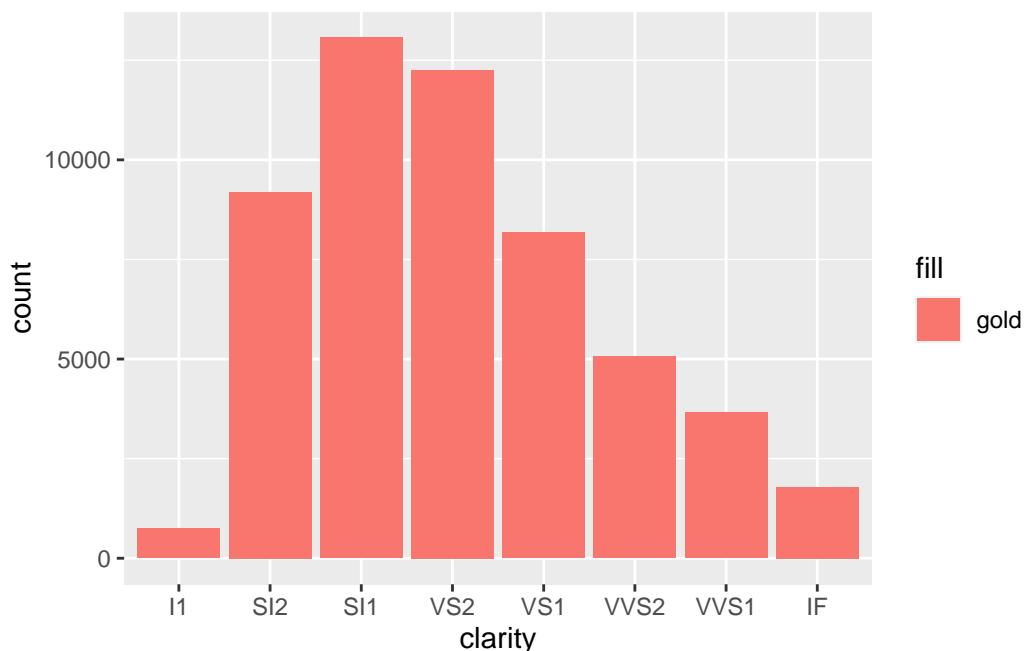
```
#define aesthetics  
ggplot(data=diamonds,aes(x=clarity,fill=cut))+  
  geom_bar()
```



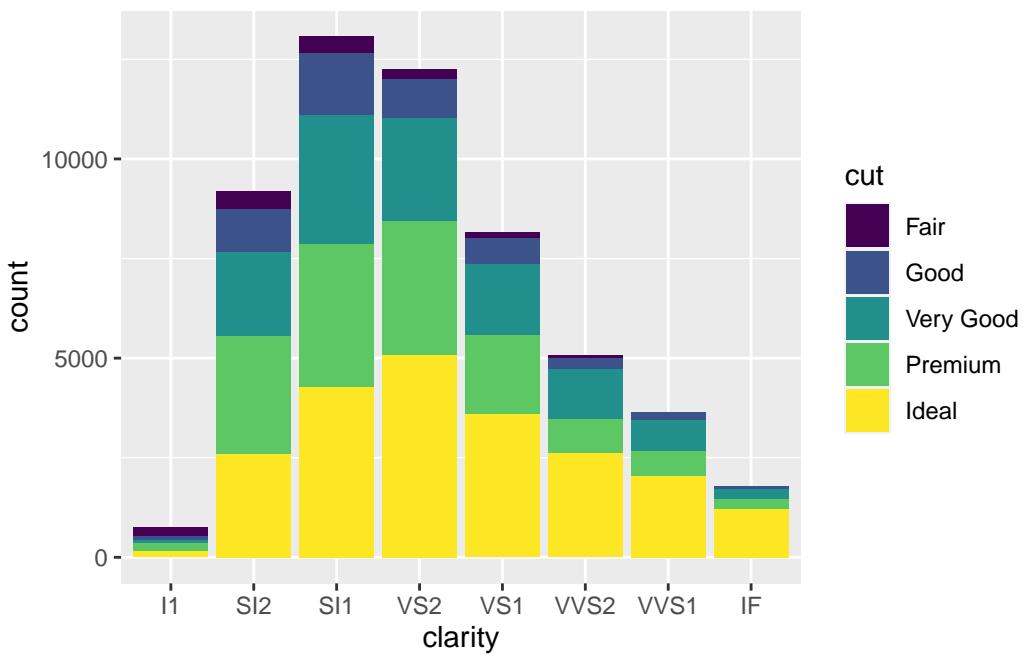
```
#aesthetics outside aes
ggplot(data=diamonds,aes(x=clarity))+
  geom_bar(fill='gold')
```



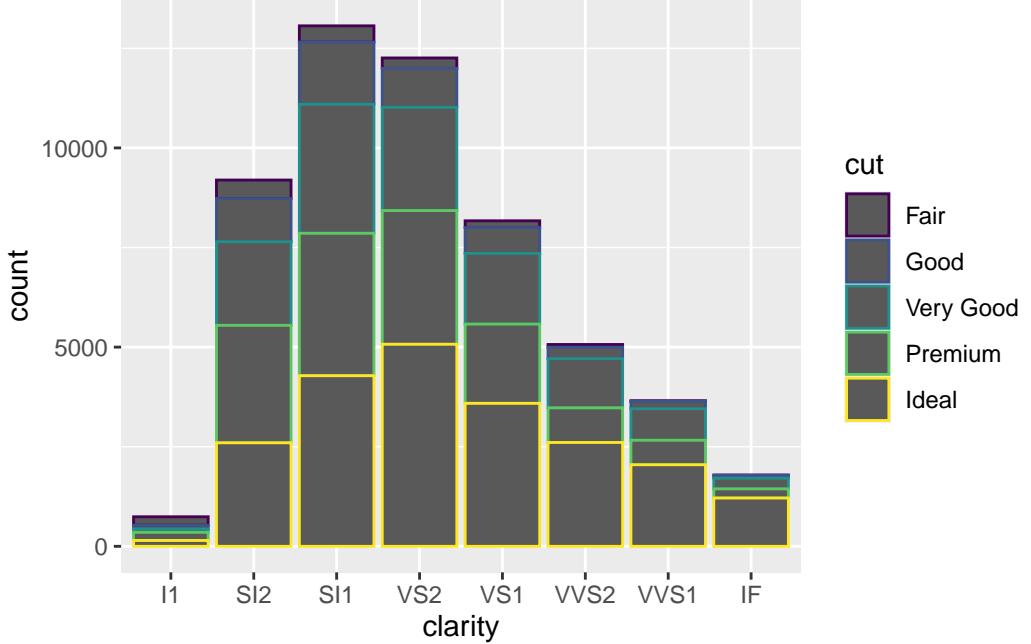
```
ggplot(data=diamonds,aes(x=clarity))+  
  geom_bar(aes(fill='gold')) #should be outside aes!
```



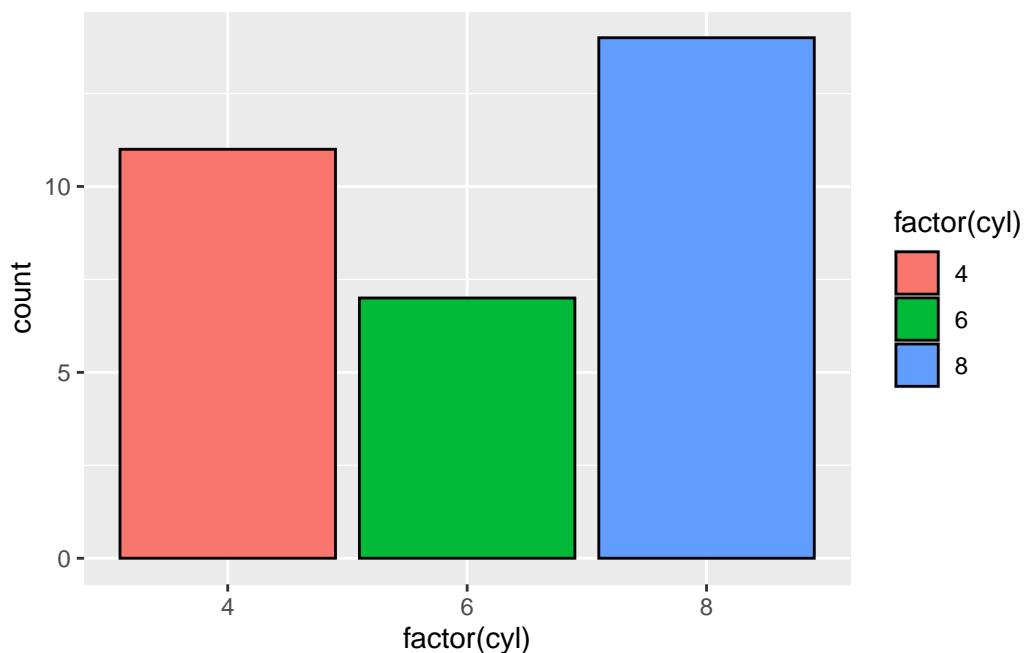
```
ggplot(data=diamonds,aes(x=clarity))+  
  geom_bar(aes(fill=cut))
```



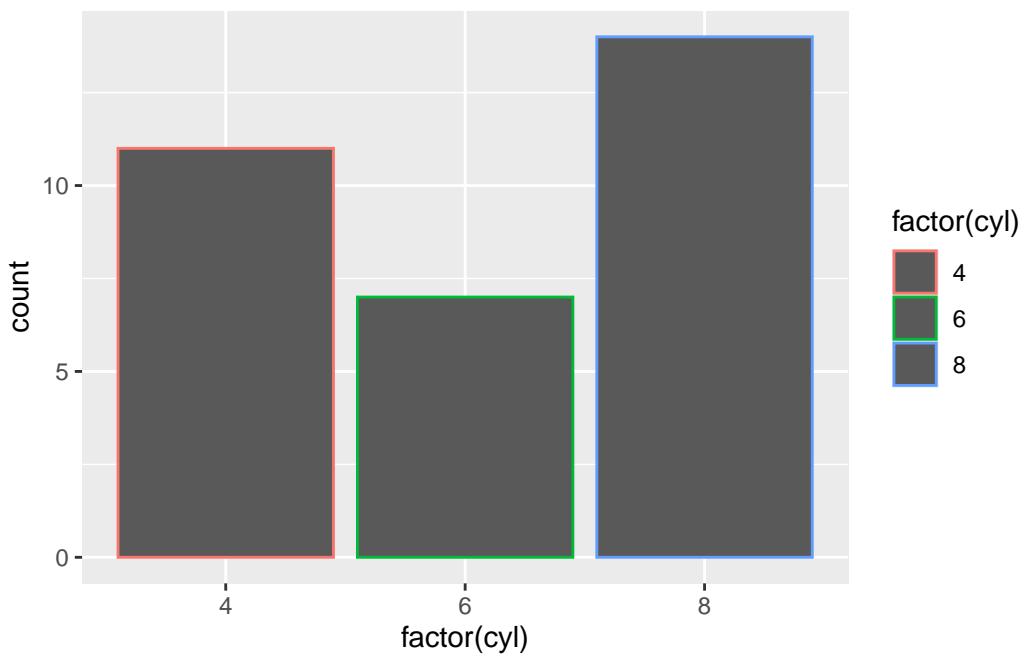
```
#fill/color
ggplot(data=diamonds,aes(x=clarity,color=cut))+  
  geom_bar()
```



```
ggplot(data=mtcars,aes(factor(cyl),fill=factor(cyl)))+  
  geom_bar(color='black')
```



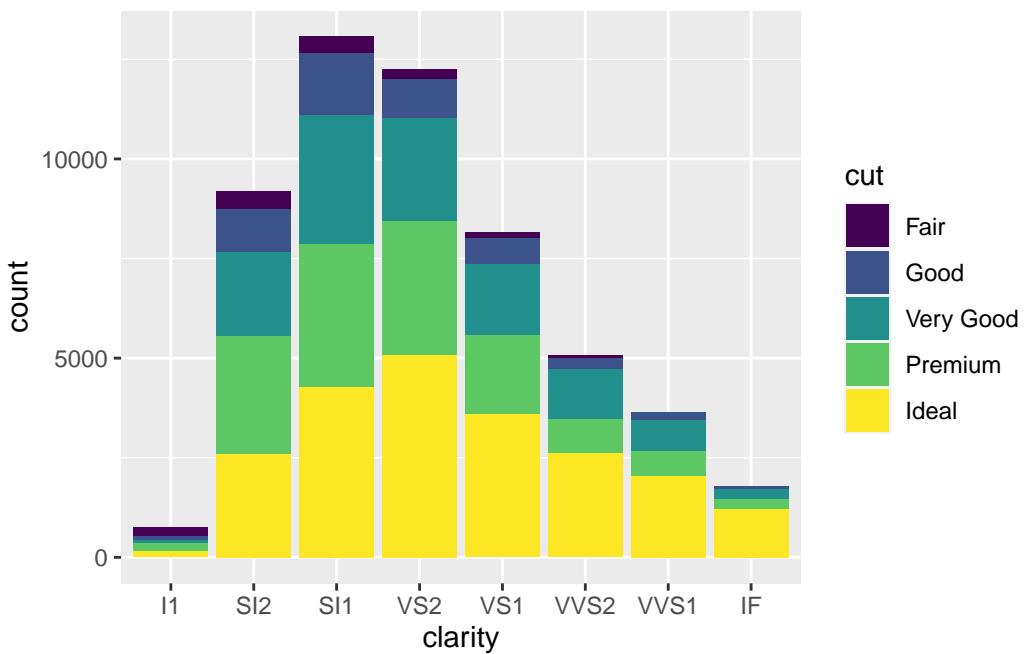
```
ggplot(data=mtcars,aes(factor(cyl),color=factor(cyl)))+  
  geom_bar()
```



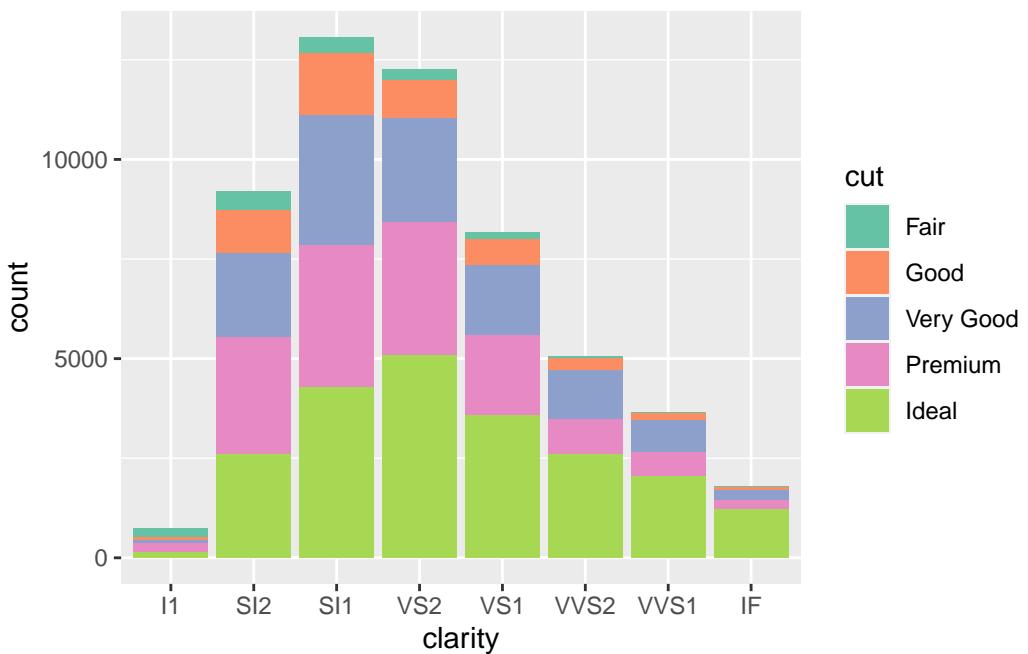
```
help(points)
```

starte den http Server für die Hilfe fertig

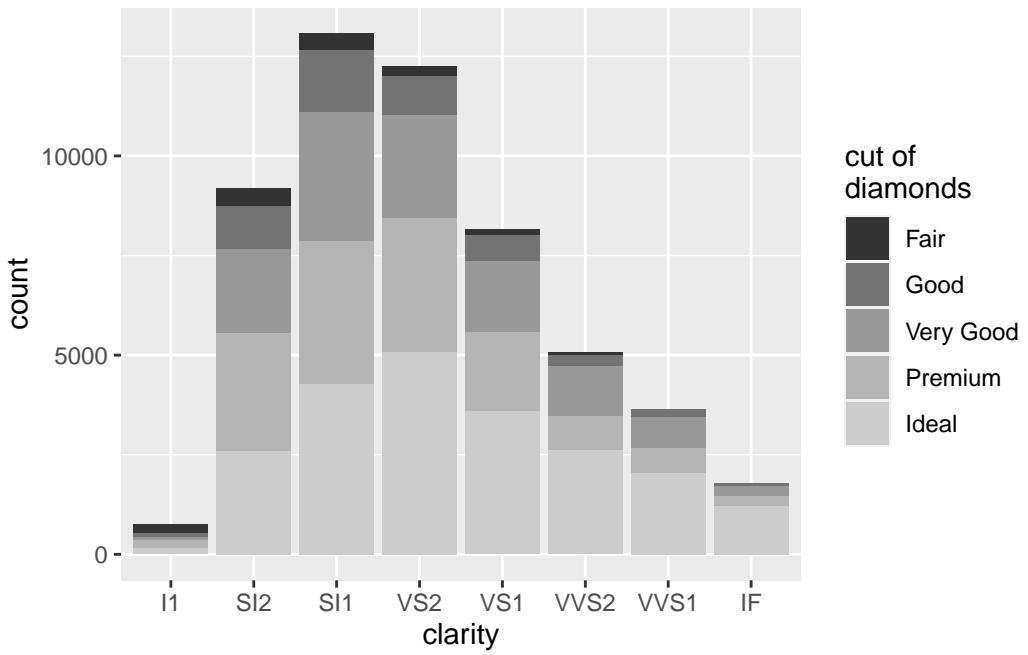
```
#other color systems
(plottemp <- ggplot(data=diamonds,aes(x=clarity,fill=cut))+  
  geom_bar())
```



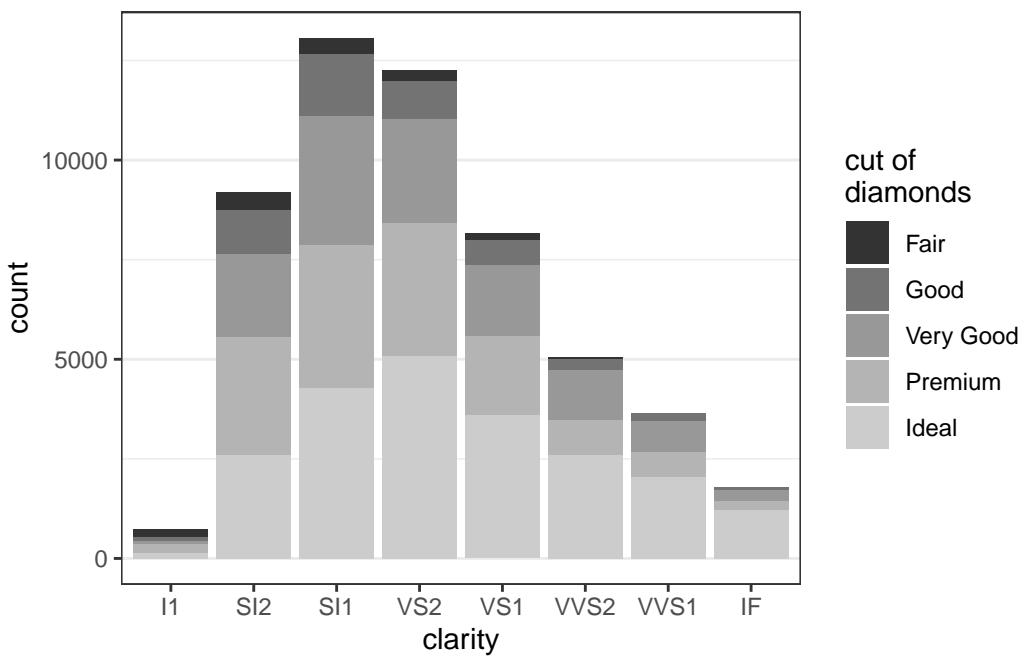
```
plottemp + scale_fill_brewer(palette='Set2') #in-built
```



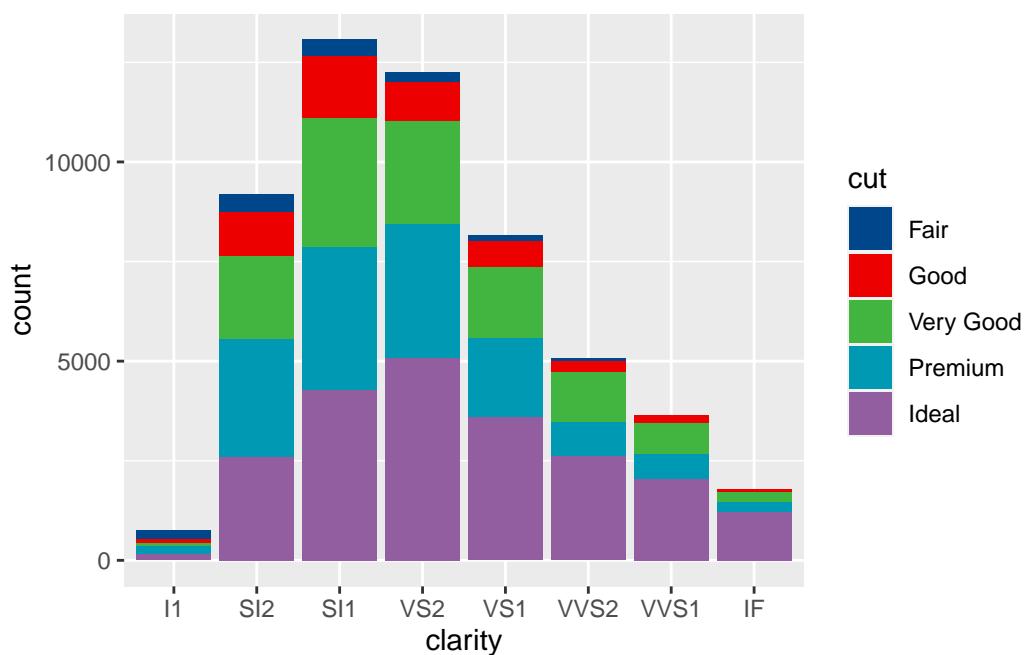
```
plottemp + scale_fill_grey(name = "cut_of\diamonds")
```



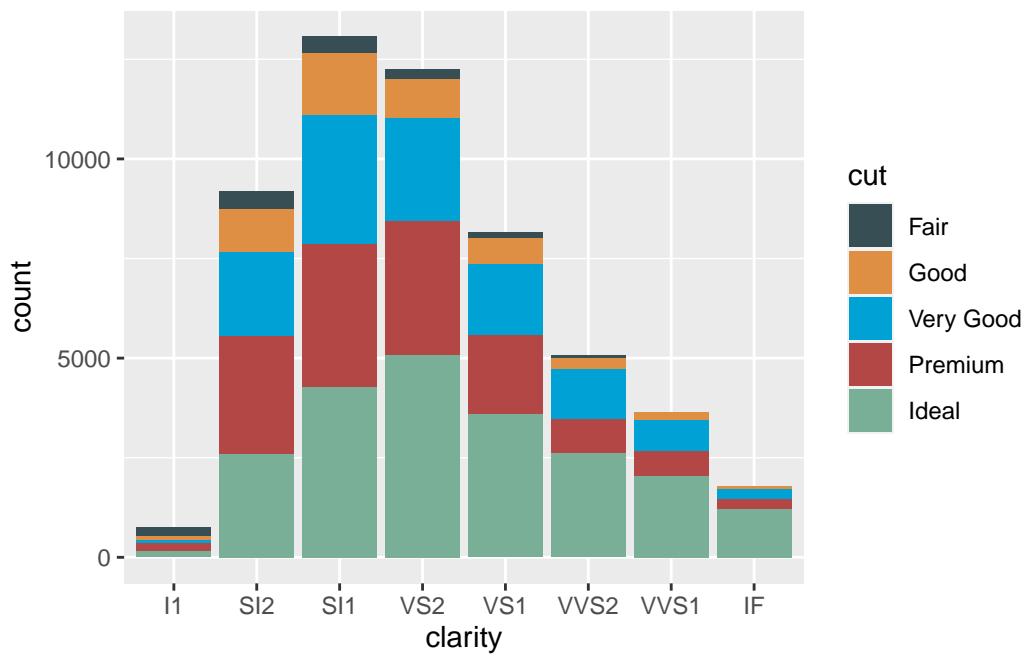
```
plottemp + scale_fill_grey(name = "cut of diamonds") +
  theme_bw() +
  theme(panel.grid.minor.x=element_blank(),
    panel.grid.major.x = element_blank()) #+
```



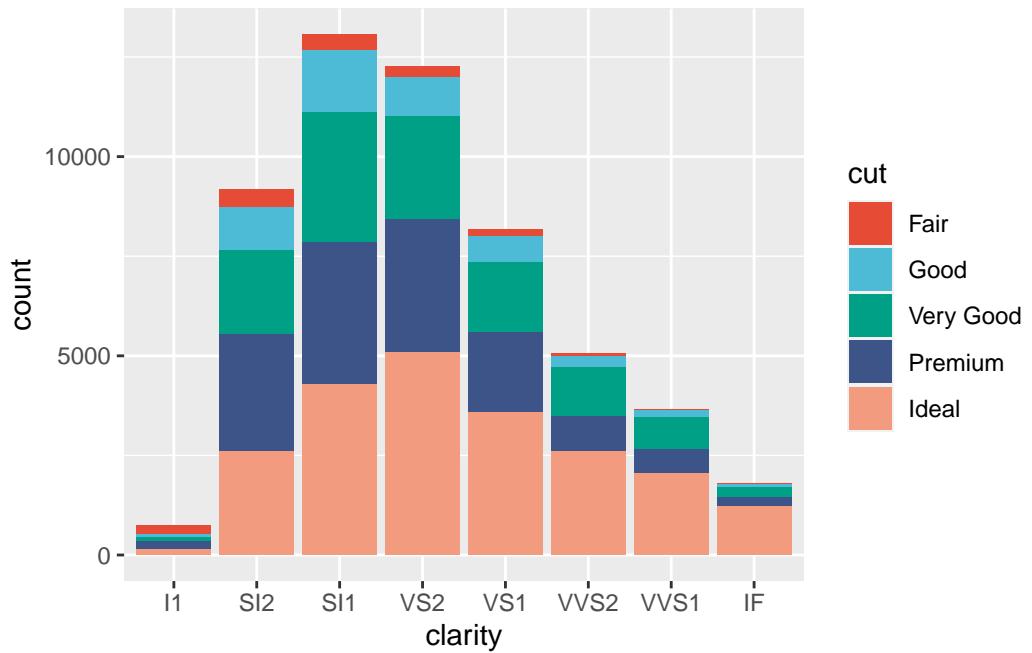
```
# scale_y_continuous(expand = expansion(mult = c(0,.5)))  
  
# ggsci #####  
plottemp+scale_fill_lancet()
```



```
plottemp+scale_fill_jama()
```



```
plottemp+scale_fill_npg()
```



```

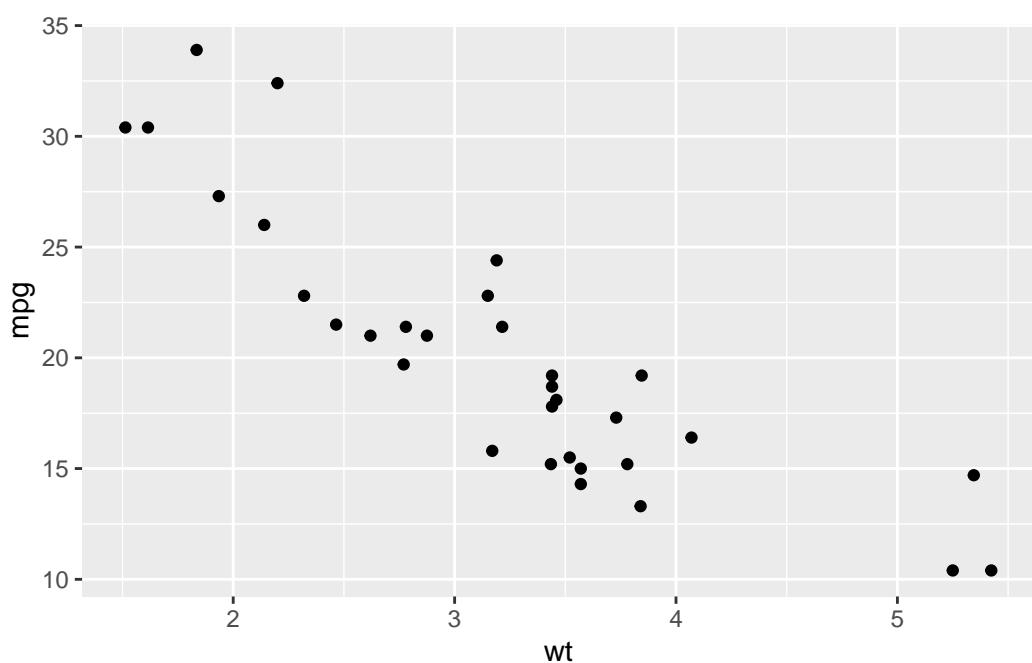
printplot <- plottemp+scale_fill_startrek()

#save ggplots
# ggsave(filename = 'Graphs/ggtestplot.png',
#        plot = printplot,
#        width=20,height=20,
#        units='cm',dpi=150)
# alternative:
# png(filename = 'Graphs/ggtestplot2.png',
#      width = 20,height = 20,units = 'cm',res = 150)
# plottemp
# dev.off()
# scatterplot

#other geoms
ggplot(data=mtcars,aes(x = wt,y = mpg))+  

  geom_point()

```

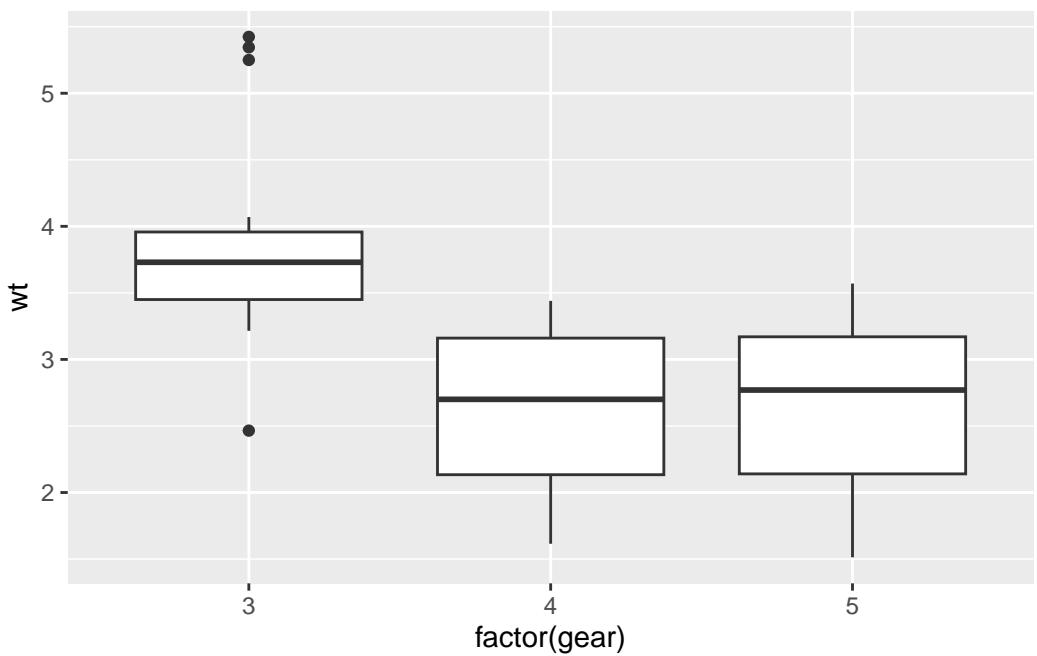


```

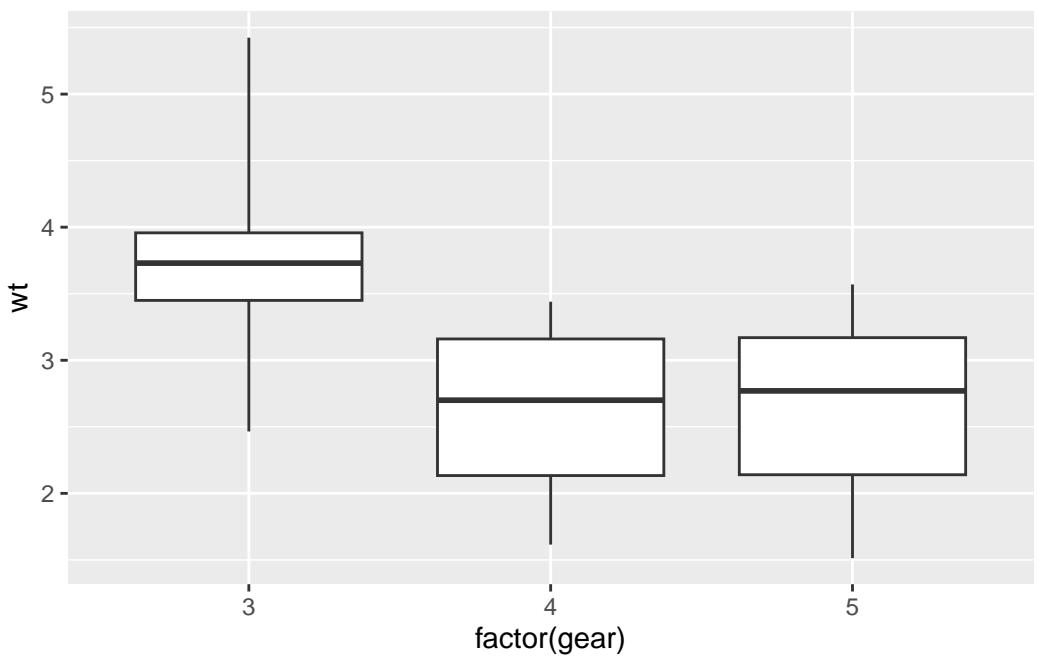
ggplot(mtcars,aes(x = factor(gear),y = wt))+  

  geom_boxplot() #default 1.5 IQR

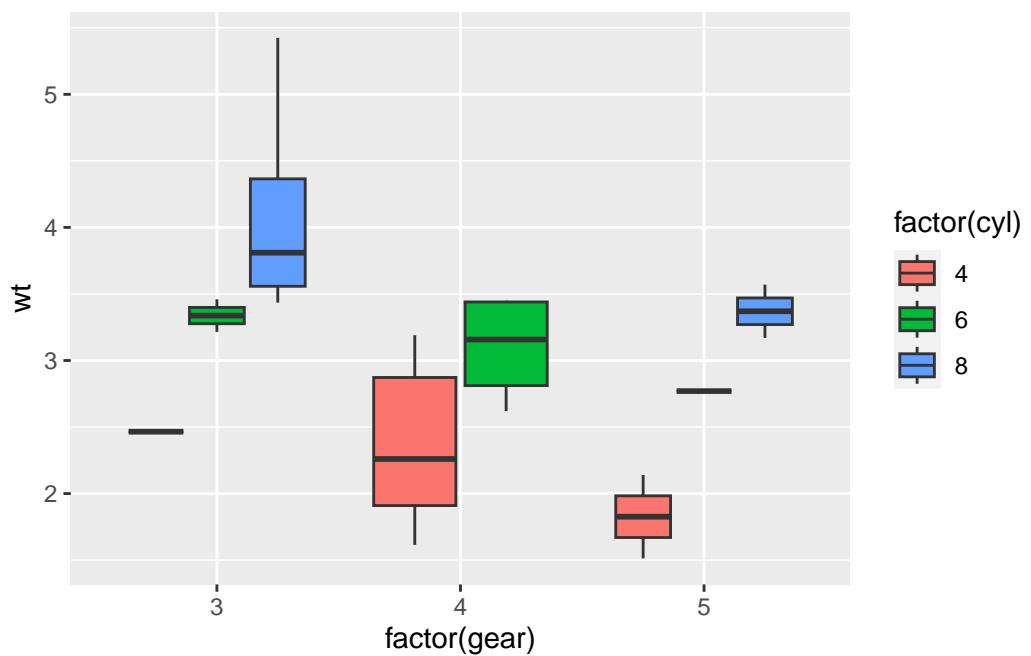
```



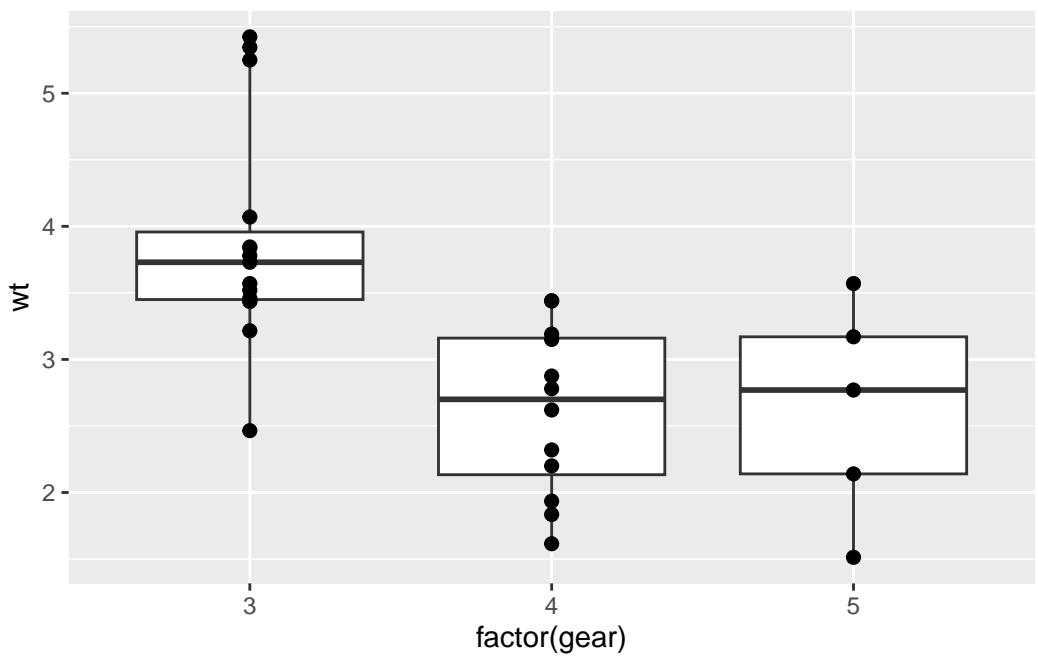
```
ggplot(mtcars,aes(x = factor(gear),y = wt))+  
  geom_boxplot(coef=3)
```



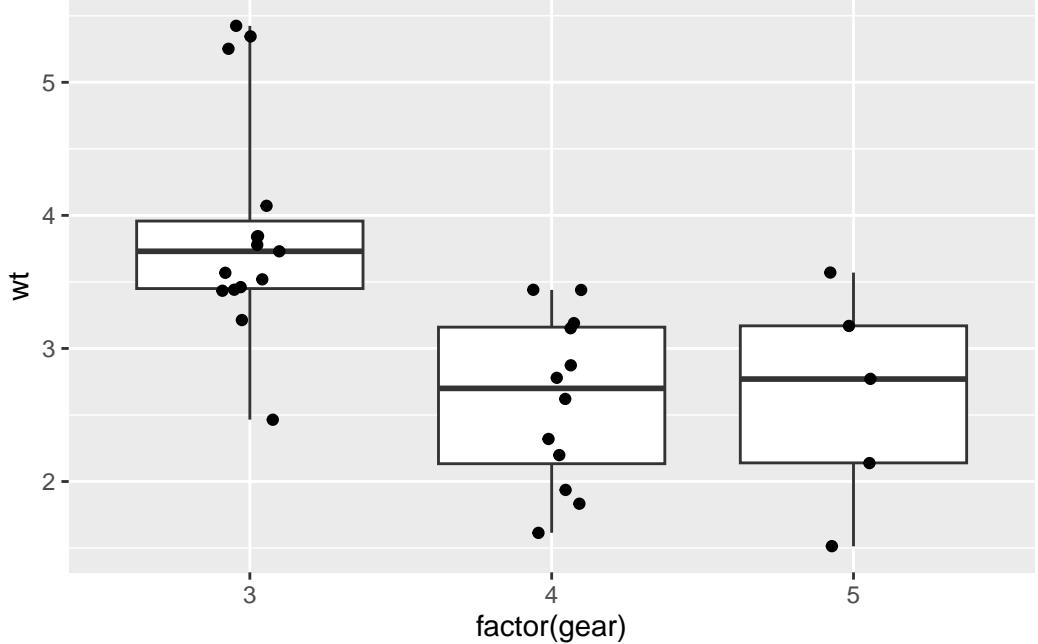
```
ggplot(mtcars,aes(x = factor(gear),y = wt,  
fill=factor(cyl)))+  
geom_boxplot(coef=3)
```



```
ggplot(mtcars,aes(x = factor(gear),y = wt))+  
geom_boxplot(coef=3)+  
geom_point(size=2)
```

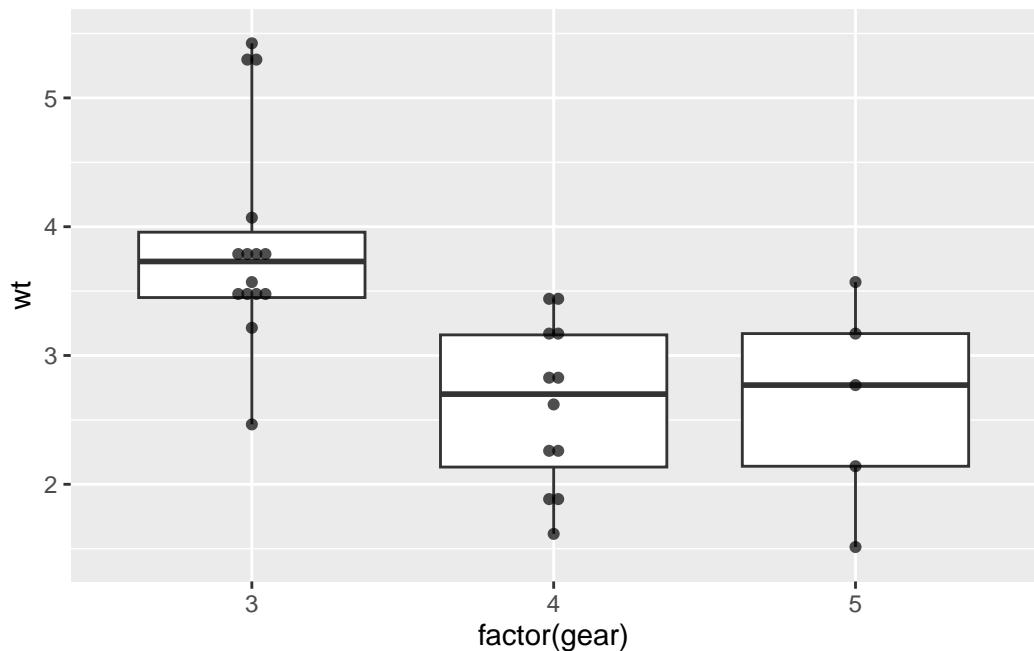


```
ggplot(mtcars,aes(x = factor(gear),y = wt))+  
  geom_boxplot(coef=3)+  
  geom_point(position = position_jitter(width = .1))
```

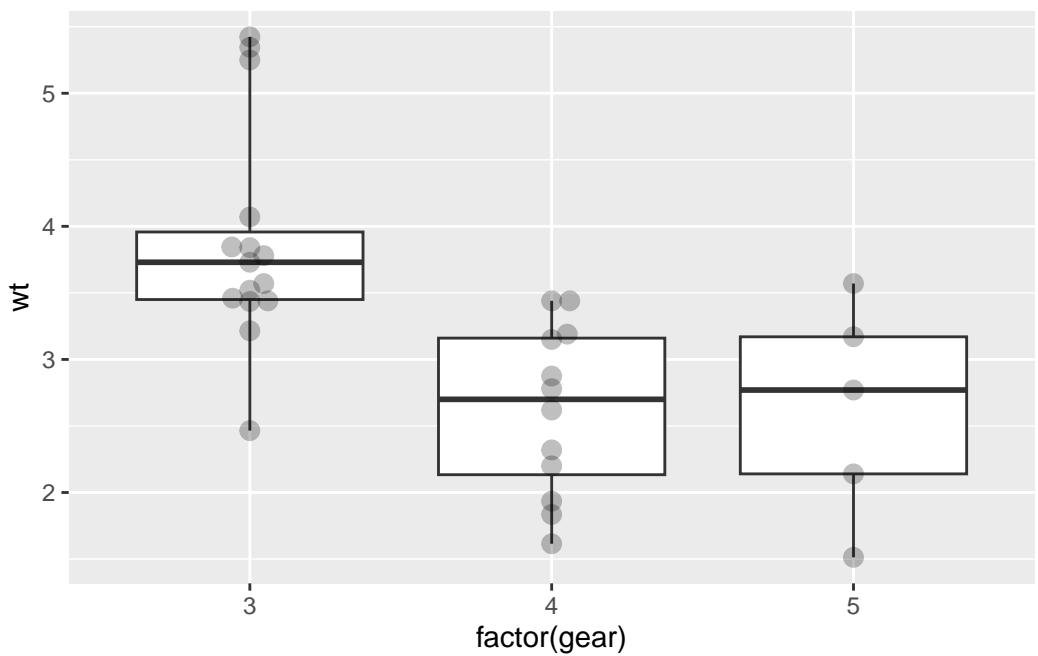


```
ggplot(mtcars,aes(x = factor(gear),y = wt))+  
  geom_boxplot(coef=3)+  
  geom_dotplot(alpha=.7,  
               binaxis = 'y',stackdir = 'center',  
               stackratio = .9,dotsize = .6)
```

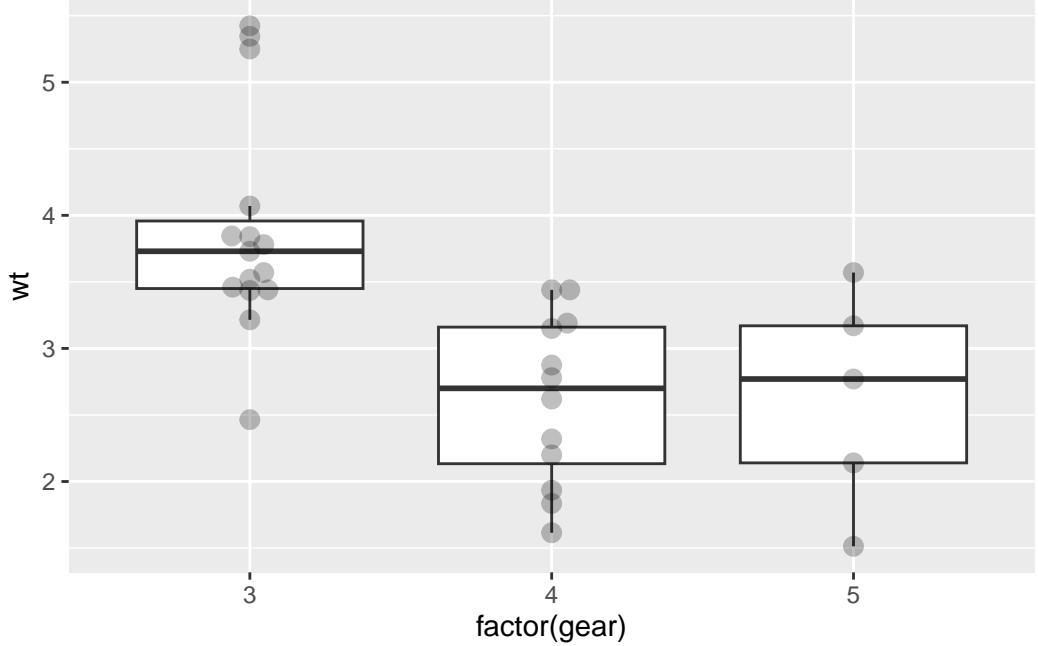
Bin width defaults to 1/30 of the range of the data. Pick better value with `binwidth`.



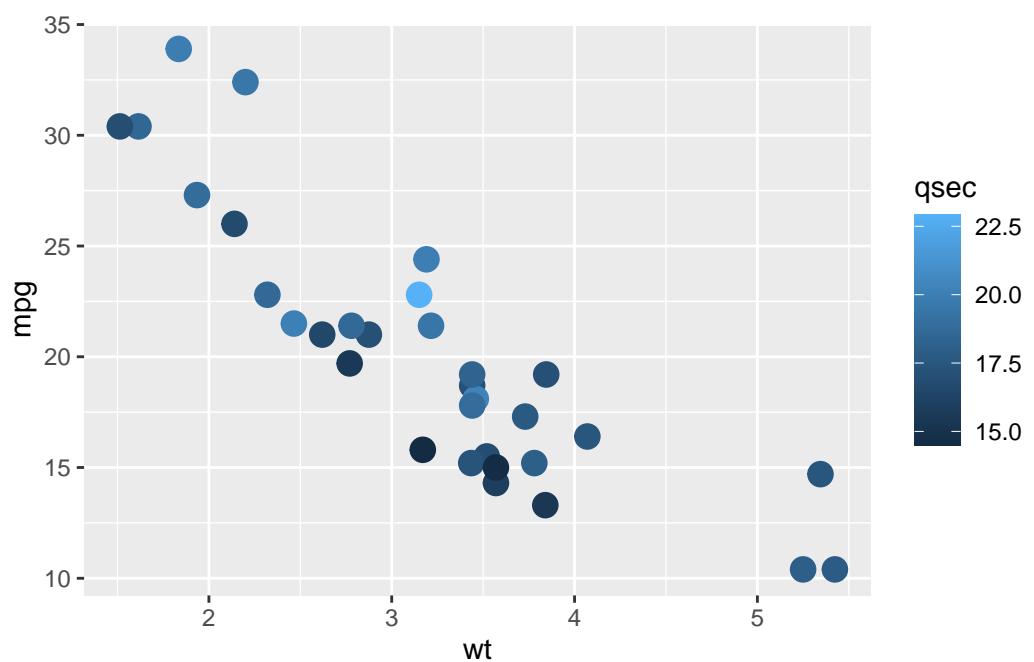
```
ggplot(mtcars,aes(x = factor(gear),y = wt))+  
  geom_boxplot(coef=3)+  
  ggbeeswarm::geom_beeswarm(cex = 2,size=3,alpha=.25)
```



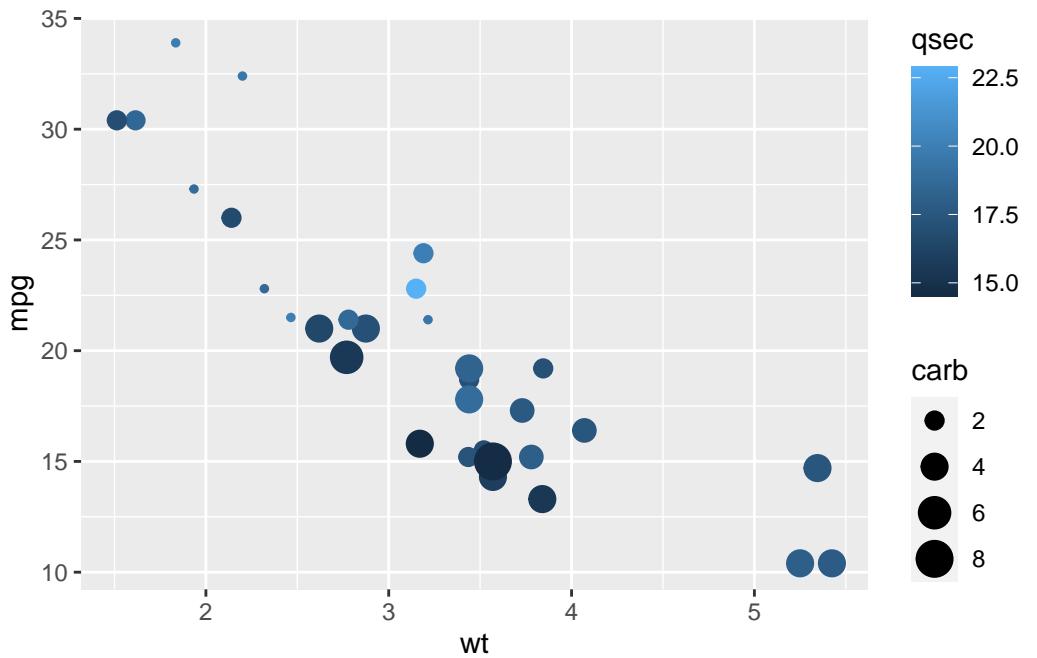
```
ggplot(mtcars,aes(x = factor(gear),y = wt))+  
  geom_boxplot(outlier.alpha = 0)+  
  geom_beeswarm(cex = 2,size=3,alpha=.25)
```



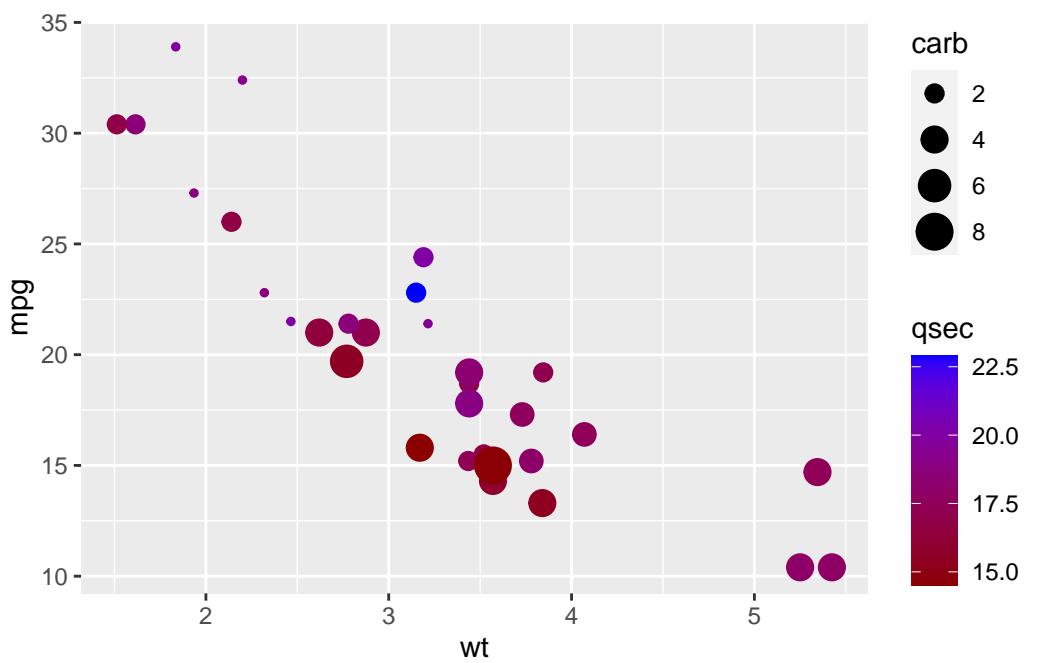
```
#aesthetics again (finetuning)
ggplot(data=mtcars,aes(wt, mpg,color=qsec))+  
  geom_point(size=4) #outside aes!
```



```
ggplot(data=mtcars,aes(wt, mpg,color=qsec, size=carb))+  
  geom_point()
```



```
ggplot(data=mtcars,aes(wt, mpg,color=qsec, size=carb))+  
  scale_color_gradient(low='darkred',high='blue')+  
  geom_point()
```



```

ggplot(data=mtcars,aes(wt, mpg,color=qsec, size=carb))+  

  scale_color_gradient2(low='red',high='darkblue',  

                        mid='white',  

                        limits=c(13,23),midpoint=18)+  

  geom_point() +  

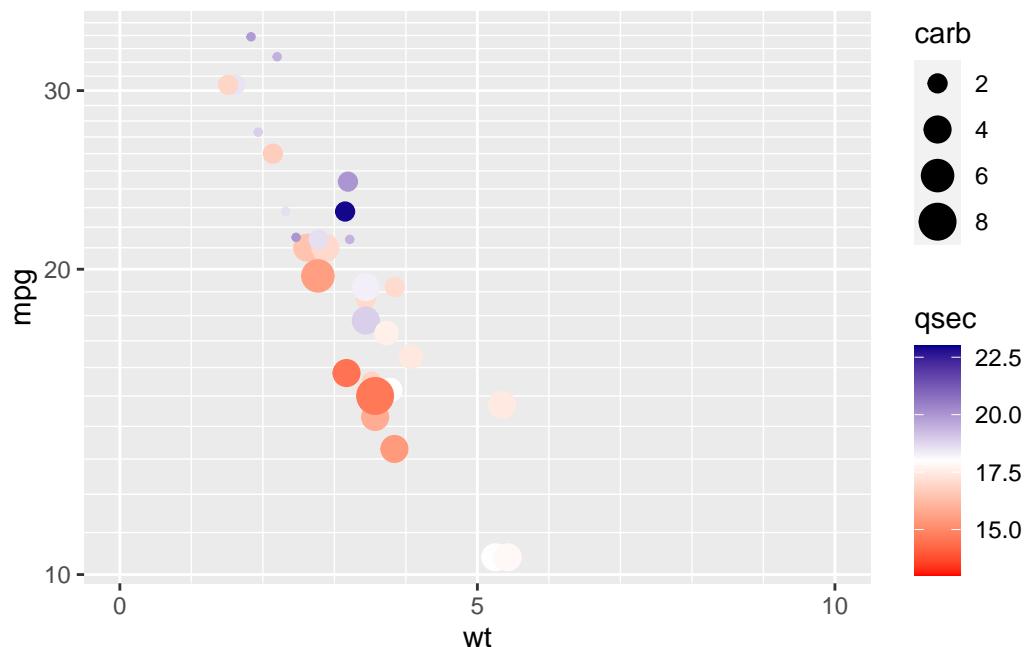
  scale_x_continuous(breaks = seq(0,100,5),  

                     minor_breaks=seq(0,100,1),  

                     limits = c(0,10))+  

  scale_y_log10(minor_breaks=seq(0,100,1))

```

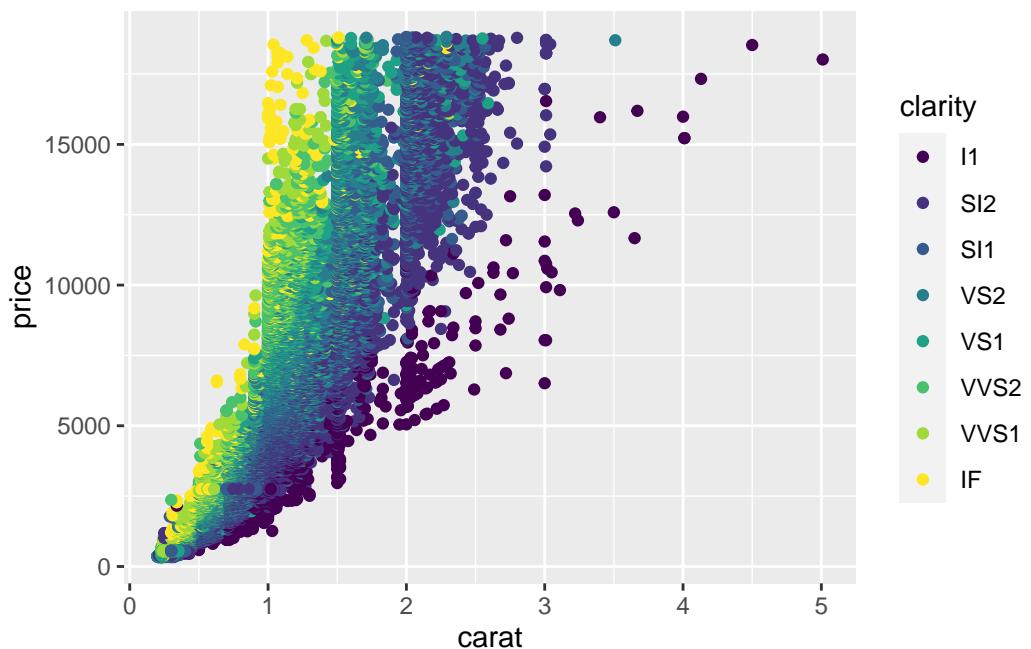


```

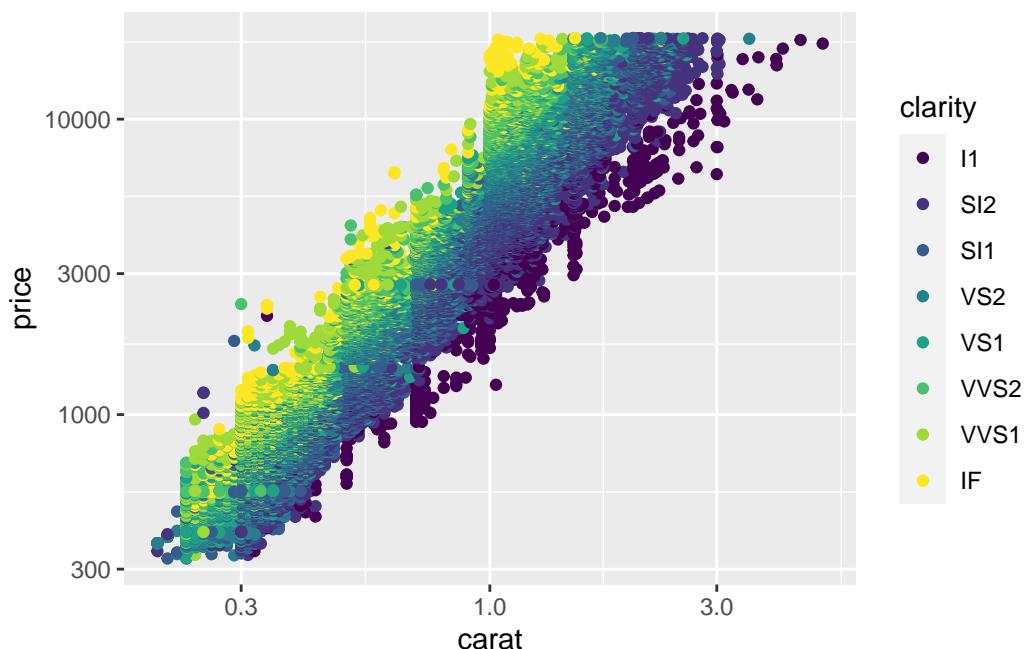
ggplot(diamonds,aes(carat,price,color=clarity))+  

  geom_point()

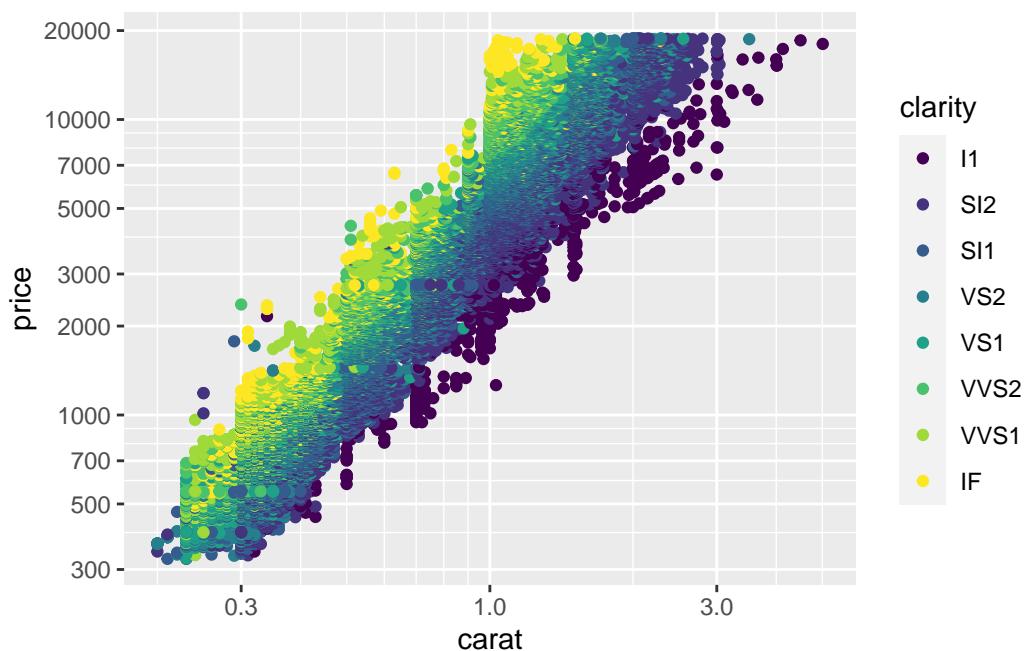
```



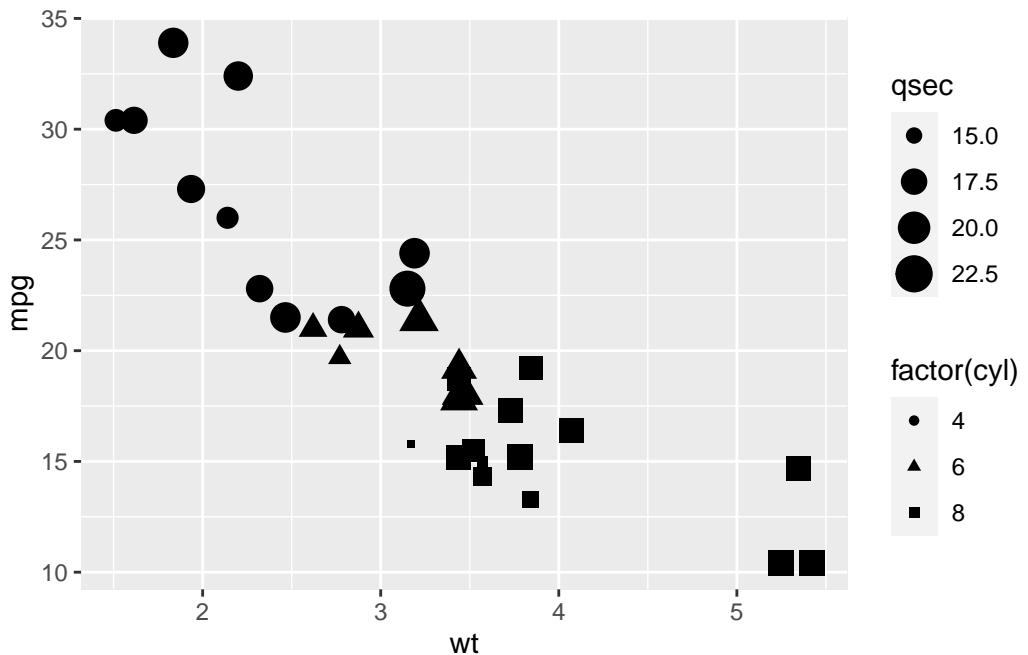
```
ggplot(diamonds,aes(carat,price,color=clarity))+  
  geom_point() +  
  scale_x_log10() +  
  scale_y_log10()
```



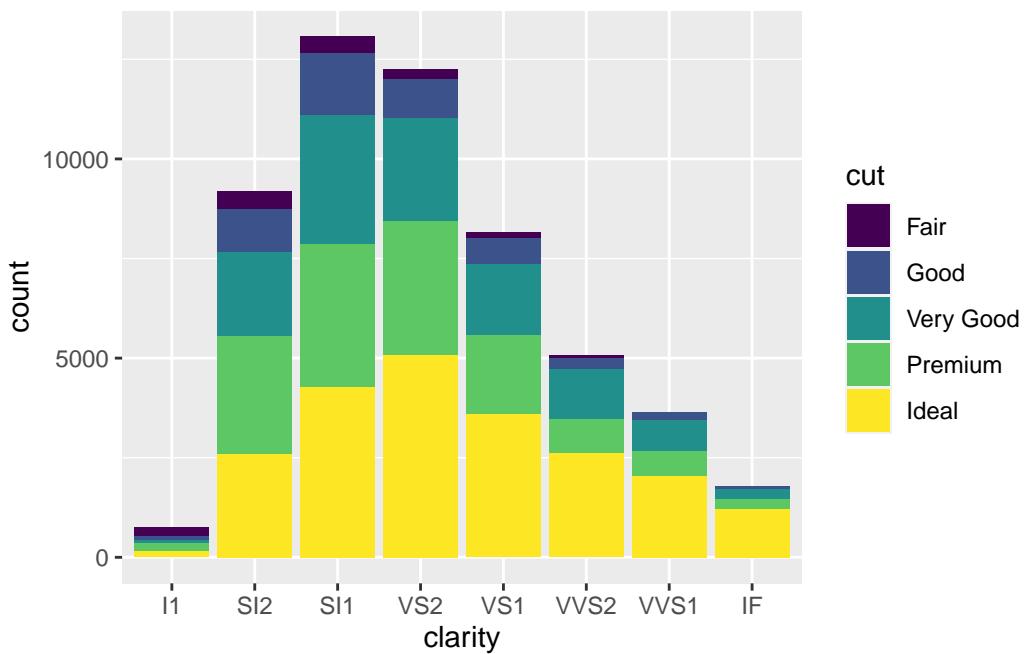
```
ggplot(diamonds,aes(carat,price,color=clarity))+  
  geom_point() +  
  scale_x_log10(minor_breaks=logrange_123456789) +  
  scale_y_log10(  
    breaks=logrange_12357,  
    minor_breaks=logrange_123456789)
```



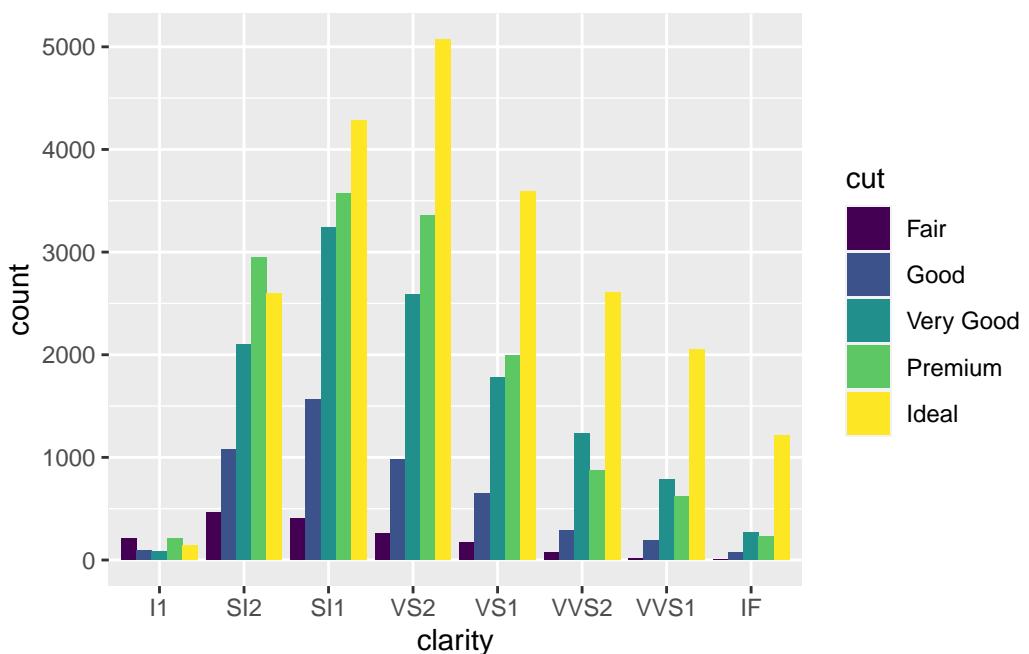
```
# use different aesthetic mappings  
ggplot(data=mtcars,  
       aes(wt, mpg, size=qsec, shape=factor(cyl)))+  
  geom_point()
```



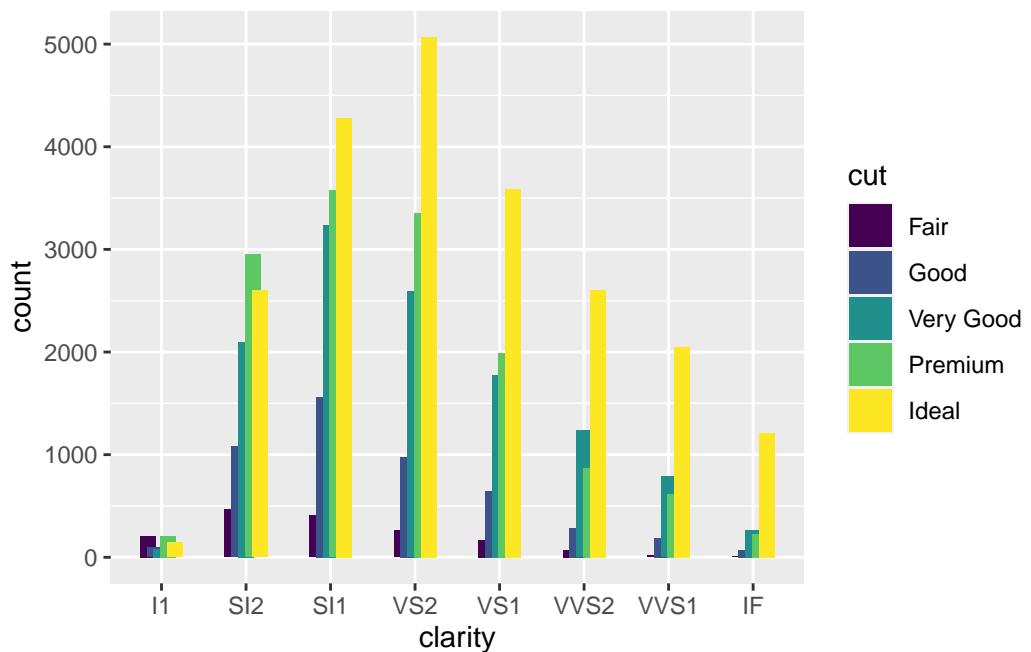
```
# ggplot(data=mtcars,aes(carb, mpg,color=qsec, size=wt))+  
#   geom_point(shape='\u2642')  
  
#location, location,position  
  
p<-ggplot(data=diamonds,aes(clarity,fill=cut))  
p+geom_bar(position="stack")
```



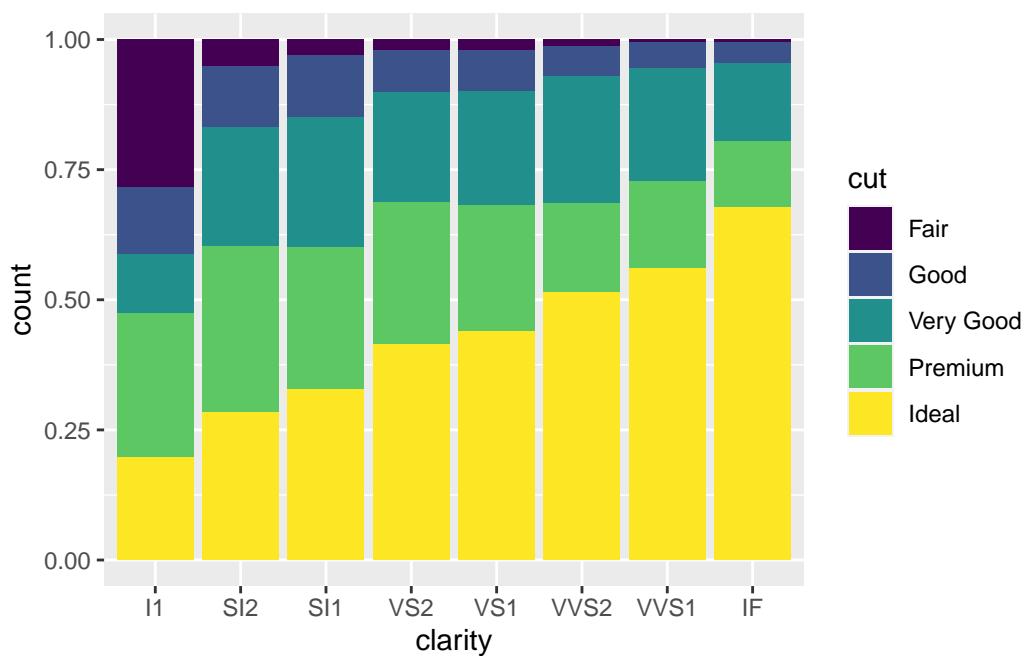
```
p+geom_bar(position="dodge")
```



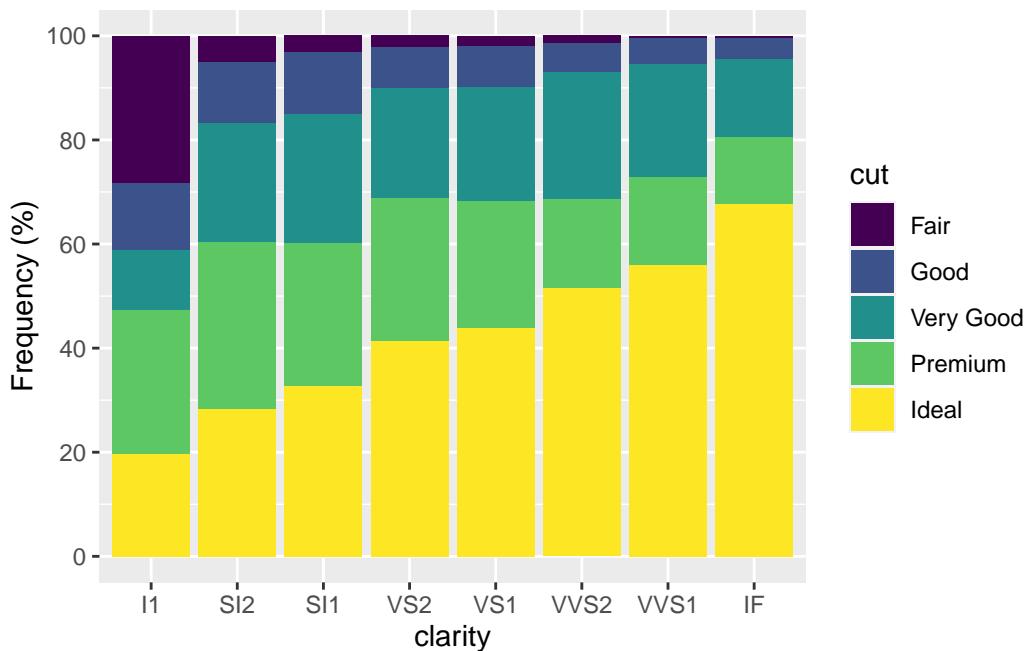
```
p+geom_bar(position=position_dodge(width = .4))
```



```
p+geom_bar(position="fill")
```



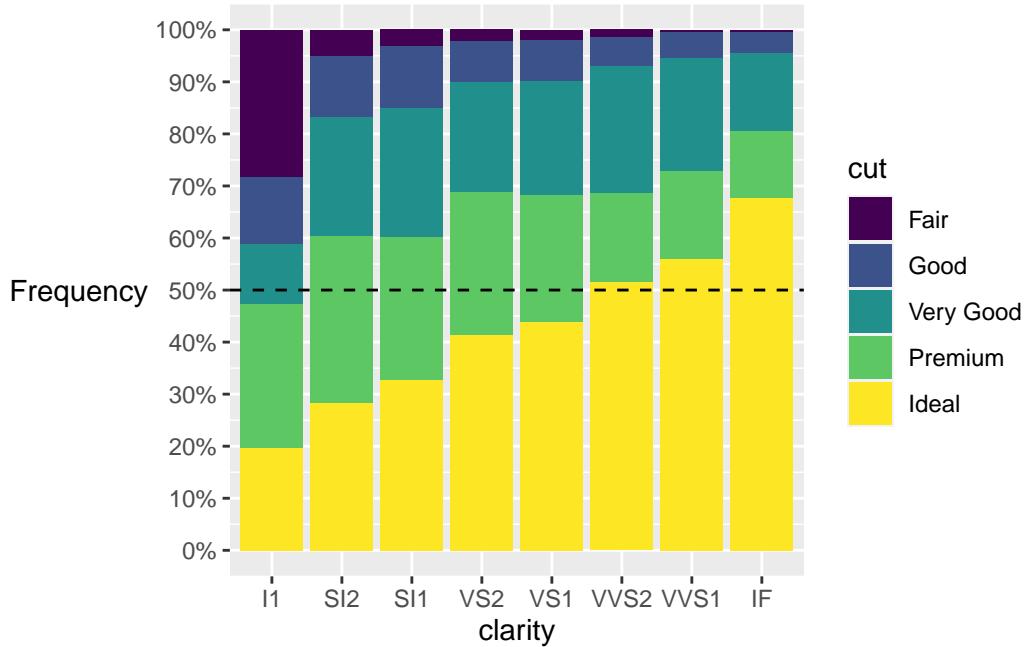
```
p+geom_bar(position="fill")+
  scale_y_continuous('Frequency (%)',
                     breaks=seq(0,1,.2),
                     labels=seq(0,100,20))
```



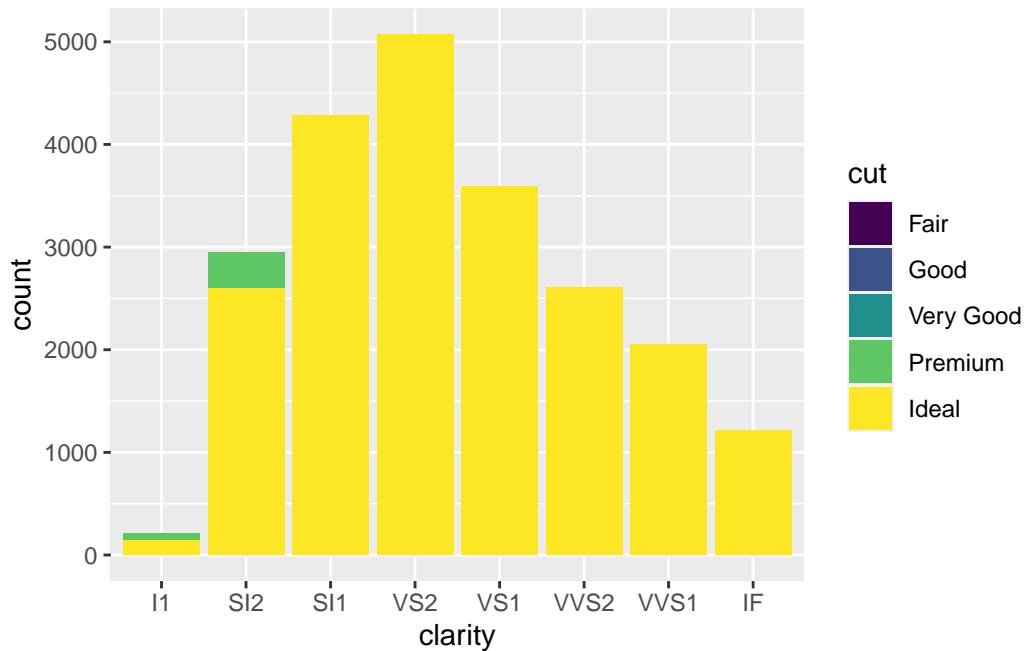
```
p+geom_bar(position="fill")+
  scale_y_continuous('Frequency',
                     breaks=seq(0,1,.1),
                     labels=scales::percent)+
```

theme(axis.title.y = element_text(angle = 0,
 vjust = .5))+

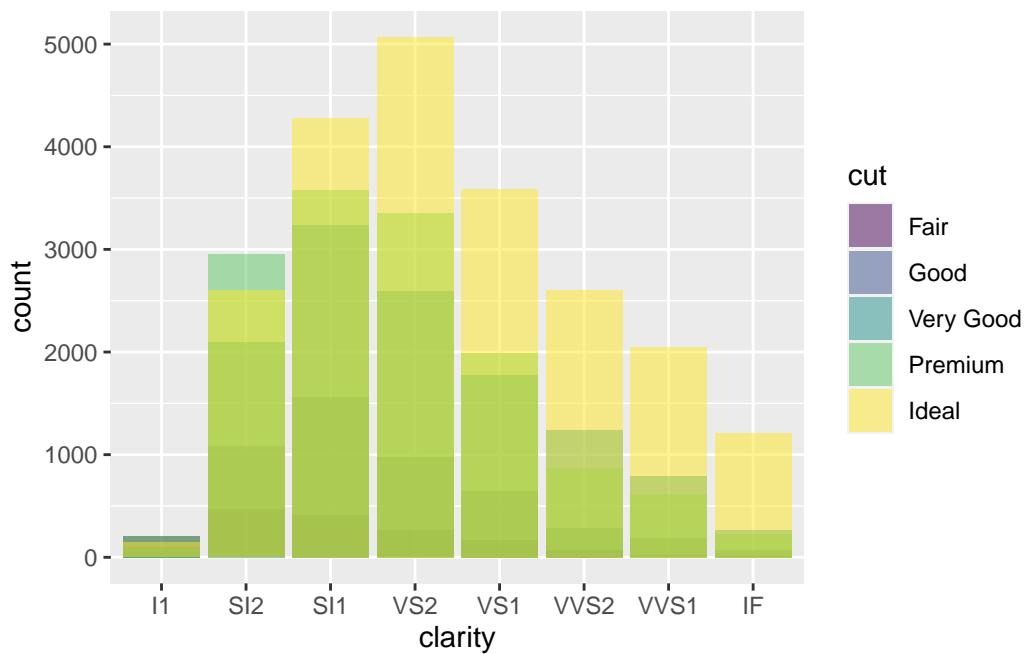
```
geom_hline(yintercept = .5, linetype=2)
```



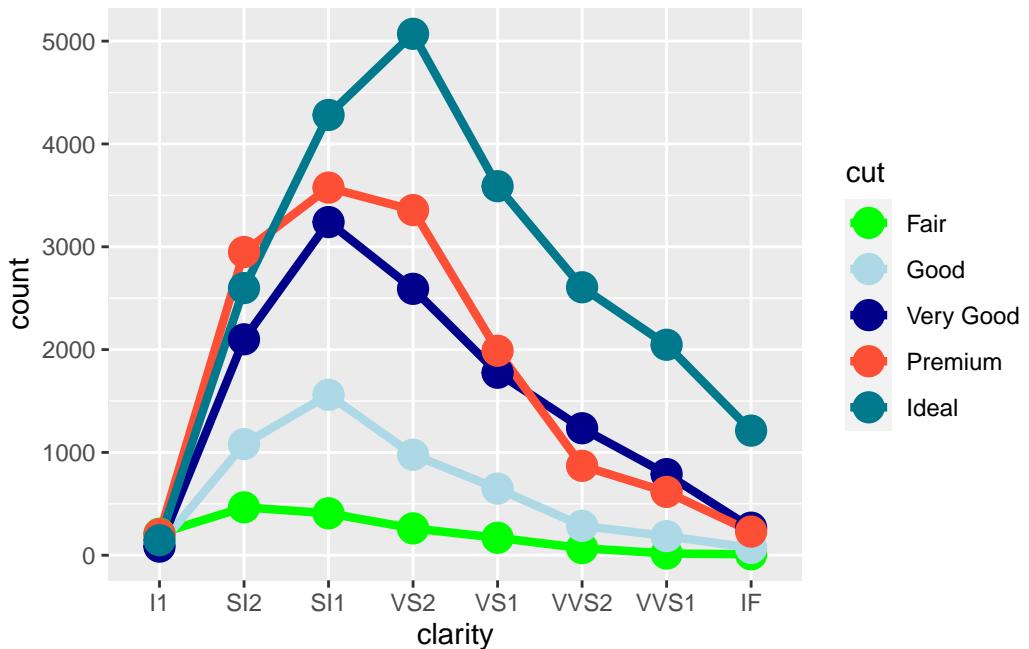
```
p+geom_bar(position="identity")
```



```
p+geom_bar(position="identity",alpha=.5)
```



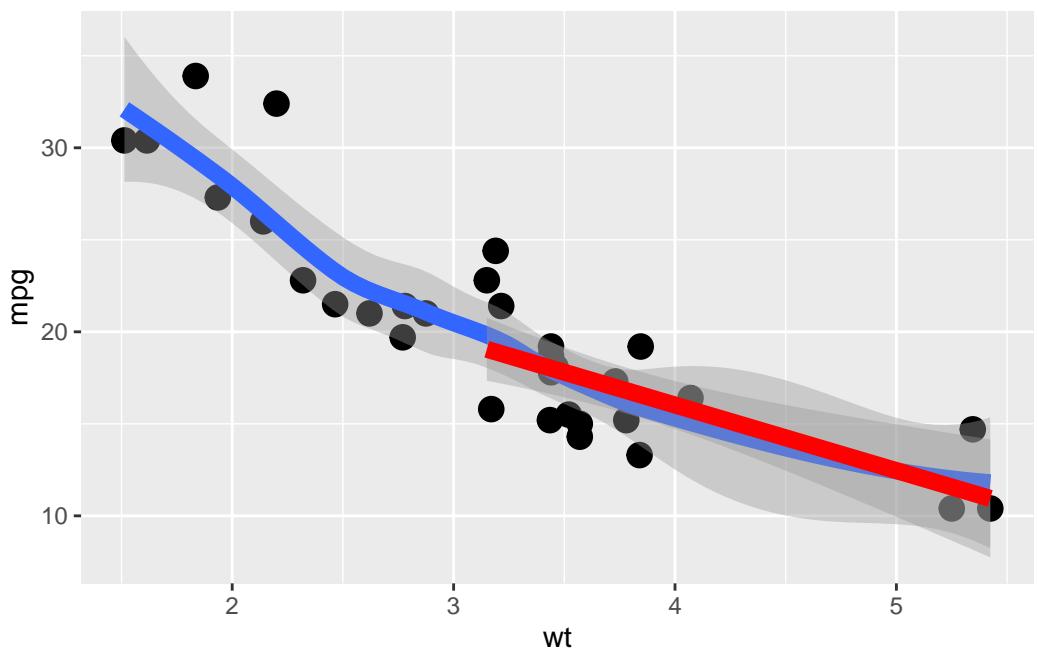
```
ggplot(data=diamonds,aes(clarity,color=cut, group=cut))+  
  geom_freqpoly(stat='count',position="identity",lwd=1.5)+  
  geom_point(stat='count',size=5)+  
  scale_color_manual(values = c('green','lightblue',  
                               'darkblue',  
                               rgb(253,79,54,maxColorValue = 255),  
                               '#00798d'))
```



```
#layer/order / computed geoms
ggplot(data=mtcars,aes(wt, mpg))+
  geom_point(size=4)+
  geom_smooth(size=3)+
  geom_smooth(data=mtcars %>% filter(wt>3),
              method='lm',size=3, color='red')
```

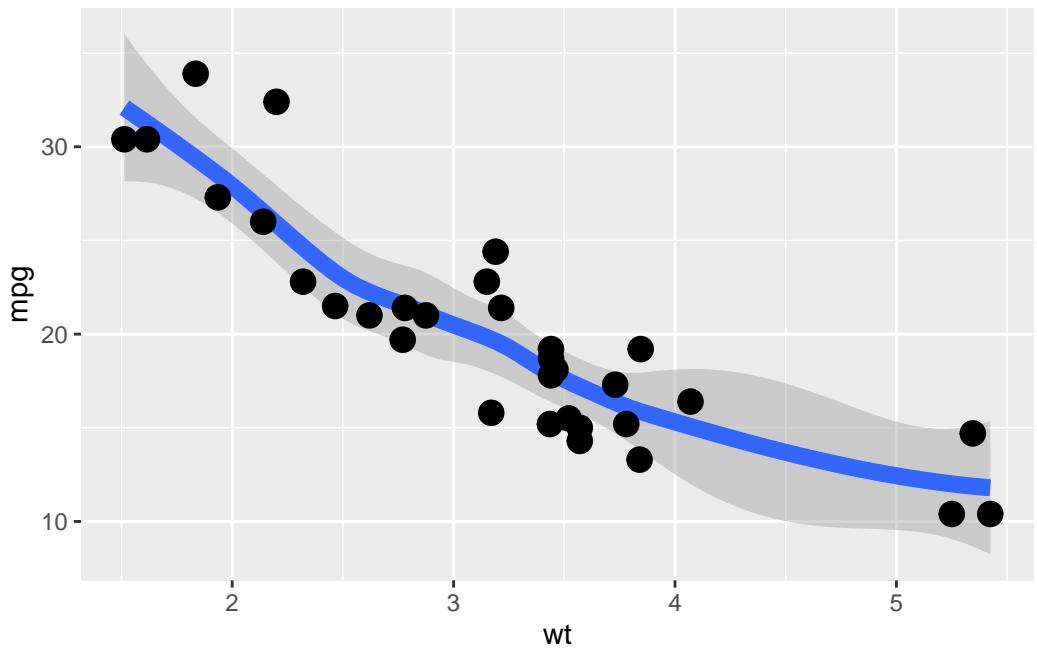
Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
i Please use `linewidth` instead.

`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
`geom_smooth()` using formula = 'y ~ x'



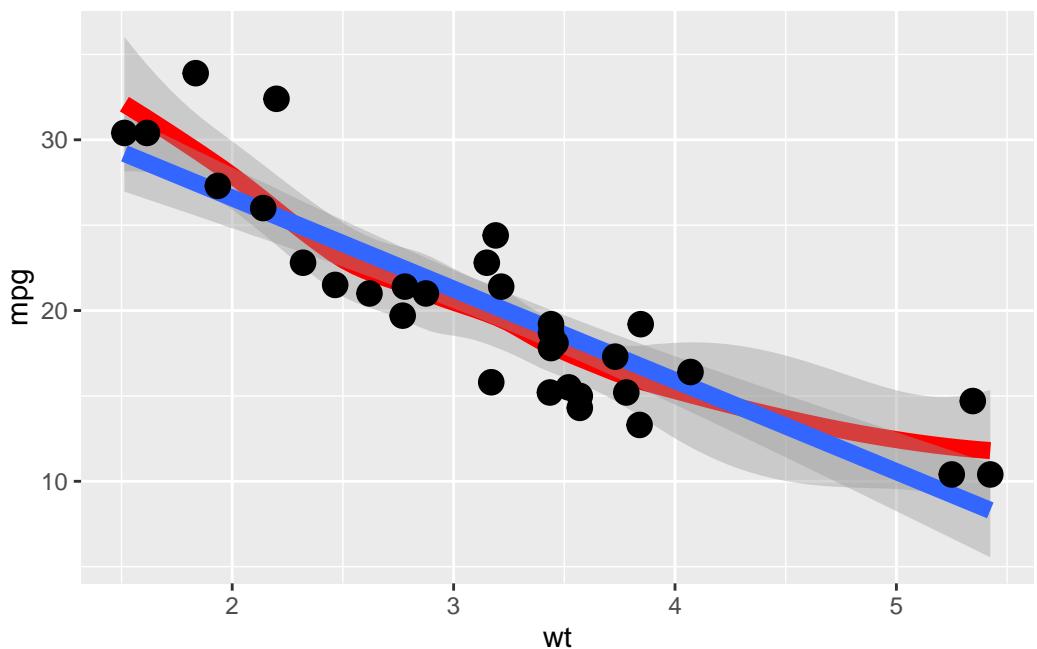
```
ggplot(data=mtcars,aes(wt, mpg))+  
  geom_smooth(size=3)+  
  geom_point(size=4)
```

```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```



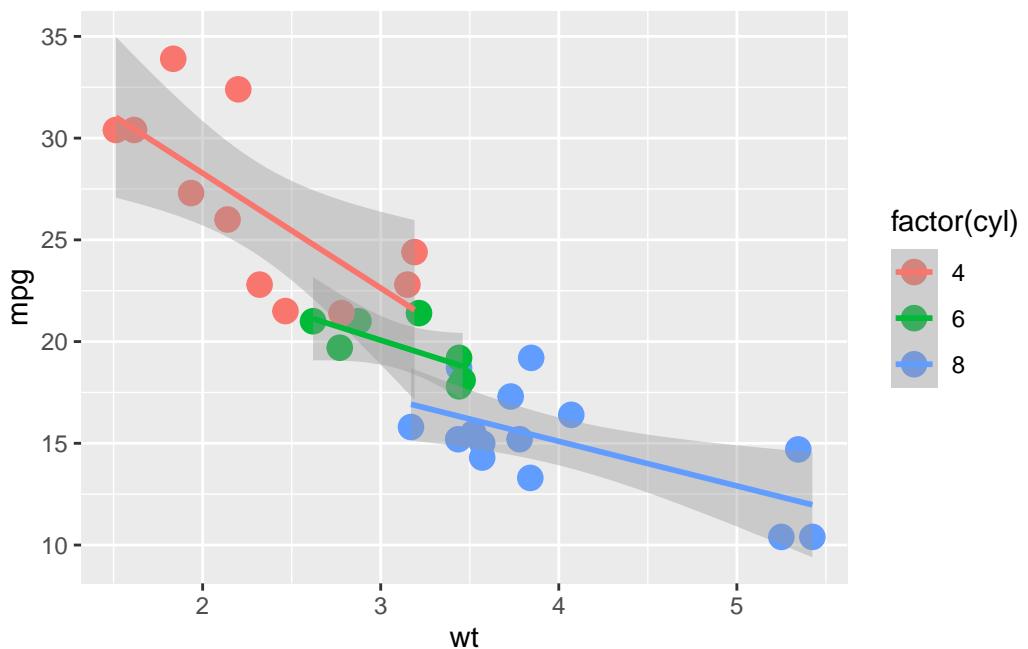
```
ggplot(data=mtcars,aes(wt, mpg))+  
  geom_smooth(size=3,color='red')+  
  geom_smooth(method='lm',size=3)+  
  geom_point(size=4)
```

```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'  
`geom_smooth()` using formula = 'y ~ x'
```



```
ggplot(data=mtcars,aes(wt, mpg,
                      color=factor(cyl)))+
  geom_point(size=4)+
  geom_smooth(method='lm',size=1)
```

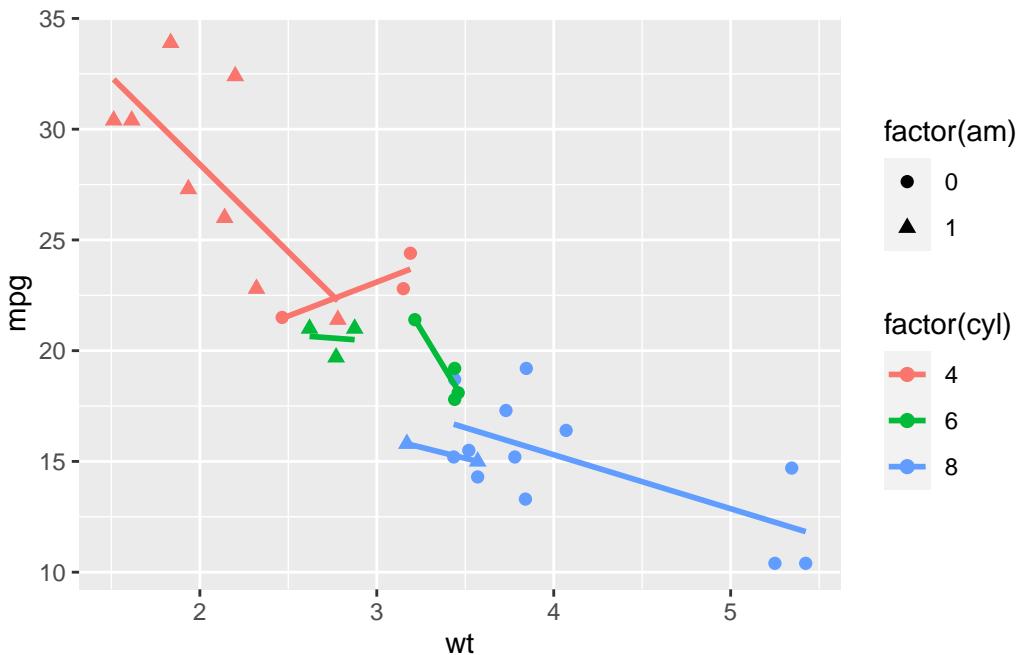
```
`geom_smooth()` using formula = 'y ~ x'
```



```
ggplot(data=mtcars,aes(wt, mpg,  
                      color=factor(cyl),  
                      shape=factor(am)))+
```

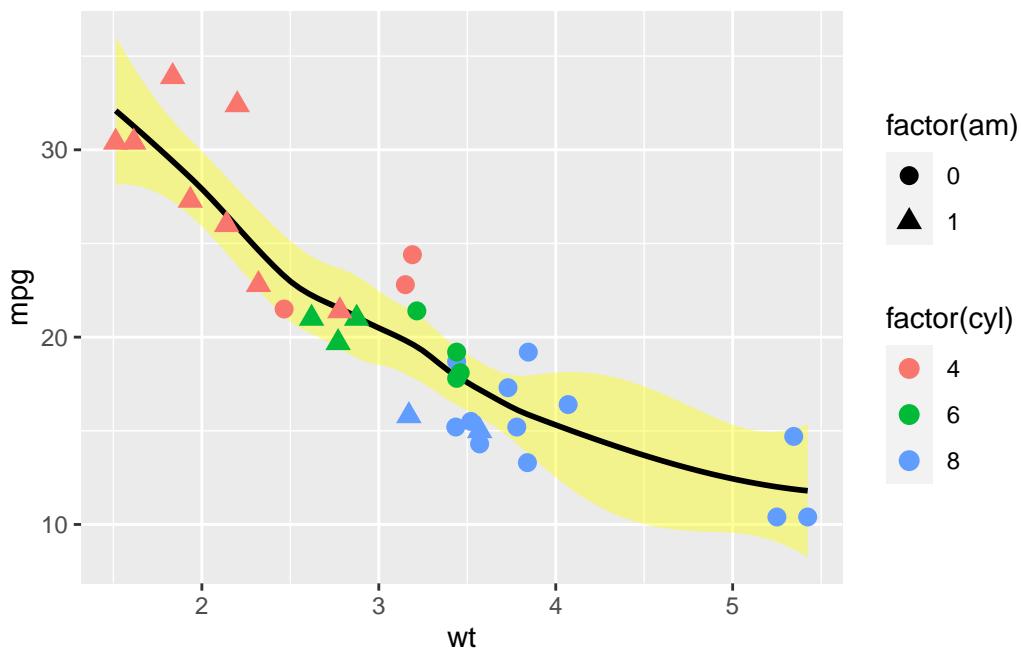
```
  geom_point(size=2)+  
  geom_smooth(method='lm',size=1,se=F)
```

```
`geom_smooth()` using formula = 'y ~ x'
```

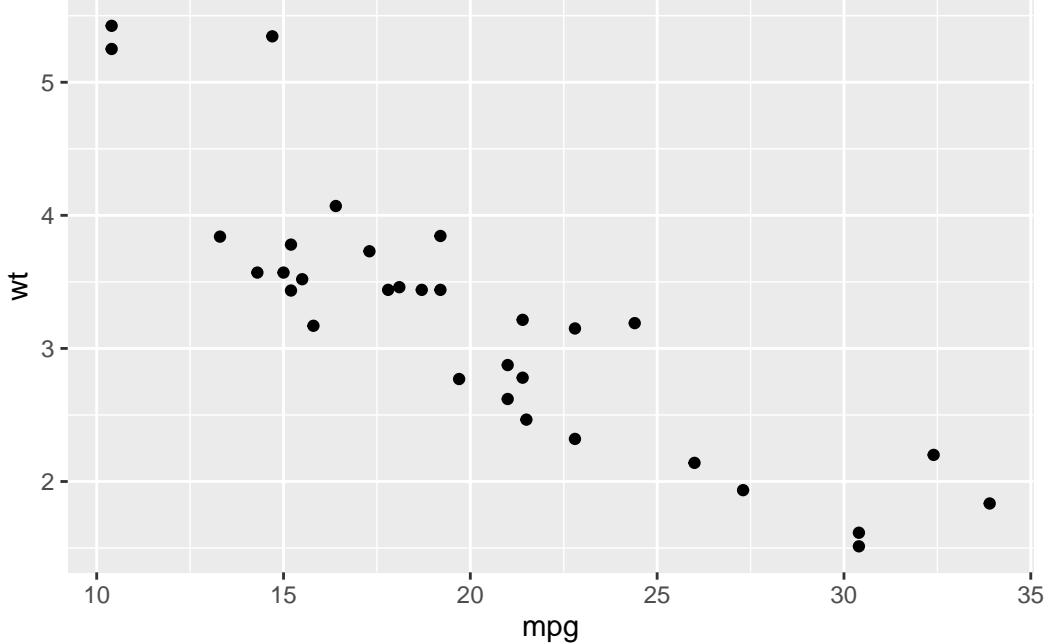


```
#? lm for all?
ggplot(data=mtcars,aes(wt, mpg))+
  geom_smooth(size=1,color='black',fill='yellow')+
  geom_point(size=3,aes(color=factor(cyl),shape=factor(am))) #aes for geom only
```

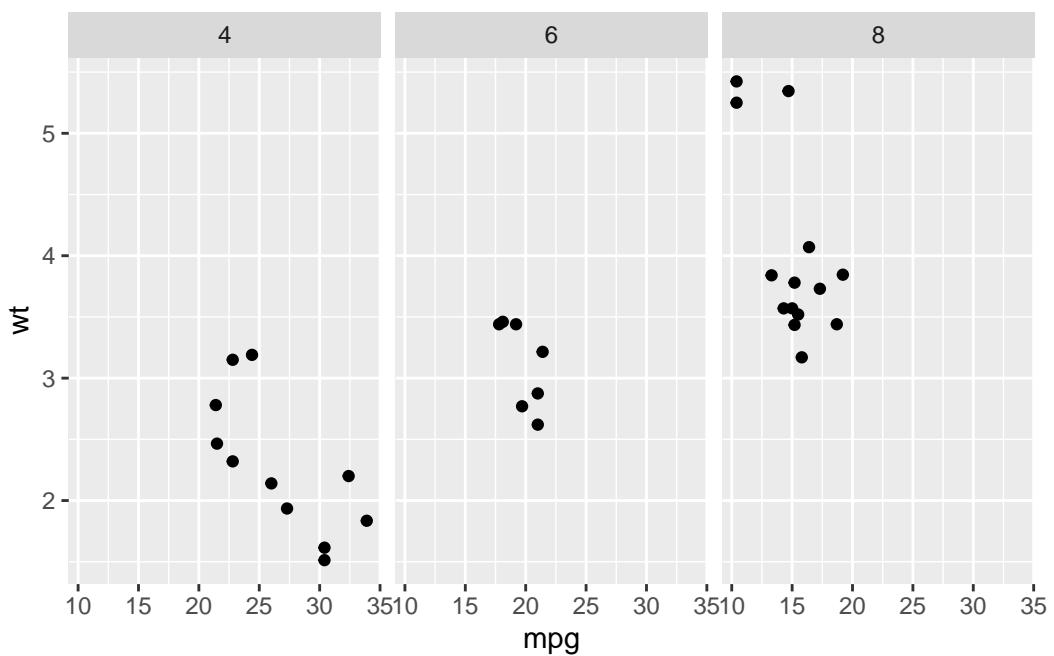
```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```



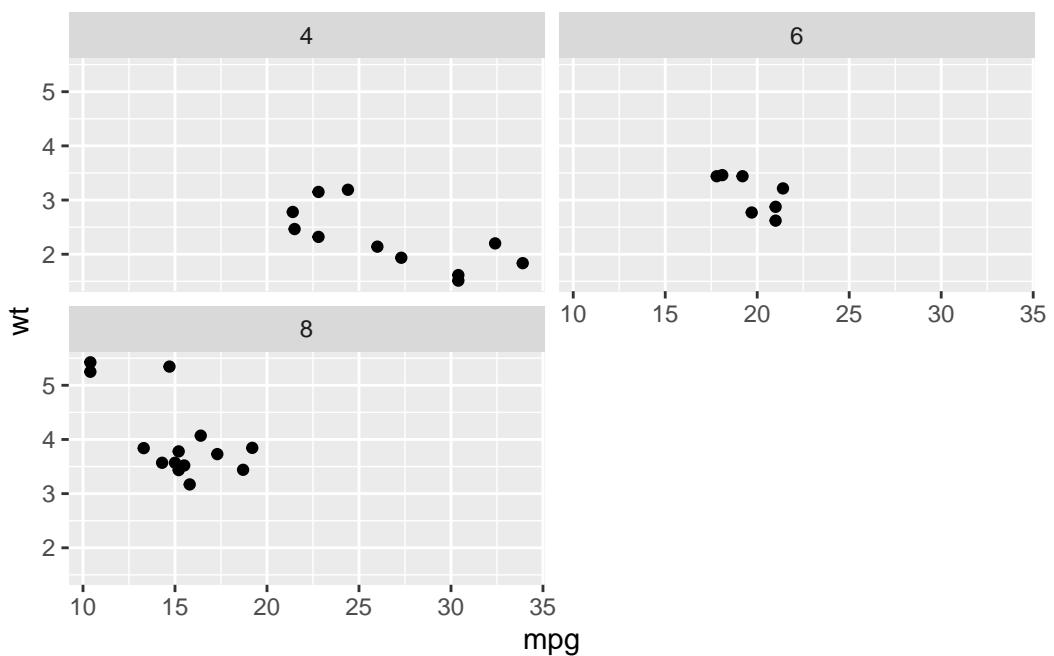
```
# facet_wrap / facet_grid
(p.tmp <- ggplot(mtcars, aes(mpg, wt)) +
  geom_point())
```



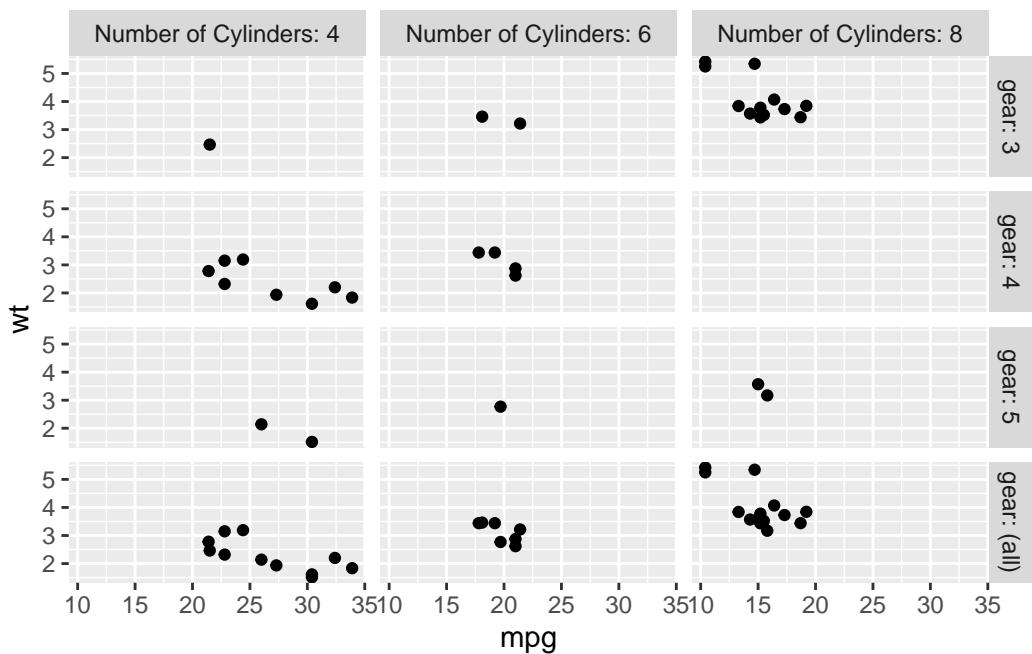
```
p.tmp + facet_wrap(facets = vars(cyl))
```



```
p.tmp + facet_wrap(facets = vars(cyl), ncol=2)
```

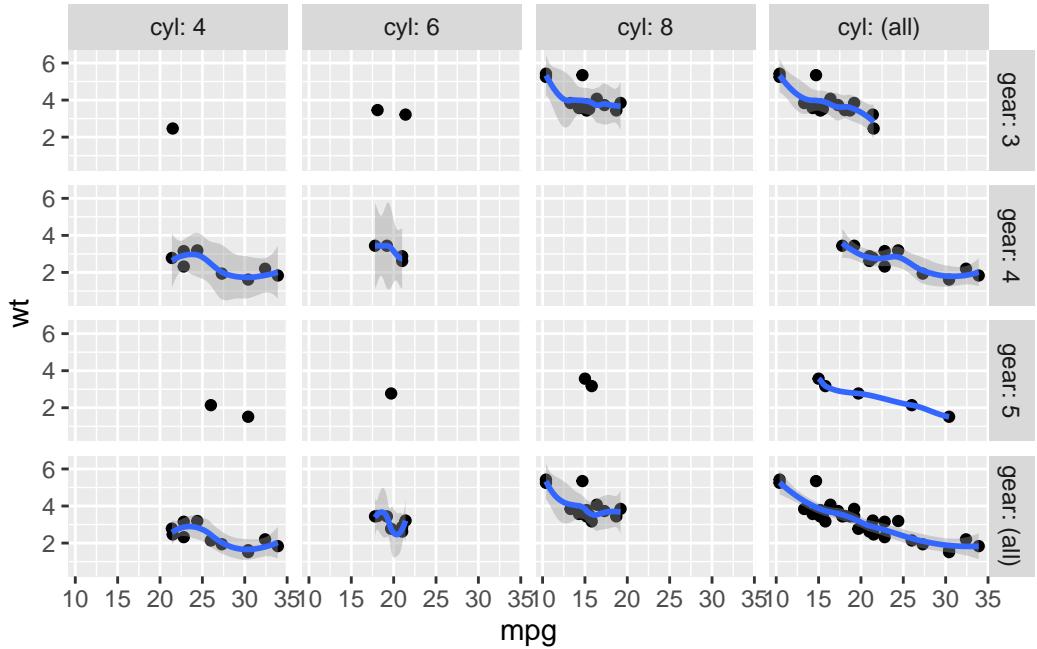


```
#p.tmp + facet_wrap(~cyl, ncol=2)
p.tmp + facet_grid(rows = vars(gear),
                    cols = vars(`Number of Cylinders` =
                                cyl),
                    labeller=label_both,margins='gear')
```



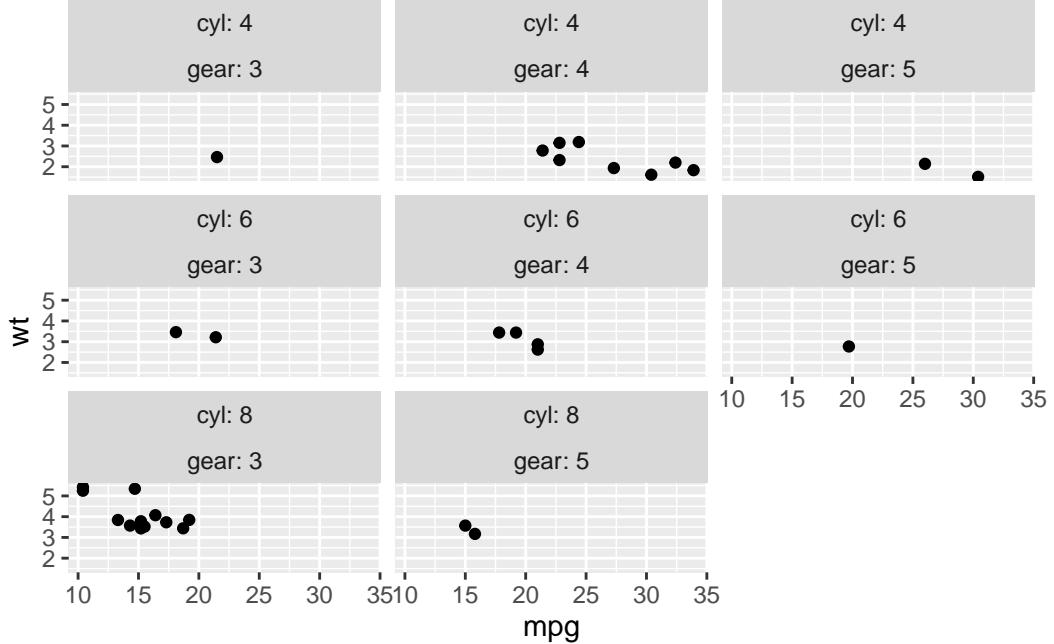
```
options(warn=-1)
p.tmp + geom_smooth()+
  facet_grid(gear~cyl, labeller=label_both,margins=T)
```

```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```

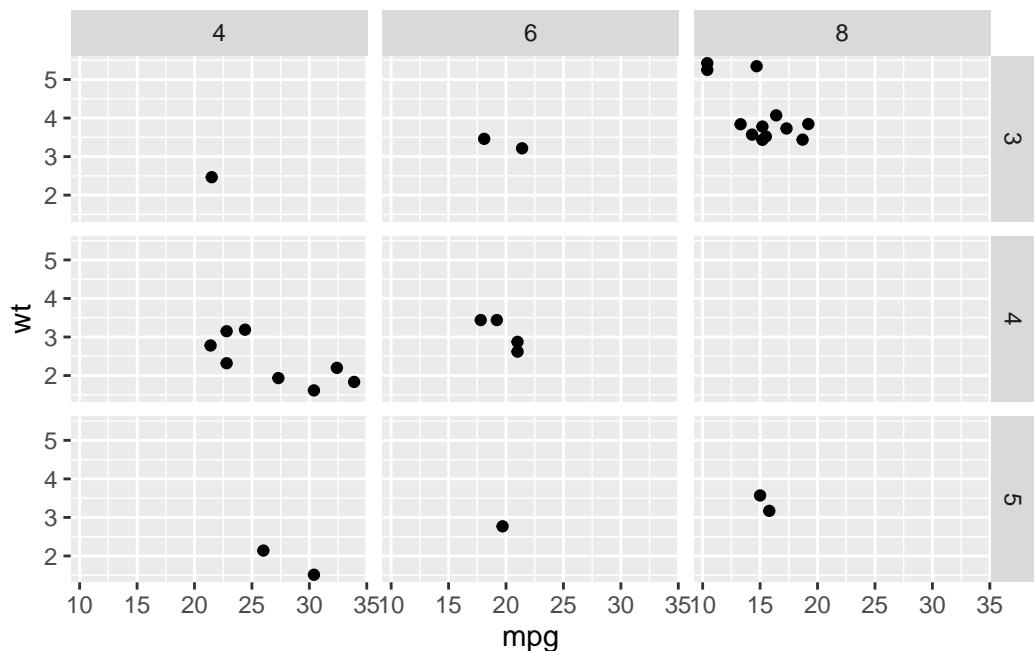


```
options(warn=0)

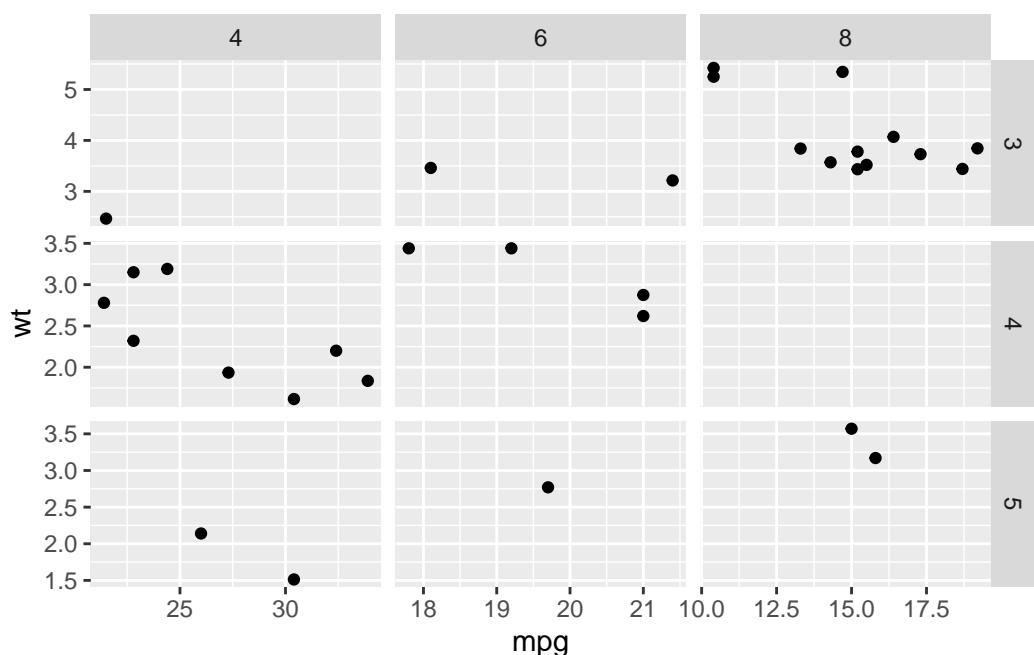
p.tmp + facet_wrap(~cyl+gear, labeller=label_both) # empty combination is dropped
```



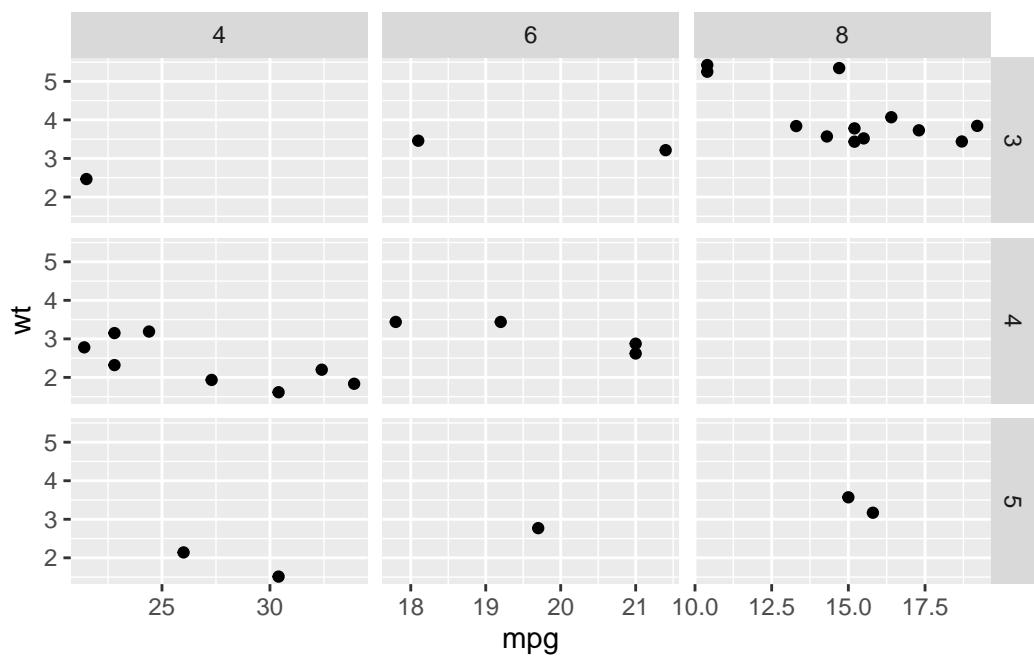
```
# controlling scales in facets (default: scales="fixed")
p.tmp + facet_grid(gear~cyl, scales="fixed")
```



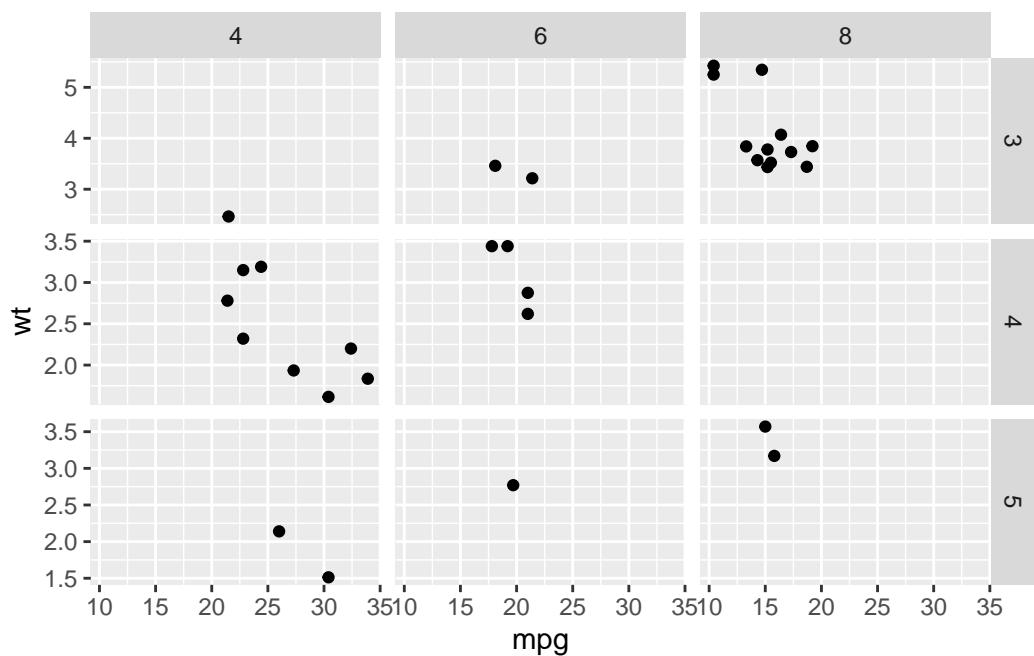
```
p.tmp + facet_grid(gear~cyl, scales="free")
```



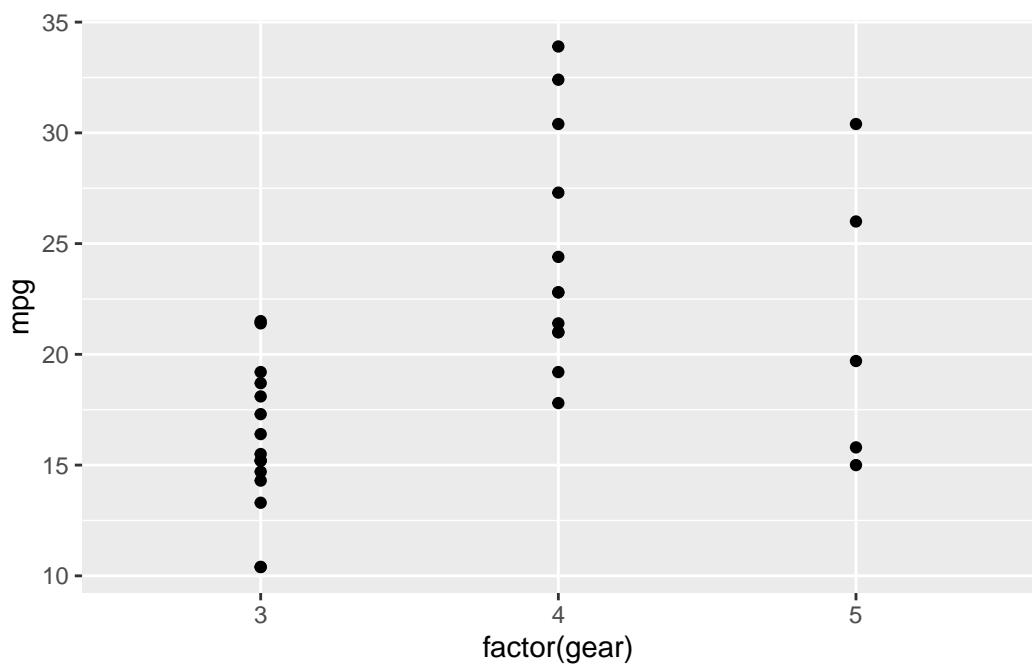
```
p.tmp + facet_grid(gear~cyl, scales="free_x")
```



```
p.tmp + facet_grid(gear~cyl, scales="free_y")
```

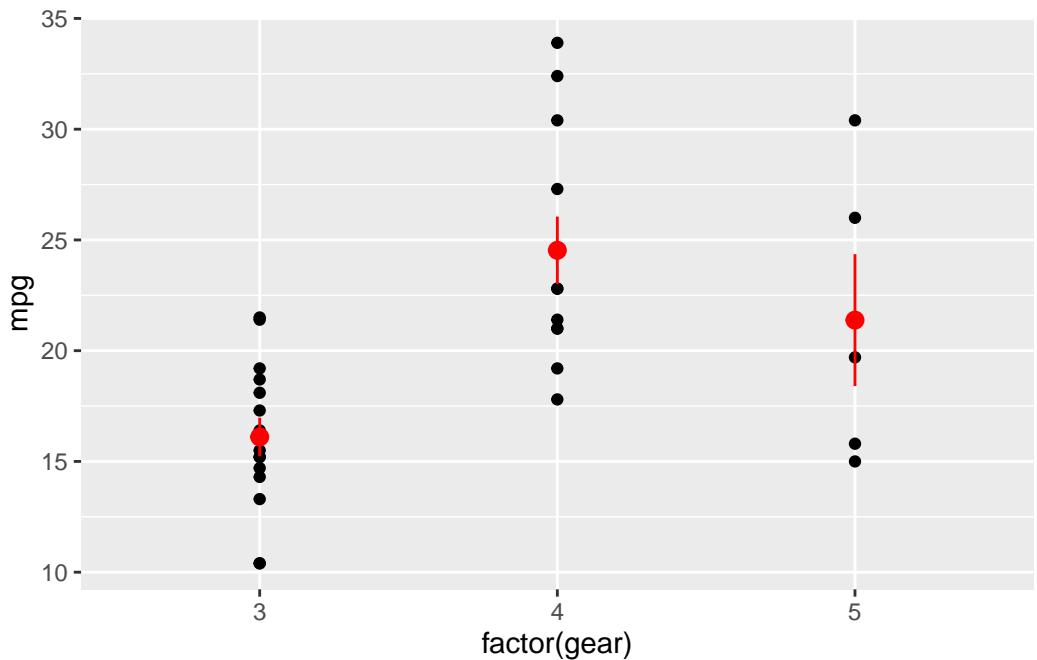


```
# summaries #####
(plottemp <- ggplot(mtcars,aes(factor(gear),mpg))+  
  geom_point())
```

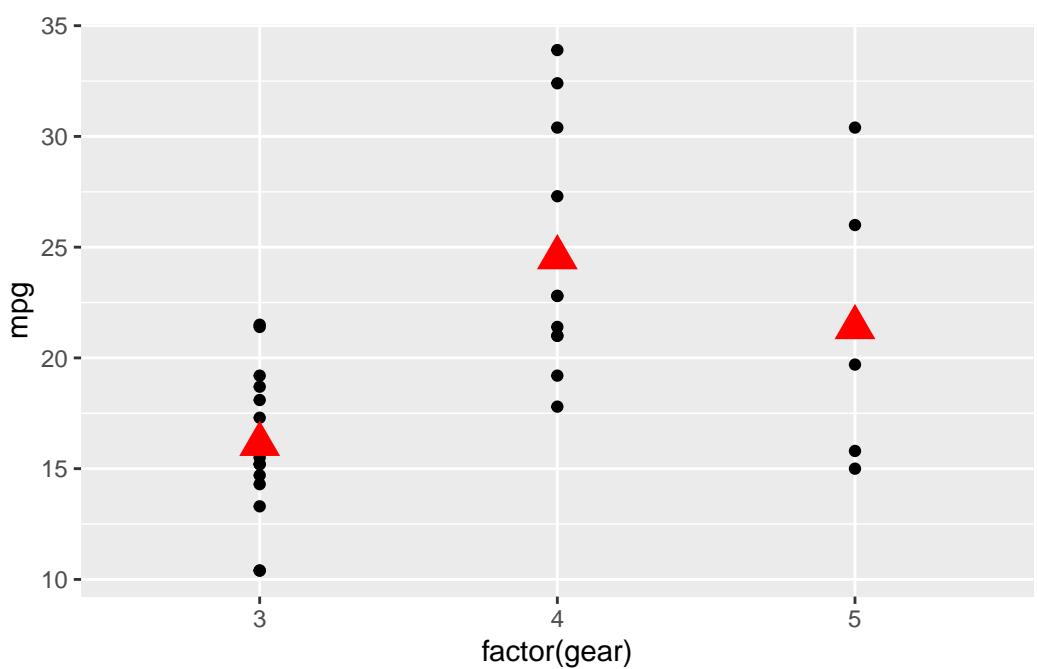


```
plottemp+stat_summary(color='red')
```

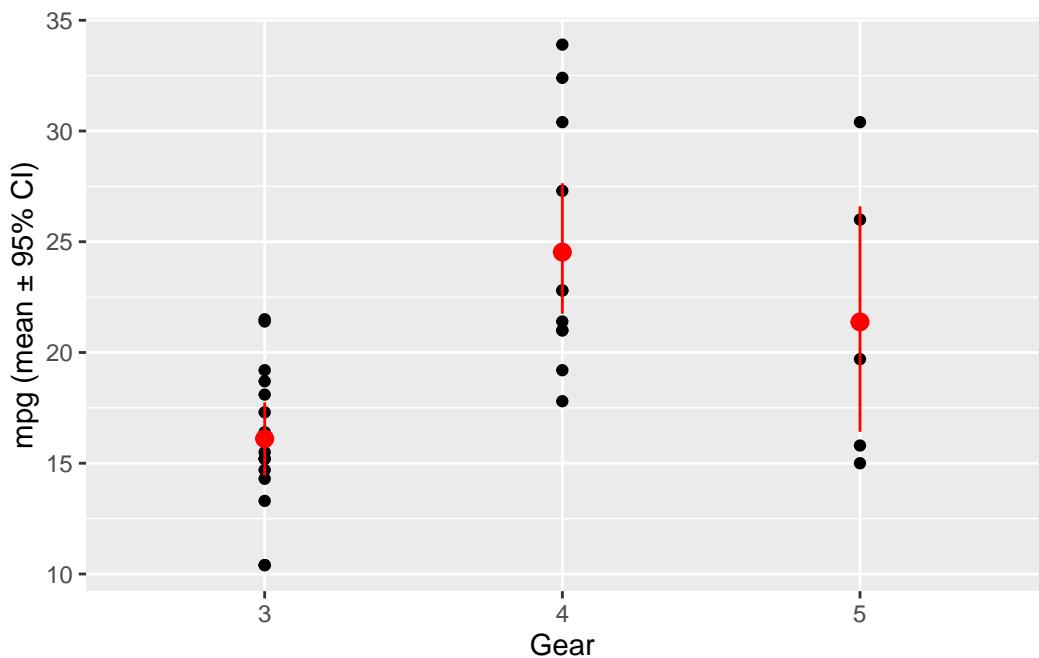
No summary function supplied, defaulting to `mean_se()`



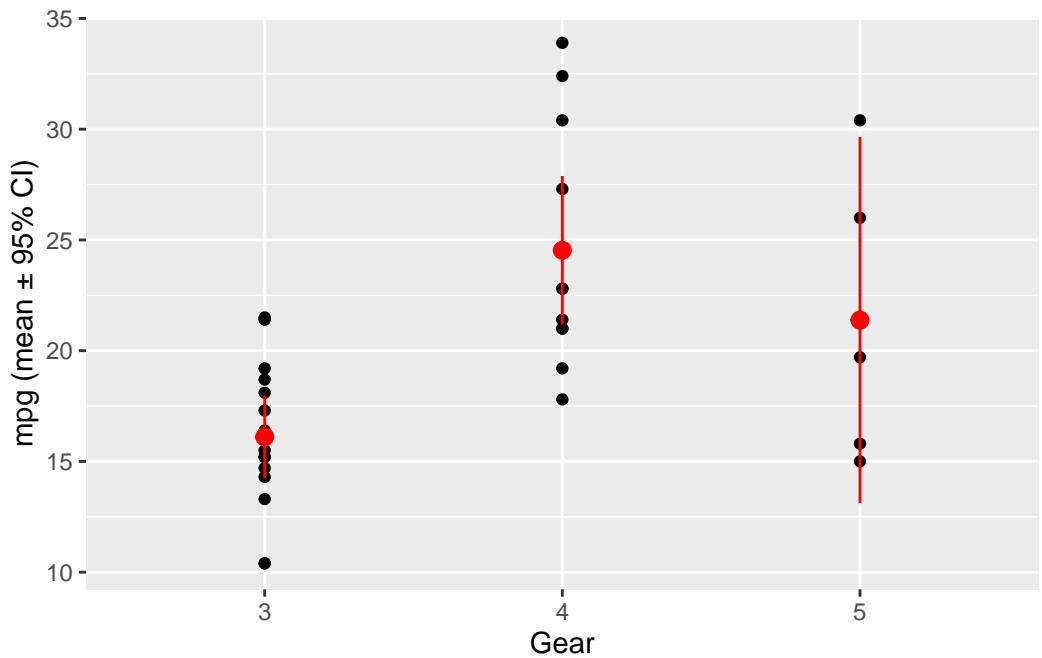
```
plottemp+stat_summary(geom = 'point', shape=17, size=5,  
                      fun = 'mean', color='red')
```



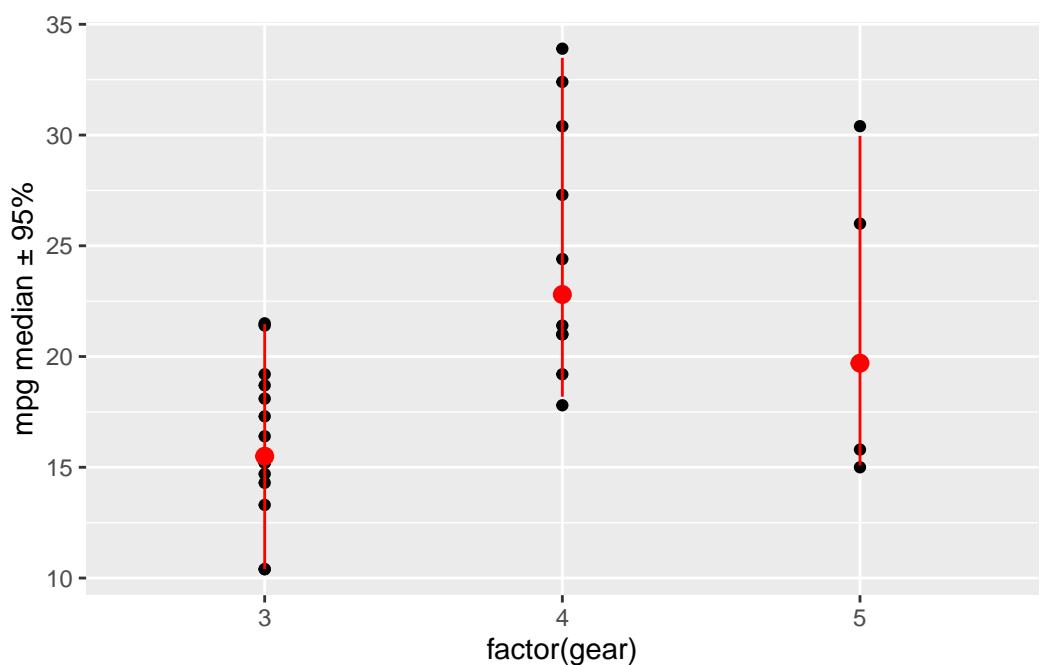
```
plottemp+stat_summary(fun.data='mean_cl_boot',color='red')+  
  ylab('mpg (mean \u00b1 95% CI)')+  
  xlab('Gear')
```



```
plottemp+stat_summary(fun.data='mean_cl_normal',color='red')+  
  ylab('mpg (mean \u00b1 95% CI)')+  
  xlab('Gear')
```



```
plottemp+stat_summary(fun.data='median_hilow',color='red')+  
ylab('mpg median \u00b1 95%)
```

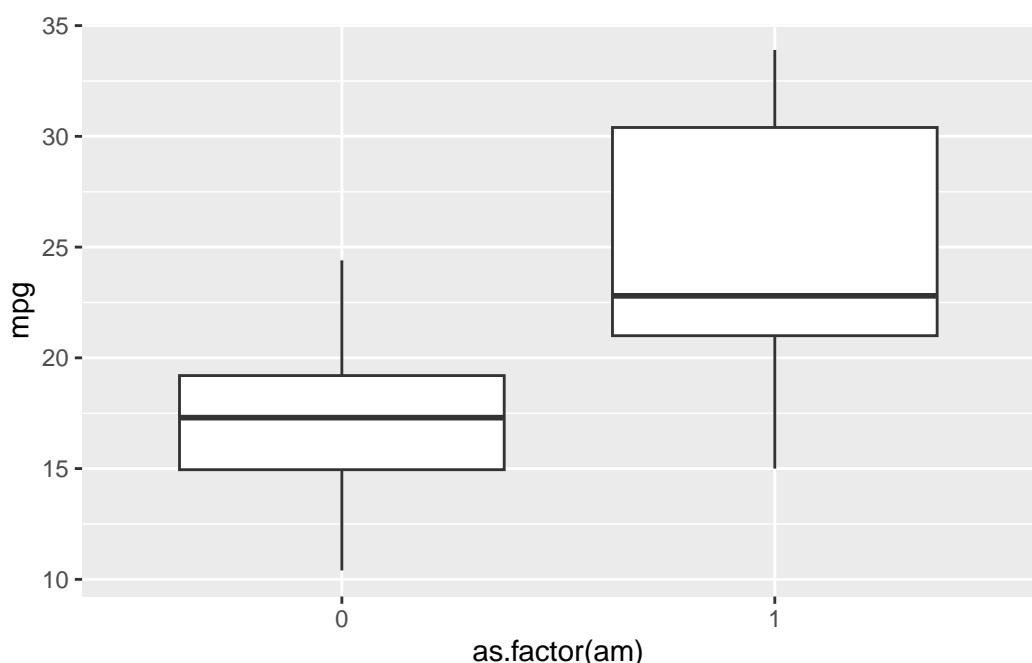


```
# geom_pointrange()

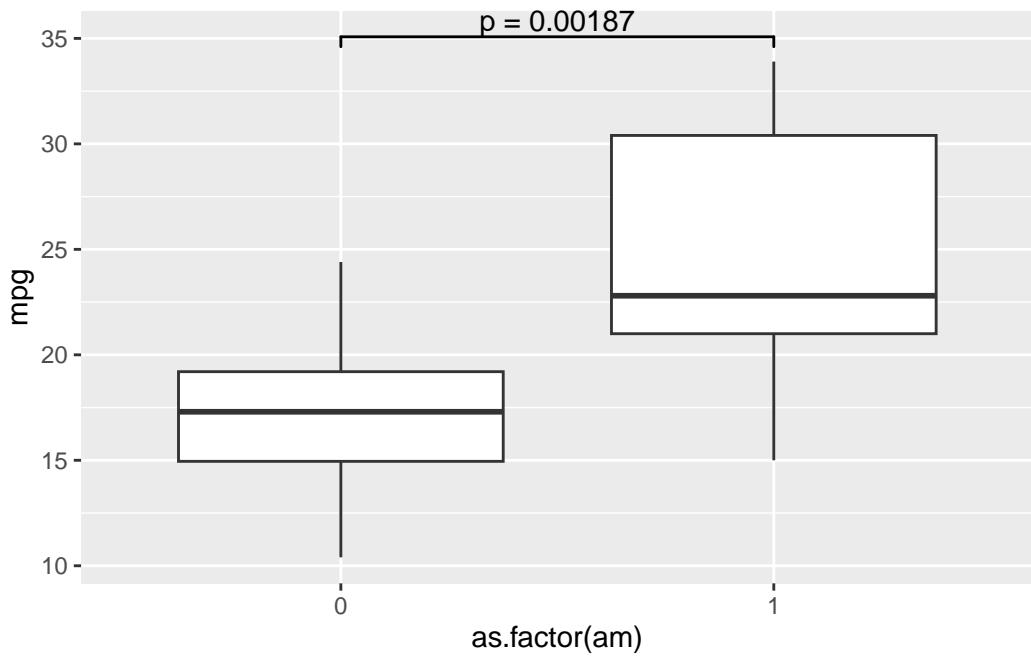
# ggsign #####
p <- round(wilcox.test(mtcars$mpg~mtcars$am)$p.value,5)
```

Warning in wilcox.test.default(x = DATA[[1L]], y = DATA[[2L]], ...): kann bei Bindungen keinen exakten p-Wert Berechnen

```
(plottemp <- ggplot(mtcars,aes(as.factor(am),mpg)+  
geom_boxplot())
```

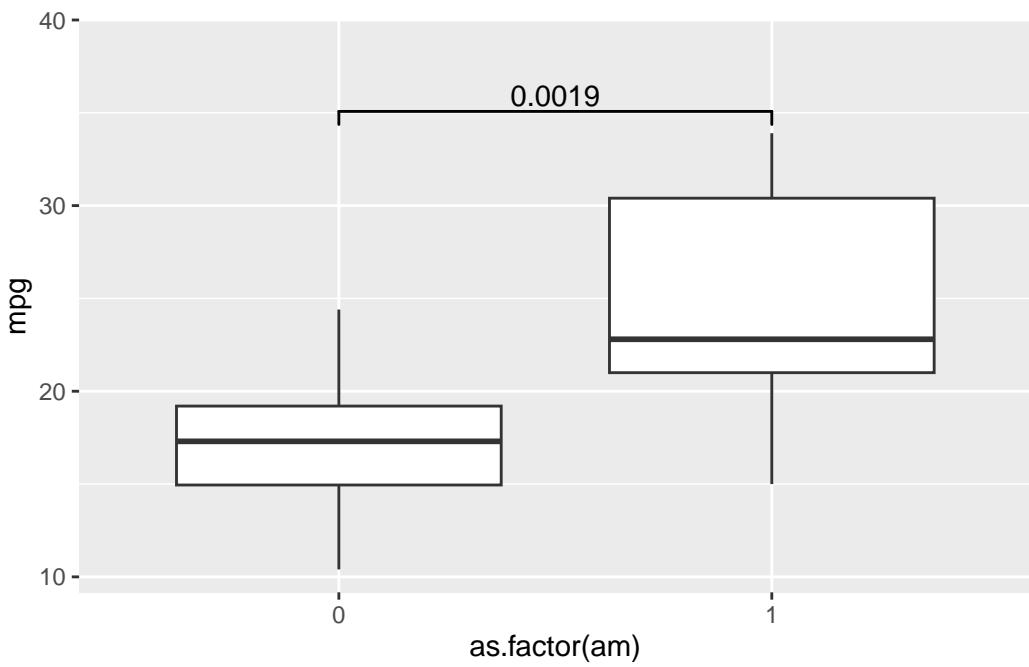


```
plottemp+geom_signif(  
comparisons=list(c(1,2)),  
# aes(y=0),  
# textsize = rel(3), vjust = .0,  
#y_position=max(mtcars$mpg+3),  
annotations=paste0('p = ', p),  
# annotations=p,  
tip_length=.02)
```

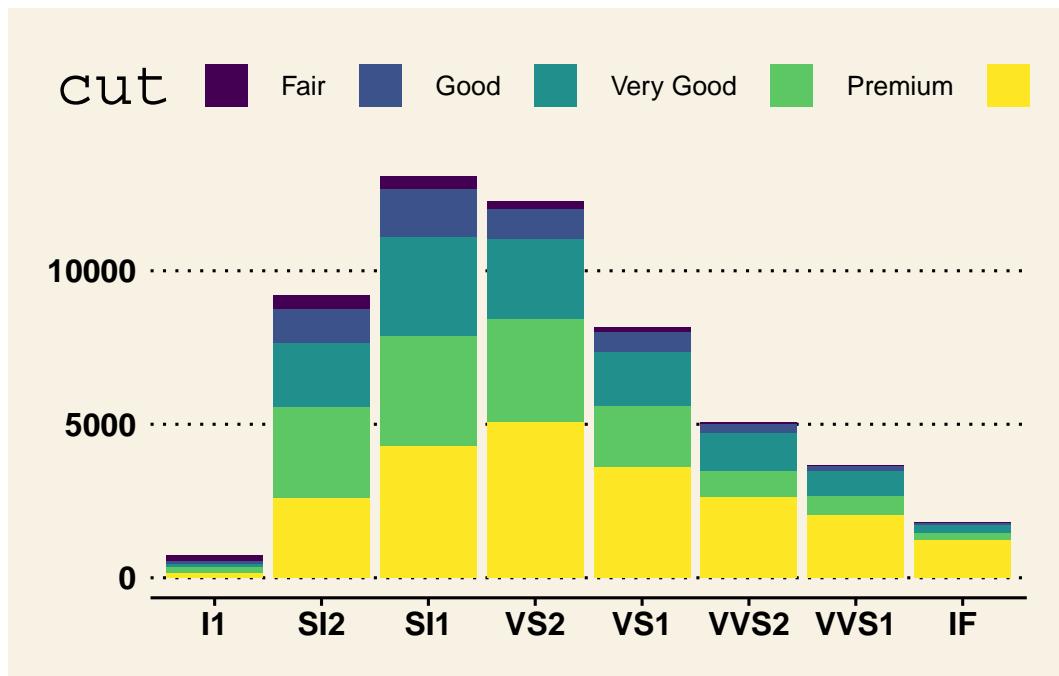


```
plottemp + geom_signif(  
  comparisons=list(1:2))+  
  scale_y_continuous(expand = expansion(mult=c(0.05,.2)))
```

Warning in wilcox.test.default(c(21.4, 18.7, 18.1, 14.3, 24.4, 22.8, 19.2, :
kann bei Bindungen keinen exakten p-Wert Berechnen



```
old <- theme_set(theme_wsj())
# theme_set(theme_wsj())
ggplot(data=diamonds,aes(x=clarity,fill=cut))+
  geom_bar()
```



```

theme_update(legend.position="bottom",
             axis.text=element_text(colour = "darkblue",
                                    size=12),
             axis.text.x=element_text(vjust=0.5,angle=45),
             axis.title=element_text(size=15),
             plot.margin=unit(c(3,4,.5,.3),'lines'),      #N,E,S,W
             axis.title.y=element_text(vjust=0.4,angle=45),
             legend.key.size=unit(2.5,'lines'),
             panel.background=element_rect(fill='darkgrey'),
             panel.grid.minor = element_line(colour='white'),
             panel.grid.major = element_line(
               linetype=1,
               color='violet',size = 2),
             legend.text = element_text(size = 8))

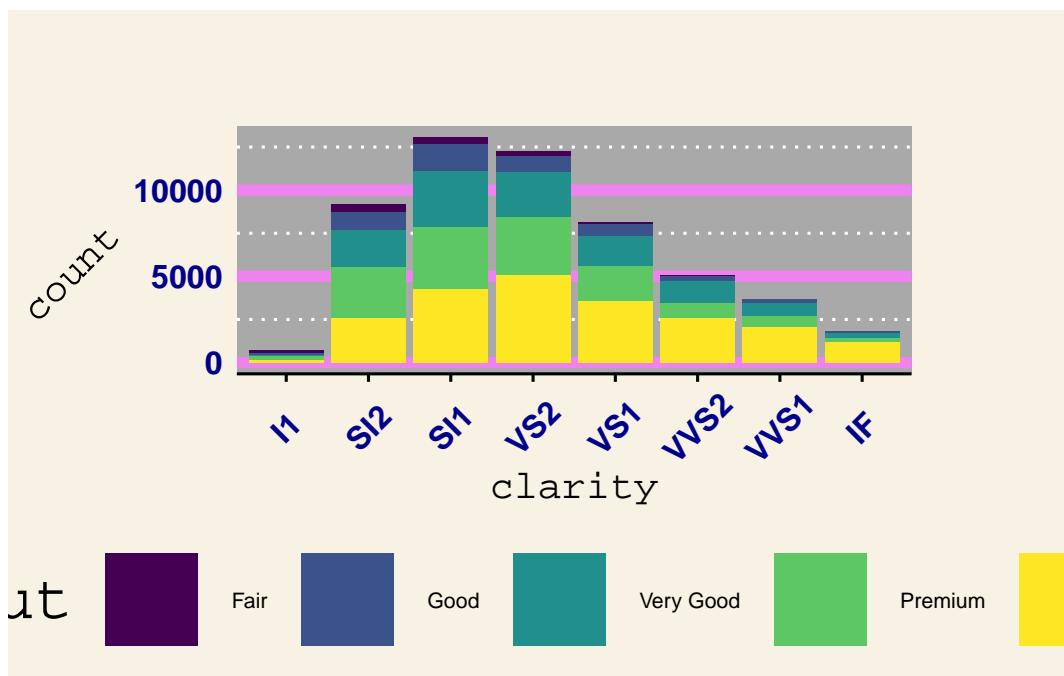
```

Warning: The `size` argument of `element_line()` is deprecated as of ggplot2 3.4.0.
i Please use the `linewidth` argument instead.

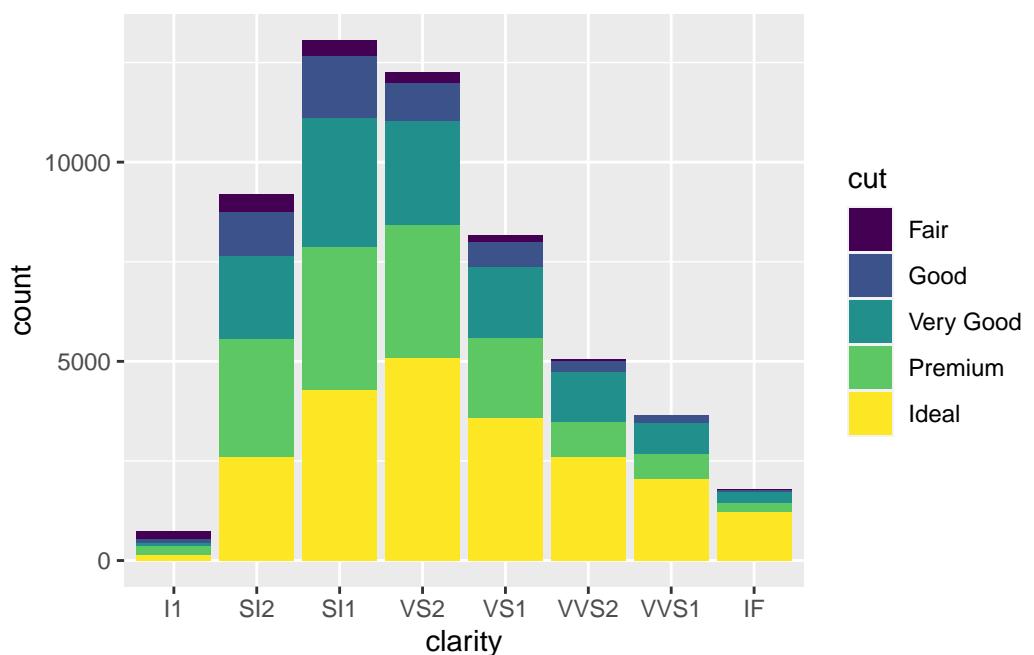
```

ggplot(data=diamonds,aes(x=clarity,fill=cut))+  
  geom_bar()

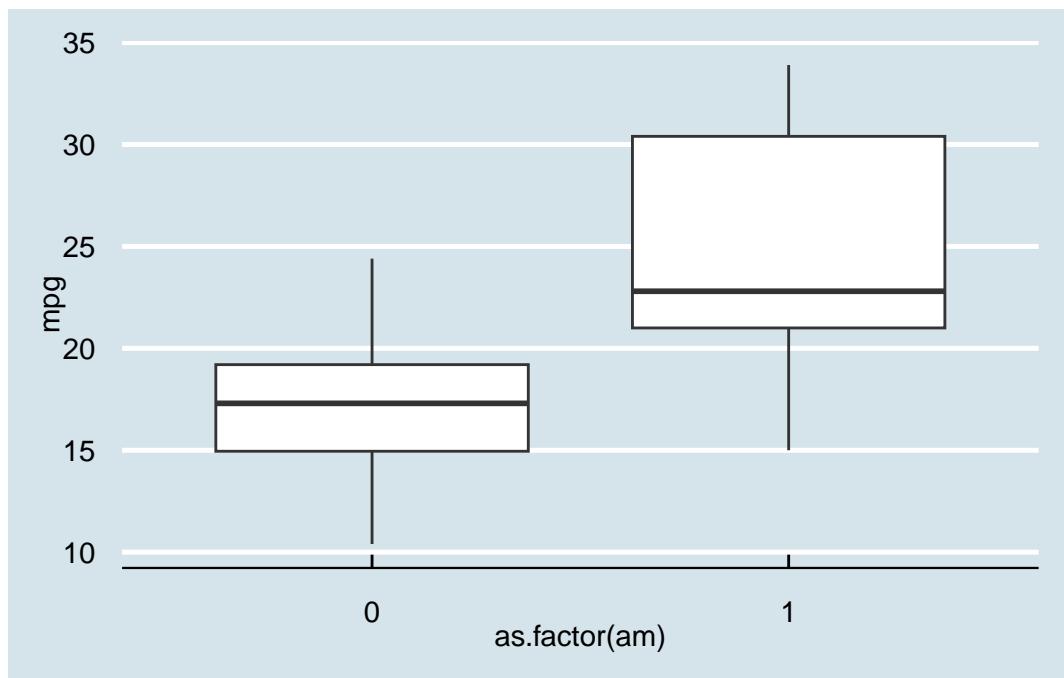
```



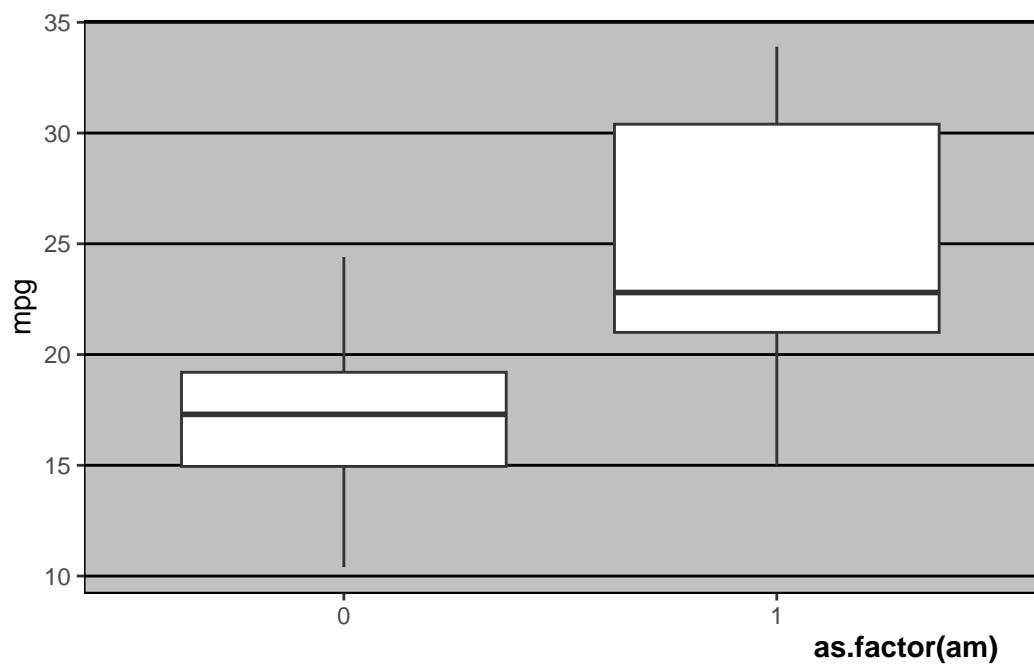
```
theme_set(theme_grey())
#theme_set(old)
ggplot(data=diamonds,aes(x=clarity,fill=cut))+  
  geom_bar()
```



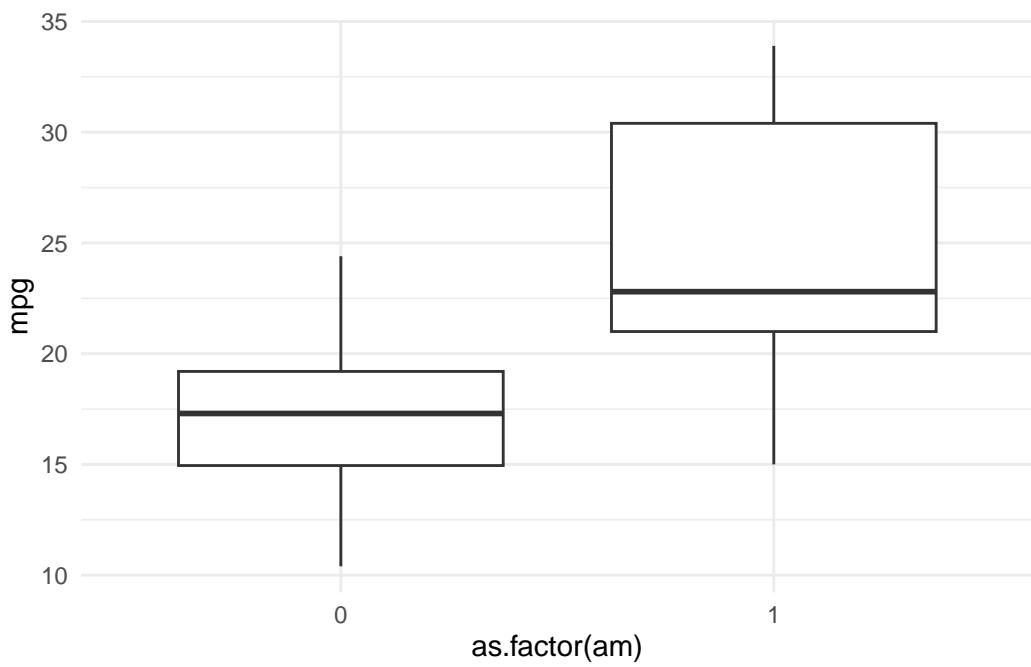
```
# ggthemes ####  
plottemp+theme_economist()
```



```
plottemp+theme_excel()+
  theme(axis.title.x = element_text(face='bold', hjust=0.95))
```



```
plottemp+theme_minimal()
```



```
# https://github.com/thomasp85/patchwork  
  
# https://www.data-imaginist.com/2019/a-flurry-of-facets/  
# https://github.com/thomasp85/gganimate
```

6 Descriptive statistics

```
pacman::p_load(tidyverse,wrappedtools)
#dir('Data/')
load('data/bookdata1.RData')

ggplot(rawdata,aes(sysBP_V0, diaBP_V0))+
  geom_point()+
  geom_smooth(se=F)+
  geom_smooth(method='lm',color='red',
              fill='gold', alpha=.15)
```

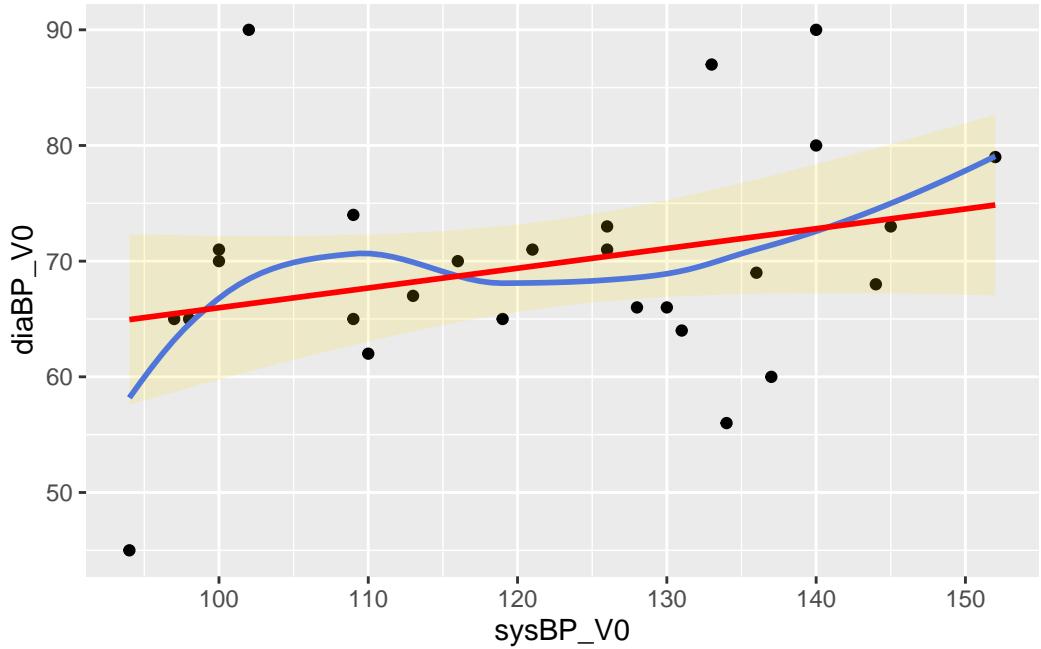
```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```

```
Warning: Removed 1 rows containing non-finite values (`stat_smooth()`).
```

```
`geom_smooth()` using formula = 'y ~ x'
```

```
Warning: Removed 1 rows containing non-finite values (`stat_smooth()`).
```

```
Warning: Removed 1 rows containing missing values (`geom_point()`).
```



```
# descriptives ####
mean_size <- mean(rawdata$`Size (cm)`)
```

```
sd_size <- sd(rawdata$`Size (cm)`)
```

```
min(rawdata$`Size (cm)`)
```

```
[1] 160
```

```
round(mean_size,digits = 2)
```

```
[1] 174.11
```

```
roundR(mean_size,level = 2)
```

```
[1] "174"
```

```
meansd(rawdata$`Size (cm)`, roundDig = 4,range = T,add_n = T)
```

```
[1] "174.1 ± 7.8 [160.0 -> 193.0] [n=28]"
```

```
meansd(rawdata$sysBP_V0, roundDig = 4, range = T,  
       add_n = T, .german = T)
```

```
[1] "121,9 ± 16,9 [94,0 -> 152,0] [n=27]"
```

```
median(rawdata$`Size (cm)`)
```

```
[1] 173.5
```

```
quantile(rawdata$`Size (cm)`, probs = c(.25, .75))
```

```
25%      75%  
168.00 178.25
```

```
median_quart(rawdata$`Size (cm)`)
```

```
[1] "174 (168/179)"
```

```
table(rawdata$sex, useNA = 'a')
```

```
f      m <NA>  
4     24     0
```

```
sex_count <- table(rawdata$sex, useNA = 'ifany')  
table(rawdata$NYHA_V2, useNA = 'always')
```

```
0      1      2      3 <NA>  
1      6      2      2     17
```

```
table(rawdata$NYHA_V2, useNA = 'i')
```

```
0      1      2      3 <NA>  
1      6      2      2     17
```

```
randomize <- table(rawdata$sex, rawdata$testmedication)
prop.table(sex_count)
```

```
f           m
0.1428571 0.8571429
```

```
prop.table(randomize,margin = 2)*100
```

```
0           1
f 14.28571 14.28571
m 85.71429 85.71429
```

```
cat_desc_stats(rawdata$NYHA_V2)
```

```
$level
# A tibble: 4 x 1
  value
  <chr>
1 0
2 1
3 2
4 3
```

```
$freq
# A tibble: 4 x 1
  desc
  <chr>
1 1 (9%)
2 6 (55%)
3 2 (18%)
4 2 (18%)
```

```
cat_desc_stats(rawdata$sex, singleline = T)
```

```
$level
[1] "f m"
```

```
$freq
# A tibble: 1 x 1
  desc
  <glue>
1 4 (14%) 24 (86%)
```

```
rawdata |>
  group_by(sex,testmedication) |>
  summarise(WeightSummary=meansd(`Weight (kg)`))
```

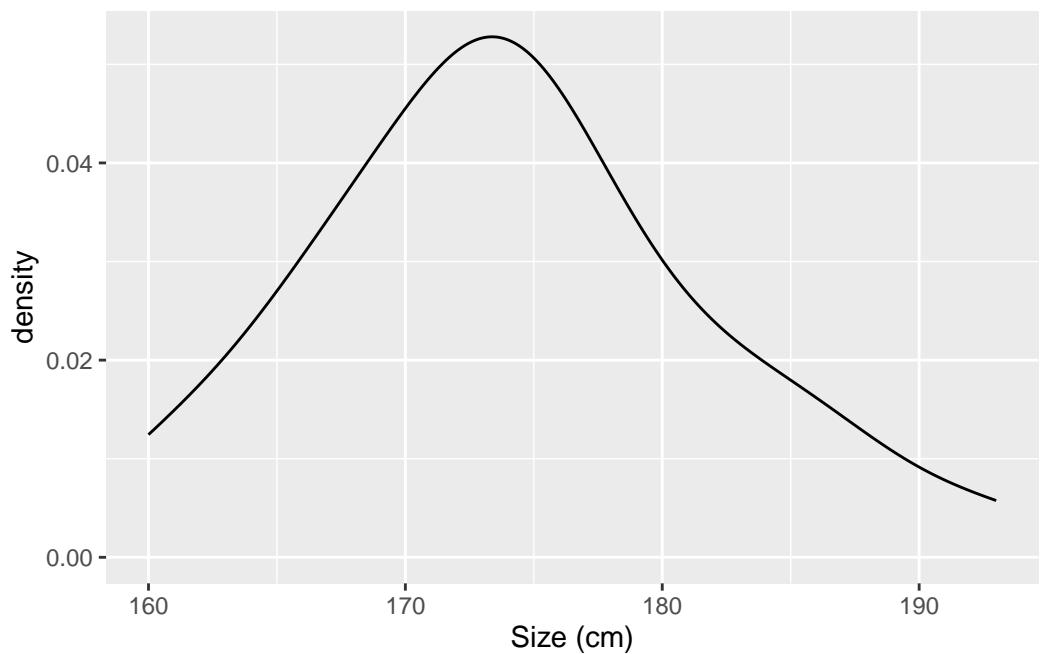
`summarise()` has grouped output by 'sex'. You can override using the `groups` argument.

```
# A tibble: 4 x 3
# Groups:   sex [2]
  sex    testmedication WeightSummary
  <chr>      <dbl> <chr>
1 f          0 86 ± 9
2 f          1 66 ± 3
3 m          0 91 ± 14
4 m          1 90 ± 14
```

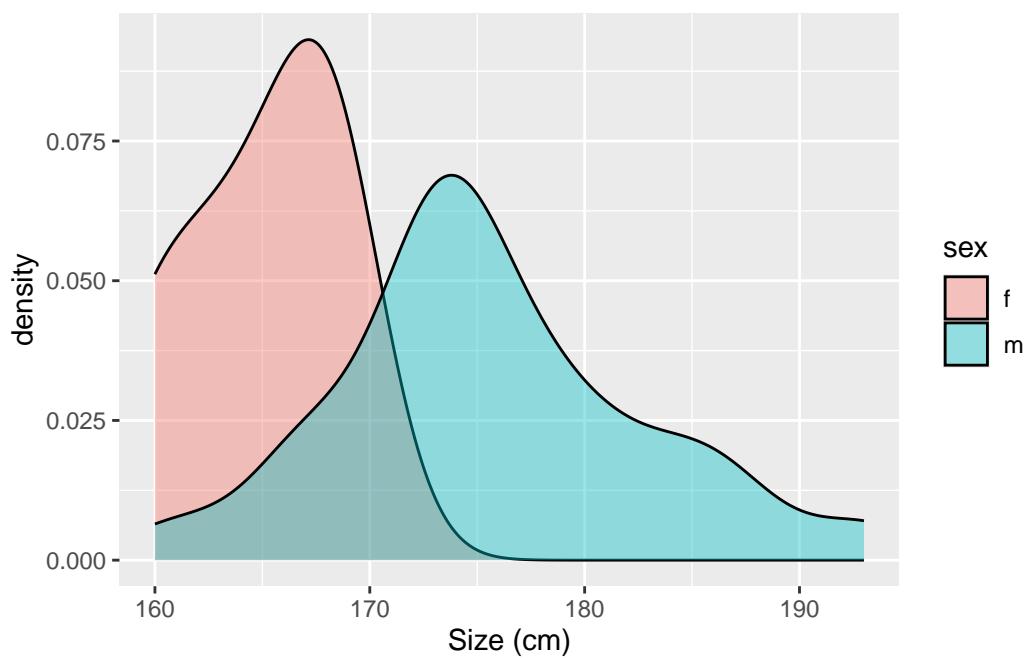
```
compare2numvars(rawdata,
  dep_vars = c( "Size (cm)", "Weight (kg)",
               "sysBP_V0", "diaBP_V0"),
  indep_var = 'sex',
  gaussian = F)
```

```
# A tibble: 4 x 5
  Variable     desc_all     `sex f`     `sex m`      p
  <fct>       <chr>        <chr>        <chr>        <chr>
1 Size (cm)  174 (168/179) 166 (162/168) 174 (172/180) 0.011
2 Weight (kg) 84 (77/96)    74 (66/88)    86 (80/104)   0.107
3 sysBP_V0   126 (109/136) 119 (105/129) 126 (109/137) 0.609
4 diaBP_V0   69 (65/73)    66 (64/80)    70 (65/73)   0.784
```

```
ggplot(rawdata,aes(`Size (cm)`))+
  geom_density()
```



```
ggplot(rawdata,aes(`Size (cm)`, fill=sex))+  
  geom_density(alpha=.4)
```



```
ks.test(rawdata$`Size (cm)`,  
       pnorm) #WRONG!!!!
```

Warning in ks.test.default(rawdata\$`Size (cm)`, pnorm): für den Komogorov-Smirnov-Test sollten keine Bindungen vorhanden sein

```
Asymptotic one-sample Kolmogorov-Smirnov test  
  
data: rawdata$`Size (cm)`  
D = 1, p-value < 2.2e-16  
alternative hypothesis: two-sided
```

```
ks.test(rawdata$`Size (cm)`,  
       pnorm,  
       mean=mean(rawdata$`Size (cm)`),  
       sd=sd(rawdata$`Size (cm)`))
```

Warning in ks.test.default(rawdata\$`Size (cm)`, pnorm, mean = mean(rawdata\$`Size (cm)`), : für den Komogorov-Smirnov-Test sollten keine Bindungen vorhanden sein

```
Asymptotic one-sample Kolmogorov-Smirnov test  
  
data: rawdata$`Size (cm)`  
D = 0.13284, p-value = 0.7064  
alternative hypothesis: two-sided
```

```
ksnormal(rawdata$`Size (cm)`)
```

[1] 0.7063825

```
shapiro.test(rawdata$`Size (cm)`)
```

```
Shapiro-Wilk normality test  
  
data: rawdata$`Size (cm)`  
W = 0.9766, p-value = 0.7627
```

7 Better tables with `flextable`

8 Simple test statistics

```
pacman::p_load(plotrix,tidyverse, wrappedtools,
                coin,ggsignif, patchwork, ggbeeswarm)
#conflicted)
# conflict_prefer("filter", "dplyr")
load('data/bookdata1.RData')
```

```
##### Test for normal distribution -----
ks.test(x = rawdata$`Size (cm)` ,
       'pnorm',
       mean(rawdata$`Size (cm)` ,na.rm=T),
       sd(rawdata$`Size (cm)` ,na.rm=T),
       exact=F)
```

Warning in ks.test.default(x = rawdata\$`Size (cm)` , "pnorm", mean(rawdata\$`Size (cm)` , : für den Komogorov-Smirnov-Test sollten keine Bindungen vorhanden sein

Asymptotic one-sample Kolmogorov-Smirnov test

```
data: rawdata$`Size (cm)`
D = 0.13284, p-value = 0.7064
alternative hypothesis: two-sided
```

```
ksnormal(rawdata$`Weight (kg)`)
```

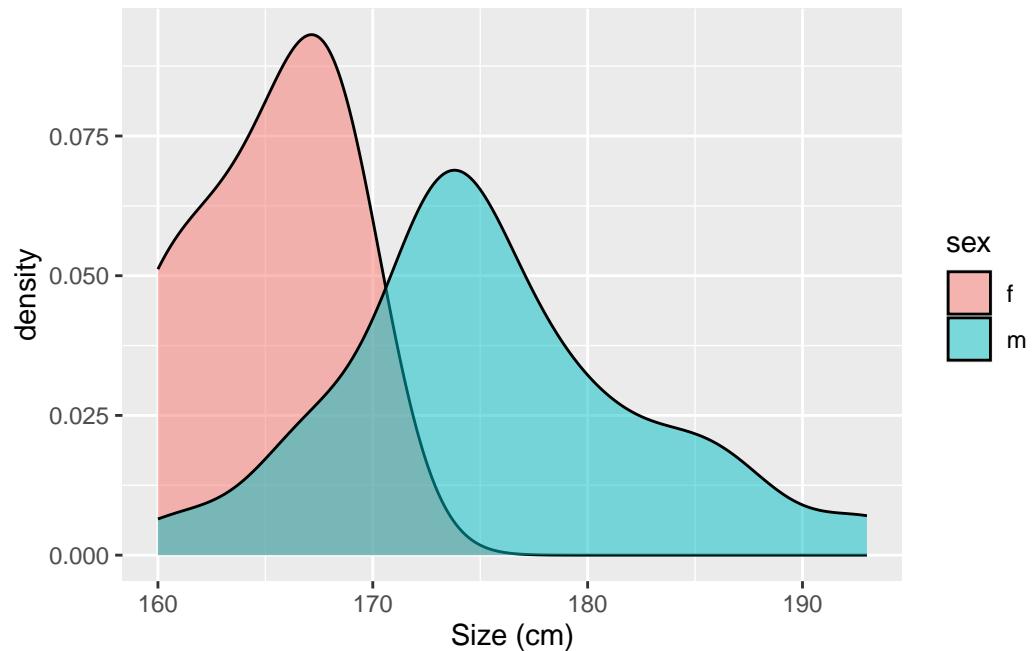
[1] 0.7598605

```
shapiro.test(rawdata$`Size (cm)`)
```

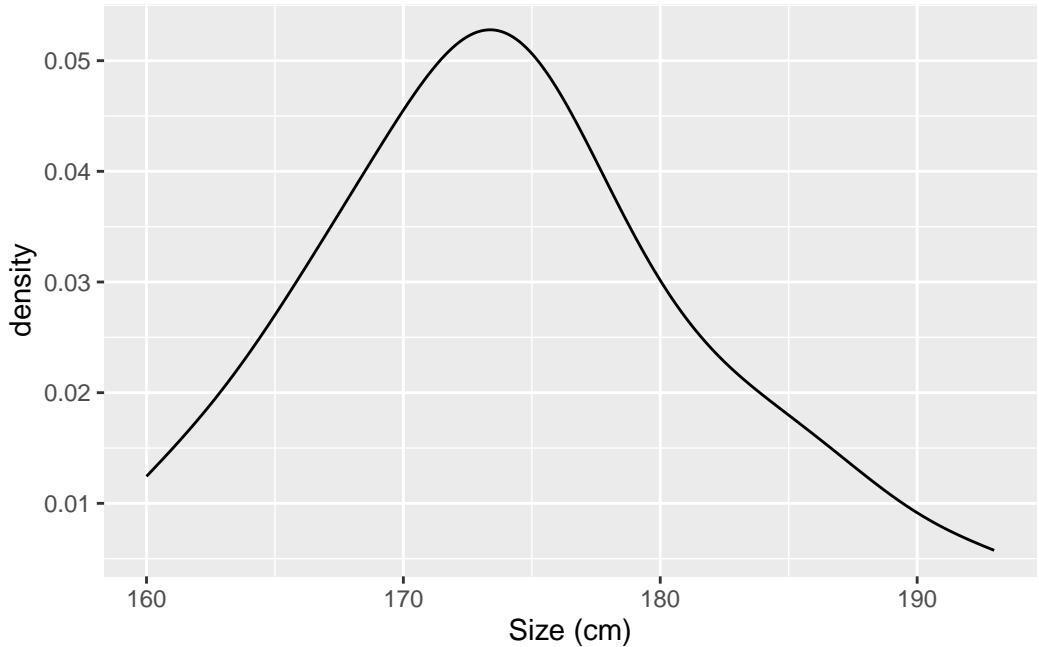
Shapiro-Wilk normality test

```
data: rawdata$`Size (cm)`  
W = 0.9766, p-value = 0.7627
```

```
ggplot(rawdata,aes(x = `Size (cm)`,fill=sex))+  
  geom_density(alpha=.5)
```



```
ggplot(rawdata,aes(x = `Size (cm)`))+  
  geom_line(stat='density')
```



```
(ksout<-ksnormal(x = rawdata$`Size (cm)`))
```

[1] 0.7063825

```
# test, if log-normal (->then transform)
if (ksnormal(rawdata$`Size (cm)`)<=.05 &
    ksnorm(log(rawdata$`Size (cm)`))>.05) {
  print('lognormal')
  # create new log-transformed variable or just transform...
} else {
  print('not lognormal')
}
```

[1] "not lognormal"

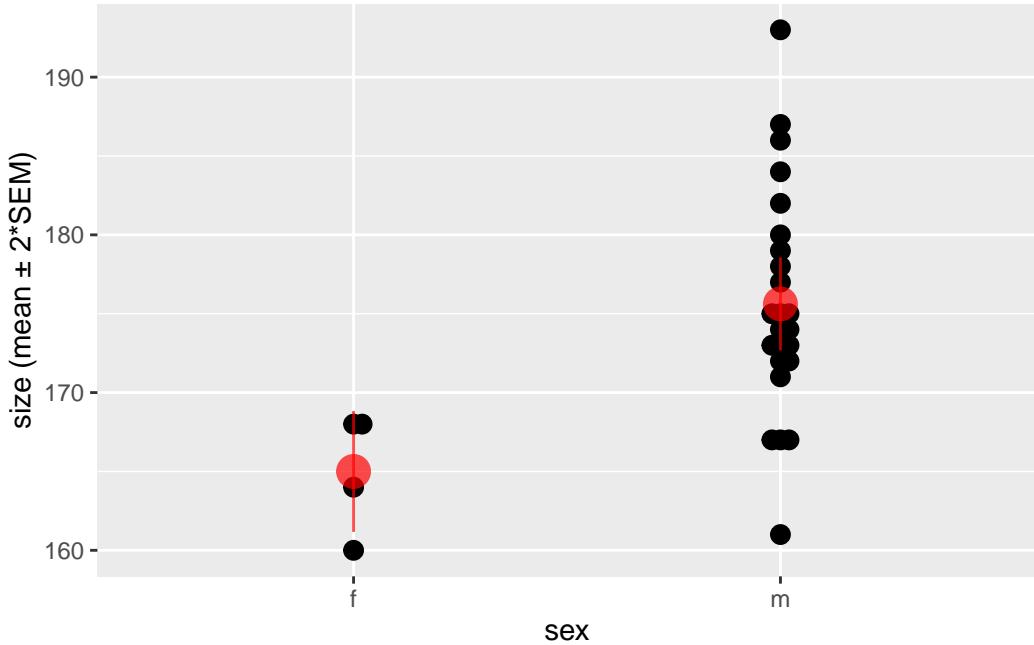
```
##### quantitative measures with Gaussian distribution -----
ggplot(rawdata,aes(x=sex,y=`Size (cm)`))+  

  geom_beeswarm(size=3)+  

  stat_summary(color='red',size=1.2,alpha=.7,  

              fun.data='mean_se',fun.args=list(mult=2))+  

  ylab('size (mean \u00B1 2*SEM)')
```



```
by(data = rawdata$`Size (cm)`, INDICES = rawdata$sex,
   FUN = meanse)
```

```
rawdata$sex: f
[1] "165±2"
```

```
-----
```

```
rawdata$sex: m
[1] "176±1"
```

```
apply(X=rawdata[quantvars$index], MARGIN=2,
      FUN=meansd, roundDig=2)
```

| | included | finalized | testmedication | Size (cm) |
|--------------|---------------|------------------|----------------|-------------|
| | "0.96 ± 0.19" | "0.86 ± 0.36" | "0.50 ± 0.51" | "174 ± 8" |
| Weight (kg) | | sysBP_V0 | diaBP_V0 | lv_edv_mri |
| "88 ± 15" | "122 ± 17" | | "70 ± 10" | "206 ± 70" |
| lv_esv_mri | lv_ef_mri | lv_ef_biplan_mri | | ptt_lab |
| "110 ± 70" | "50 ± 15" | | "49 ± 14" | "32 ± 6" |
| ferritin_lab | iron_lab | transferrin_lab | | sysBP_V2 |
| "281 ± 237" | "85 ± 37" | | "258 ± 36" | "119 ± 13" |
| diaBP_V2 | | BMI | | NYHA_V1 |
| "66 ± 9" | | "29 ± 4" | "60 ± 8" | "1.4 ± 0.9" |

```
NYHA_V2           NYHA_V3  
"1.5 ± 0.9"      "1.8 ± 0.9"
```

```
rawdata %>% group_by(sex) %>%  
  summarize(Mean=mean(`Size (cm)` ,na.rm=T)) %>%  
  ungroup()
```

```
# A tibble: 2 x 2  
  sex     Mean  
  <chr> <dbl>  
1 f       165  
2 m       176.
```

```
t.test(x = rawdata$`Size (cm)`[which(rawdata$sex=='f')],  
       y = rawdata$`Size (cm)`[which(rawdata$sex=='m')))
```

Welch Two Sample t-test

```
data: rawdata$`Size (cm)`[which(rawdata$sex == "f")] and rawdata$`Size (cm)`[which(rawdat  
t = -4.3967, df = 7.2767, p-value = 0.002887  
alternative hypothesis: true difference in means is not equal to 0  
95 percent confidence interval:  
 -16.295575 -4.954425  
sample estimates:  
mean of x mean of y  
 165.000   175.625
```

```
(t0out<-t.test(rawdata$`Size (cm)`~rawdata$sex))
```

Welch Two Sample t-test

```
data: rawdata$`Size (cm)` by rawdata$sex  
t = -4.3967, df = 7.2767, p-value = 0.002887  
alternative hypothesis: true difference in means between group f and group m is not equal  
95 percent confidence interval:  
 -16.295575 -4.954425  
sample estimates:  
mean in group f mean in group m  
 165.000          175.625
```

```
tOut$p.value
```

```
[1] 0.00288704
```

```
# equal variances assumption?  
(vartestOut<-var.test(rawdata$`Size (cm)`~rawdata$sex))
```

F test to compare two variances

```
data: rawdata$`Size (cm)` by rawdata$sex  
F = 0.2812, num df = 3, denom df = 23, p-value = 0.3232  
alternative hypothesis: true ratio of variances is not equal to 1  
95 percent confidence interval:  
 0.07497668 3.97434769  
sample estimates:  
ratio of variances  
 0.281199
```

```
(tOut<-t.test(rawdata$`Size (cm)`~rawdata$sex,  
               var.equal = vartestOut$p.value>.05))
```

Two Sample t-test

```
data: rawdata$`Size (cm)` by rawdata$sex  
t = -2.8446, df = 26, p-value = 0.008552  
alternative hypothesis: true difference in means between group f and group m is not equal  
95 percent confidence interval:  
 -18.302594 -2.947406  
sample estimates:  
mean in group f mean in group m  
 165.000          175.625
```

```
(tOut<=  
 t.test(rawdata$`Size (cm)`~rawdata$sex,  
        var.equal=var.test(  
           rawdata$`Size (cm)`~rawdata$sex)$p.value>.05))
```

Two Sample t-test

```
data: rawdata$`Size (cm)` by rawdata$sex
t = -2.8446, df = 26, p-value = 0.008552
alternative hypothesis: true difference in means between group f and group m is not equal
95 percent confidence interval:
-18.302594 -2.947406
sample estimates:
mean in group f mean in group m
165.000          175.625
```

```
t_var_test(data = rawdata,formula = ``Size (cm)`~sex`)
```

Two Sample t-test

```
data: Size (cm) by sex
t = -2.8446, df = 26, p-value = 0.008552
alternative hypothesis: true difference in means between group f and group m is not equal
95 percent confidence interval:
-18.302594 -2.947406
sample estimates:
mean in group f mean in group m
165.000          175.625
```

```
print(c(mean(rawdata$sysBP_V0,na.rm=T),
       mean(rawdata$sysBP_V2,na.rm=T)))
```

[1] 121.8519 119.4583

```
t.test(rawdata$sysBP_V0,
       rawdata$sysBP_V2,
       alternative='greater', # x>y
       paired=T) #pairwise t-test, within subject
```

Paired t-test

```
data: rawdata$sysBP_V0 and rawdata$sysBP_V2
```

```
t = 0.88151, df = 23, p-value = 0.1936
alternative hypothesis: true mean difference is greater than 0
95 percent confidence interval:
-2.793386      Inf
sample estimates:
mean difference
2.958333
```

```
t.test(rawdata$sysBP_V0,
       rawdata$sysBP_V2,
       # alternative='greater', # x>y
       paired=T)$p.value/2 #pairwise t-test, within subject
```

```
[1] 0.1935805
```

```
t.test(rawdata`Size (cm)`,mu = 173)
```

One Sample t-test

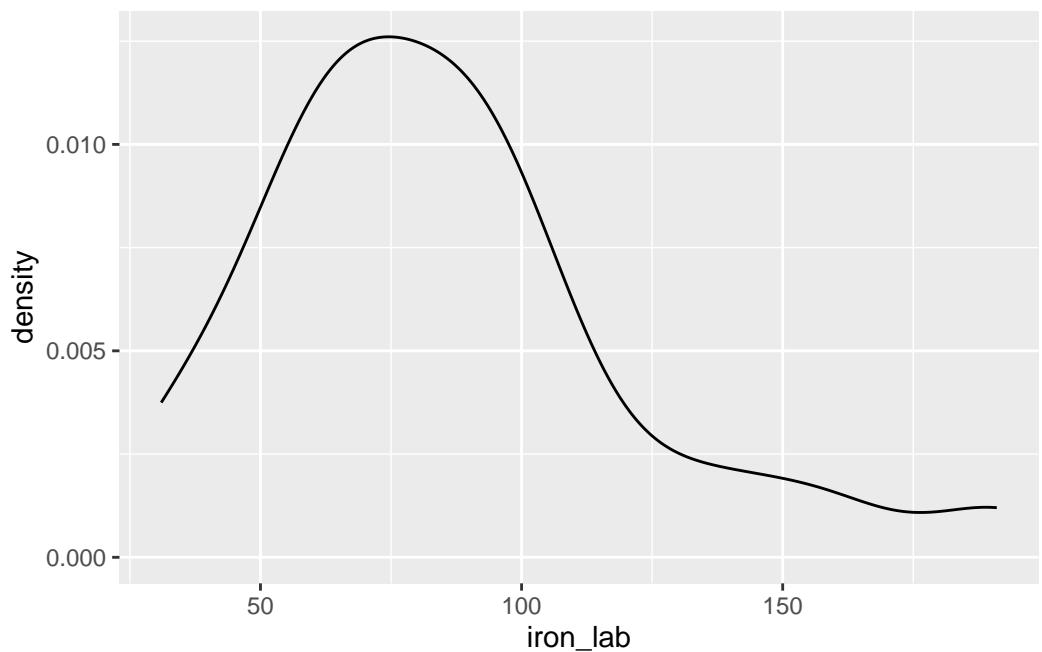
```
data: rawdata`Size (cm)`
t = 0.75384, df = 27, p-value = 0.4575
alternative hypothesis: true mean is not equal to 173
95 percent confidence interval:
171.0937 177.1206
sample estimates:
mean of x
174.1071
```

```
##### ordinal data -----
ordvars$names
```

```
[1] "ptt_lab"          "ferritin_lab"     "iron_lab"        "transferrin_lab"
[5] "age"
```

```
ggplot(rawdata,aes(iron_lab))+
  geom_density()
```

```
Warning: Removed 1 rows containing non-finite values (`stat_density()`).
```

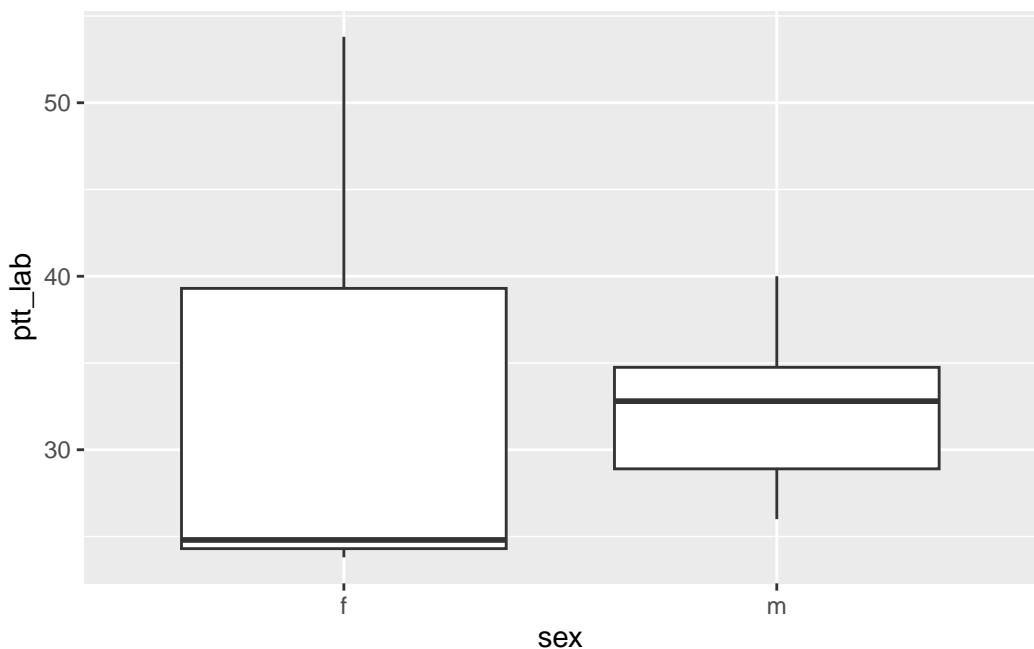


```
by(data = rawdata[[ordvars$index[1]]],  
   INDICES = rawdata$sex, FUN = median_quart)
```

```
rawdata$sex: f  
[1] "25 (24/49)"  
-----  
rawdata$sex: m  
[1] "33 (29/35)"
```

```
ggplot(rawdata,aes(sex,ptt_lab))+  
  geom_boxplot()
```

Warning: Removed 1 rows containing non-finite values (`stat_boxplot()`).



```
(uOut<-wilcox.test(
  rawdata[[ordvars$index[1]]] ~ rawdata$sex, exact=F))
```

Wilcoxon rank sum test with continuity correction

```
data: rawdata[[ordvars$index[1]]] by rawdata$sex
W = 24, p-value = 0.3748
alternative hypothesis: true location shift is not equal to 0
```

```
uOut$p.value
```

```
[1] 0.3748016
```

```
# coin:::wilcox_test
(uOut2<-wilcox_test(ptt_lab~as.factor(sex),
  data=rawdata))
```

Asymptotic Wilcoxon-Mann-Whitney Test

```
data: ptt_lab by as.factor(sex) (f, m)
Z = -0.9261, p-value = 0.3544
alternative hypothesis: true mu is not equal to 0
```

```
pvalue(uOut2) #no list-object, but methods to extract infos like p
```

```
[1] 0.3543925
```

```
wilcox.test(ptt_lab~sex,exact=F,correct=F,
            data=rawdata)
```

```
Wilcoxon rank sum test
```

```
data: ptt_lab by sex
W = 24, p-value = 0.3544
alternative hypothesis: true location shift is not equal to 0
```

```
wilcox.test(x=rawdata$sysBP_V0,y=rawdata$sysBP_V2,
            exact=F,
            correct=T,paired=T)
```

```
Wilcoxon signed rank test with continuity correction
```

```
data: rawdata$sysBP_V0 and rawdata$sysBP_V2
V = 143, p-value = 0.3478
alternative hypothesis: true location shift is not equal to 0
```

```
##### categorial data -----
factvars$names
```

```
[1] "testmedication" "sex"                 "NYHA_V1"           "NYHA_V2"
[5] "NYHA_V3"
```

```
(crosstab<-table(rawdata$sex,rawdata$testmedication))
```

```
 0  1  
f  2  2  
m 12 12
```

```
chisq.test(crosstab,simulate.p.value=T,B=10^5)  #empirical p-value
```

Pearson's Chi-squared test with simulated p-value (based on 1e+05 replicates)

```
data: crosstab  
X-squared = 0, df = NA, p-value = 1
```

```
chisq.test(table(rawdata$sex,rawdata$NYHA_V1))  #based on table
```

Warning in chisq.test(table(rawdata\$sex, rawdata\$NYHA_V1)):
Chi-Quadrat-Approximation kann inkorrekt sein

Pearson's Chi-squared test

```
data: table(rawdata$sex, rawdata$NYHA_V1)  
X-squared = 4.3849, df = 3, p-value = 0.2228
```

```
chisq.test(x=rawdata$sex,y=rawdata$NYHA_V1,  
simulate.p.value=T,B=10^5)  #based on rawdata
```

Pearson's Chi-squared test with simulated p-value (based on 1e+05 replicates)

```
data: rawdata$sex and rawdata$NYHA_V1  
X-squared = 4.3849, df = NA, p-value = 0.1741
```

```
(crosstab1<-table(rawdata$sex,  
rawdata$`Weight (kg)`<=  
median(rawdata$`Weight (kg)`)))
```

```
    FALSE TRUE  
f      1     3  
m     13    11
```

```
prop.table(crosstab1)
```

```
    FALSE      TRUE  
f 0.03571429 0.10714286  
m 0.46428571 0.39285714
```

```
round(prop.table(crosstab1)*100)
```

```
    FALSE TRUE  
f      4     11  
m     46    39
```

```
round(prop.table(crosstab1,margin=2)*100) #% per column
```

```
    FALSE TRUE  
f      7    21  
m     93   79
```

```
round(prop.table(crosstab1,margin=1)*100) #% per row
```

```
    FALSE TRUE  
f     25    75  
m     54    46
```

```
(tabletestOut<-chisq.test(crosstab1,simulate.p.value=T,  
                           B=10^5))
```

```
Pearson's Chi-squared test with simulated p-value (based on 1e+05  
replicates)
```

```
data: crosstab1  
X-squared = 1.1667, df = NA, p-value = 0.5988
```

```
tabletestOut$p.value
```

```
[1] 0.598784
```

```
tabletestOut$expected
```

| | FALSE | TRUE |
|---|-------|------|
| f | 2 | 2 |
| m | 12 | 12 |

```
tabletestOut$observed
```

| | FALSE | TRUE |
|---|-------|------|
| f | 1 | 3 |
| m | 13 | 11 |

```
tabletestOut$statistic
```

```
X-squared  
1.166667
```

```
# if minimum(expected<5) then Fishers exact test  
if (min(tabletestOut$expected)<5) {  
  tabletestOut<-fisher.test(crosstab1)  
}  
tabletestOut$p.value
```

```
[1] 0.5955556
```

```

groupvars <- ColSeeker(namepattern = c('sex','test'))


##### report -----
# report_qv %<>%
#   mutate(
#     Variable=factor(Variable, levels=quantvars$names),
#     female='', male='', `p sexdiff`="") %>%
#   arrange(Variable)
# for (var_i in 1:quantvars$count) {
#   report_qv[var_i, c('female','male')] <-
#   meansd(rawdata[[quantvars$index[var_i]]]),
#   groupvar = rawdata %>% pull(quantvars$names[2]),##$sex,
#   add_n = T,rangesep = '  ',
#   range = T) %>%
#   as.list()
#   evOut<-var.test((rawdata %>% pull(quantvars$index[var_i]))~
#                     rawdata$sex)
#   tOut<-t.test((rawdata %>% pull(quantvars$index[var_i]))~
#                     rawdata$sex,
#                     var.equal=evOut$p.value>.05)
#   report_qv$p sexdiff`[var_i] <- formatP(tOut$p.value)
#   rm(evOut,tOut)
# }

compare2numvars(data = rawdata,dep_vars = quantvars$names,
                 indep_var = "sex",gaussian = T)

```

```

# A tibble: 22 x 5
  Variable    desc_all    `sex f`    `sex m`      p
  <fct>       <chr>       <chr>       <chr>       <chr>
1 included    0.96 ± 0.19 1.0 ± 0.0  1.0 ± 0.2  0.328
2 finalized   0.86 ± 0.36 0.75 ± 0.50 0.88 ± 0.34 0.526
3 testmedication 0.50 ± 0.51 0.50 ± 0.58 0.50 ± 0.51 1.000
4 Size (cm)   174 ± 8    165 ± 4    176 ± 7    0.009
5 Weight (kg) 88 ± 15    76 ± 13    90 ± 14    0.072
6 sysBP_V0    122 ± 17   118 ± 14   123 ± 18   0.587
7 diaBP_V0    70 ± 10    71 ± 13    69 ± 9     0.780
8 lv_edv_mri  206 ± 70   235 ± 72   203 ± 71   0.559
9 lv_esv_mri  110 ± 70   158 ± 56   105 ± 71   0.322
10 lv_ef_mri  50 ± 15    33 ± 3     52 ± 15   0.095
# i 12 more rows

```

```
compare2numvars(data = rawdata,dep_vars = quantvars$names,
                indep_var = "testmedication",gaussian = T)
```

```
# A tibble: 21 x 5
  Variable      desc_all `testmedication 0` `testmedication 1` p
  <fct>        <chr>     <chr>          <chr>          <chr>
1 included    0.96 ± 0.19 1.0 ± 0.0   0.9 ± 0.3   0.336
2 finalized   0.86 ± 0.36 0.79 ± 0.43  0.93 ± 0.27  0.297
3 Size (cm)  174 ± 8    173 ± 6       175 ± 9    0.653
4 Weight (kg) 88 ± 15    90 ± 14       86 ± 16    0.448
5 sysBP_V0   122 ± 17    122 ± 15      122 ± 19   0.966
6 diaBP_V0   70 ± 10    70 ± 7        70 ± 12    0.943
7 lv_edv_mri 206 ± 70   243 ± 77      173 ± 45   0.019
8 lv_esv_mri 110 ± 70   138 ± 87      86 ± 41    0.108
9 lv_ef_mri   50 ± 15    48 ± 18       52 ± 12    0.532
10 lv_ef_biplan_mri 49 ± 14   47 ± 17      50 ± 13   0.747
# i 11 more rows
```

```
for(group_i in seq_len(groupvars$count)){
  resulttmp <- compare2numvars(data = rawdata,dep_vars = quantvars$names,
                                indep_var = groupvars$names[group_i],gaussian = T)
  print(resulttmp)
}
```

```
# A tibble: 21 x 5
  Variable      desc_all `testmedication 0` `testmedication 1` p
  <fct>        <chr>     <chr>          <chr>          <chr>
1 included    0.96 ± 0.19 1.0 ± 0.0   0.9 ± 0.3   0.336
2 finalized   0.86 ± 0.36 0.79 ± 0.43  0.93 ± 0.27  0.297
3 Size (cm)  174 ± 8    173 ± 6       175 ± 9    0.653
4 Weight (kg) 88 ± 15    90 ± 14       86 ± 16    0.448
5 sysBP_V0   122 ± 17    122 ± 15      122 ± 19   0.966
6 diaBP_V0   70 ± 10    70 ± 7        70 ± 12    0.943
7 lv_edv_mri 206 ± 70   243 ± 77      173 ± 45   0.019
8 lv_esv_mri 110 ± 70   138 ± 87      86 ± 41    0.108
9 lv_ef_mri   50 ± 15    48 ± 18       52 ± 12    0.532
10 lv_ef_biplan_mri 49 ± 14   47 ± 17      50 ± 13   0.747
# i 11 more rows
# A tibble: 22 x 5
  Variable      desc_all `sex f`   `sex m`   p
  <fct>        <chr>     <chr>     <chr>     <chr>
1 included    0.96 ± 0.19 1.0 ± 0.0  1.0 ± 0.2  0.328
2 finalized   0.86 ± 0.36 0.75 ± 0.50 0.88 ± 0.34 0.526
```

```

3 testmedication 0.50 ± 0.51 0.50 ± 0.58 0.50 ± 0.51 1.000
4 Size (cm)      174 ± 8       165 ± 4       176 ± 7       0.009
5 Weight (kg)    88 ± 15      76 ± 13       90 ± 14       0.072
6 sysBP_V0       122 ± 17      118 ± 14      123 ± 18       0.587
7 diaBP_V0       70 ± 10       71 ± 13       69 ± 9        0.780
8 lv_edv_mri    206 ± 70      235 ± 72      203 ± 71       0.559
9 lv_esv_mri    110 ± 70      158 ± 56      105 ± 71       0.322
10 lv_ef_mri    50 ± 15       33 ± 3        52 ± 15       0.095
# i 12 more rows

```

```

# report_ov

# report_ov %<>%
#   mutate(
#     Variable=factor(Variable, levels=ordvars$names),
#     female='', male='`p sexdiff`=""') %>%
#   arrange(Variable)
# for (var_i in seq_len(ordvars$count)) {
#   report_ov[var_i,c('female','male')] <-
#     # by(rawdata[[ordvars$names[var_i]]],
#     # rawdata$sex,quantile,probs=c(.25,.75),na.rm=T)
#   median_quart(rawdata[[ordvars$index[var_i]]],
#                 groupvar = rawdata$sex,
#                 add_n = T,rangesep = '  ',
#                 range = T) %>%
#     as.list()
#   wOut<-wilcox.test((rawdata %>% pull(ordvars$index[var_i]))~
#                       rawdata$sex,exact=F)
#   report_ov`p sexdiff`[var_i] <- formatP(wOut$p.value)
#   plottmp <-
#     rawdata %>% ggplot(aes_string('sex',ordvars$bticked[var_i]))+
#     geom_boxplot()+
#     geom_signif(comparisons = list(c(1,2)),
#                 annotations = paste0('p ',
#                                       formatP(wOut$p.value,
#                                               pretext = T)))+
#     scale_y_continuous(expand = expansion(mult = c(.1,.15)))
#   print(plottmp)
# }

compare2numvars(data = rawdata,dep_vars = ordvars$names,
                 indep_var = "sex",gaussian = F)

```

```
# A tibble: 5 x 5
```

| Variable | desc_all | `sex f` | `sex m` | p |
|-------------------|---------------|---------------|---------------|-------|
| | <fct> | <chr> | <chr> | <chr> |
| 1 ptt_lab | 33 (28/35) | 25 (24/49) | 33 (29/35) | 0.375 |
| 2 ferritin_lab | 222 (162/339) | 138 (90/591) | 224 (172/316) | 0.616 |
| 3 iron_lab | 80 (61/102) | 95 (92/103) | 75 (60/99) | 0.165 |
| 4 transferrin_lab | 261 (233/276) | 260 (227/299) | 262 (235/276) | 1.000 |
| 5 age | 62 (53/67) | 66 (58/69) | 60 (53/66) | 0.250 |

```

# report_cat
groupvar <- 'sex'
# report_cat %<>%
#   mutate(
#     Variable=factor(Variable, levels=factvars$names),
#     female='', male='', `p sexdiff`="") %>%
#   arrange(Variable)
#
# for(var_i in seq_along(factvars$names)){
#   # if(factvars$names[var_i]!=groupvar){
#   report_cat[var_i,c('female','male')] <-
#     cat_desc_stats(rawdata[[factvars$index[var_i]]],
#                   groupvar = rawdata$sex,
#                   singleline = T,separator = ' / ',
#                   return_level = F) %>%
#       as.list()
#   test_out <- fisher.test(rawdata[[factvars$index[var_i]]],
#                           rawdata[[groupvar]])
#   report_cat$p sexdiff`[var_i] <- formatP(test_out$p.value)
#
#   p1 <- ggplot(rawdata,aes_string(groupvar,
#                                     fill=factvars$bticked[var_i]))+
#     geom_bar()+
#     geom_signif(
#       aes(y=max(table(sex))+2),
#       comparisons = list(c(1,2)),
#       annotations = paste0('p ',
#                             formatP(test_out$p.value,
#                                     pretext = T)))+
#     scale_y_continuous(expand = expansion(mult = c(.1,.15)))
#   p2 <- ggplot(rawdata,aes_string(groupvar,
#                                     fill=factvars$bticked[var_i]))+
#     geom_bar(position='fill')+
#     geom_signif(
#       aes(y=1.05),
#       comparisons = list(c(1,2)),
#       annotations = paste0('p ',
#                             formatP(test_out$p.value,
#                                     pretext = T)))+
#     scale_y_continuous(expand = expansion(mult = c(.1,.15)))
#   }
# }
```

```

#           annotations = paste0('p ',
#                                     formatP(test_out$p.value,
#                                             pretext = T)))+
#           scale_y_continuous(expand = expansion(mult = c(.1,.15)),
#                               labels = scales::percent)
# p3 <- ggplot(rawdata %>%
#               filter(!is.na (!!sym(factvars$names[var_i]))),
#               aes_string(groupvar,
#                          fill=factvars$bticked[var_i]))+
#           geom_bar(position='fill')+
#           geom_signif(
#             aes(y=1.05),
#             comparisons = list(c(1,2)),
#             annotations = paste0('p ',
#                                   formatP(test_out$p.value,
#                                           pretext = T)))+
#           scale_y_continuous(expand = expansion(mult = c(.1,.15)),
#                               labels = scales::percent)
# print(p1/(p2+p3))
# print(p1/(p2+p3)+plot_layout(guides = "collect") &
#       theme(legend.position = 'bottom'))
# # }
# }

compare2qualvars(rawdata,dep_vars = factvars$names,
                  indep_var = groupvar,spacer = ' ')

```

```

# A tibble: 20 x 5
  Variable      desc_all `sex f` `sex m`    p
  <chr>        <chr>     <chr>     <chr>    <chr>
1 "testmedication" " "      " "       " "      "1.000"
2 " 0"          "14 (50%)" "2 (50%)" "12 (50%)" " "
3 " 1"          "14 (50%)" "2 (50%)" "12 (50%)" " "
4 "sex"         " "       " "       " "      "0.001"
5 "  f"          "4 (14.29%)" "4 (100%)" "0 (0%)" " "
6 "  m"          "24 (85.71%)" "0 (0%)"  "24 (100%)" " "
7 "NYHA_V1"     " "       " "       " "      "0.096"
8 "  0"          "2 (11.76%)" "1 (33.33%)" "1 (7.14%)" " "
9 "  1"          "9 (52.94%)" "0 (0%)"   "9 (64.29%)" " "
10 "  2"          "3 (17.65%)" "1 (33.33%)" "2 (14.29%)" " "
11 "  3"          "3 (17.65%)" "1 (33.33%)" "2 (14.29%)" " "
12 "NYHA_V2"     " "       " "       " "      "1.000"
13 "  0"          "1 (9.09%)"  "0 (0%)"   "1 (12.5%)" " "
14 "  1"          "6 (54.55%)" "2 (66.67%)" "4 (50%)" " "

```

| | | | | | |
|--------------|-----|--------------|--------------|--------------|---------|
| 15 " | 2" | "2 (18.18%)" | "1 (33.33%)" | "1 (12.5%)" | " " |
| 16 " | 3" | "2 (18.18%)" | "0 (0%)" | "2 (25%)" | " " |
| 17 "NYHA_V3" | " " | " " | " " | " " | "0.091" |
| 18 " | 1" | "6 (50%)" | "0 (0%)" | "6 (66.67%)" | " " |
| 19 " | 2" | "3 (25%)" | "1 (33.33%)" | "2 (22.22%)" | " " |
| 20 " | 3" | "3 (25%)" | "2 (66.67%)" | "1 (11.11%)" | " " |

9 Intro to lm

In this chapter, linear models (including linear regression and ANOVA) will be introduced. Output is not optimized for print, but rather for interactive use.

9.1 Setup

All packages necessary will be invoked by p_load. Packages with only a single function call or potential for name conflicts can be unloaded, this way we still checked for their existence and installed them if need be.

```
pacman::p_load(conflicted,wrappedtools,car,nlme,broom,
                 multcomp,tidyverse,foreign,DescTools, ez,
                 ggbeeswarm,
                 lme4, nlme,merTools,
                 easystats, patchwork,here)#conflicted,
# rayshader,av)
# pacman::p_unload(DescTools, foreign)
# conflict_scout()
conflicts_prefer(dplyr::select,
                  dplyr::filter,
                  modelbased::standardize)
```

```
[conflicted] Will prefer dplyr::select over any other package.
[conflicted] Will prefer dplyr::filter over any other package.
[conflicted] Will prefer modelbased::standardize over any other package.
```

```
base_dir <- here::here()
```

9.2 Import / Preparation

Data are read from an SPSS file. Numeric column Passage is mutated into a factor as Passage_F, this is necessary for group comparisons in ANOVA. The call to here() expands the path to a file from the project directory to the full system path.

```

rawdata<-foreign::read.spss(file=here('Data/Zellbeads.sav'),
                             use.value.labels=T,to.data.frame=T) %>%
  as_tibble() %>%
  dplyr::select(-ZahlZellen) |>
  rename(Growth=Wachstum,Treatment=Bedingung) |>
  mutate(Passage_F=factor(Passage),
         Treatment=fct_recode(Treatment,
                               Control="Kontrolle"))

```

re-encoding from CP1252

9.3 Graphical exploration

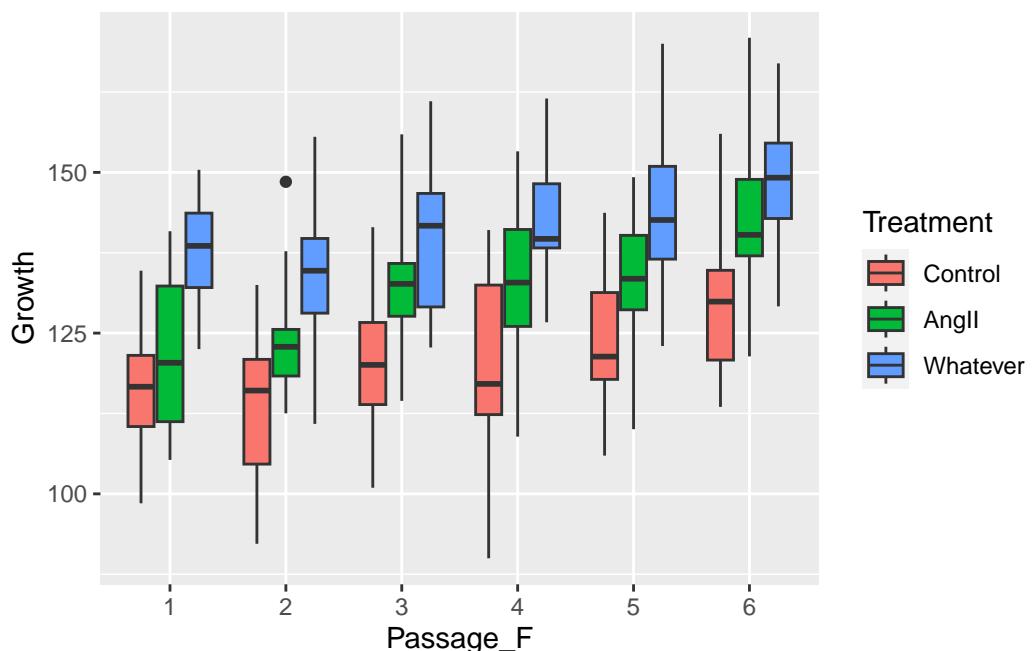
First impression of the data will be attempted by grouped boxplot, followed by interaction plots, both as basic and ggplot with variations.

```

ggplot(rawdata,aes(Passage_F,Growth, fill=Treatment))+  

  geom_boxplot(coef=3)

```



```

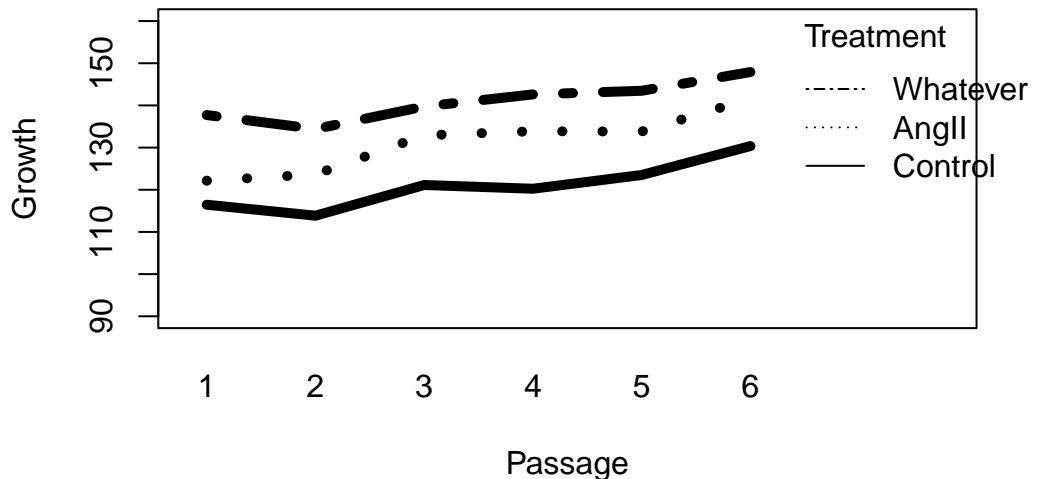
with(rawdata, interaction.plot(  

  x.factor=Passage, trace.factor=Treatment, response=Growth,  

  ylim = c(90, 160), lty = c(1,3,12), lwd = 5,

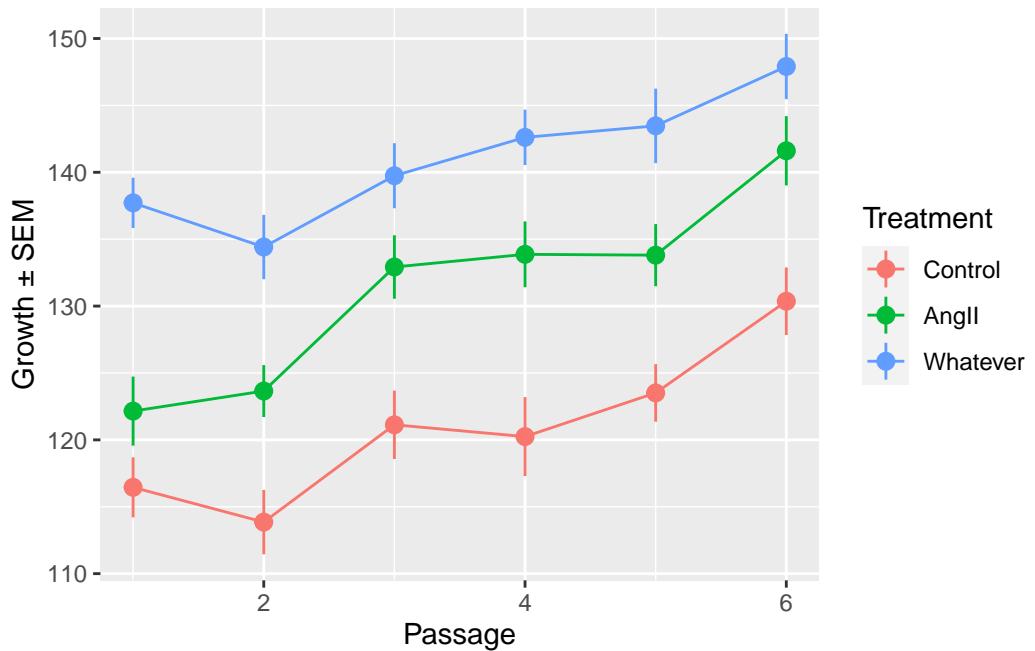
```

```
ylab = "Growth", xlab = "Passage",
trace.label = "Treatment"))
```



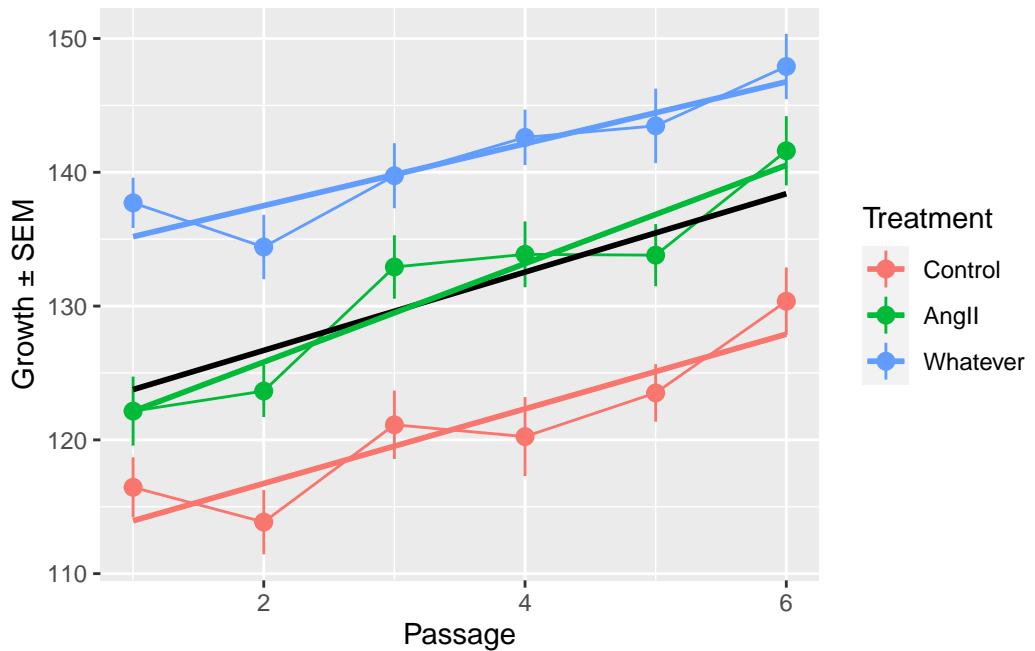
```
# p1<-ggplot(rawdata,aes(x=Passage,y=Growth))+  
#   stat_summary(geom='line',fun='mean',aes(color=Treatment))+  
#   stat_summary(geom='line',fun='mean')  
p1<-ggplot(rawdata,aes(x=Passage,y=Growth))+  
  stat_summary(geom='line',fun='mean',aes(color=Treatment))+  
  stat_summary(aes(color=Treatment))+  
  ylab('Growth \u00b1 SEM')  
p1
```

No summary function supplied, defaulting to `mean_se()`



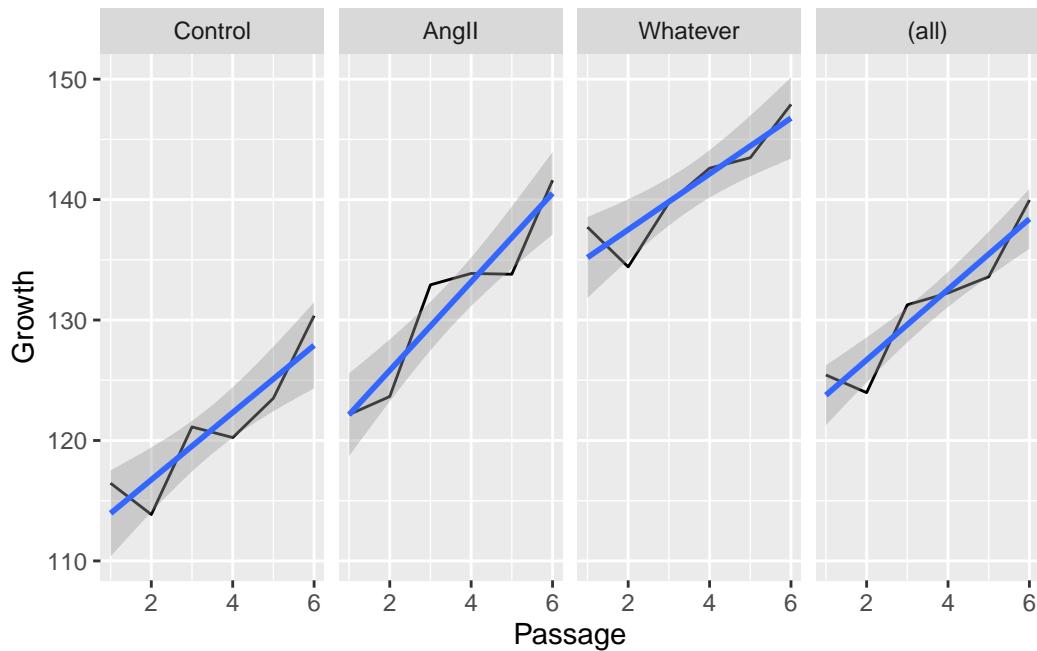
```
p1+geom_smooth(method='lm',color='black',se=F)+  
  geom_smooth(method='lm',aes(color=Treatment),se=F)
```

No summary function supplied, defaulting to `mean_se()`
`geom_smooth()` using formula = 'y ~ x'
`geom_smooth()` using formula = 'y ~ x'



```
ggplot(rawdata,aes(x=Passage,y=Growth))+  
  stat_summary(geom='line',fun='mean')+  
  geom_smooth(method='lm')+  
  facet_grid(cols = vars(Treatment), margins=T)
```

```
`geom_smooth()` using formula = 'y ~ x'
```



9.4 Linear Models

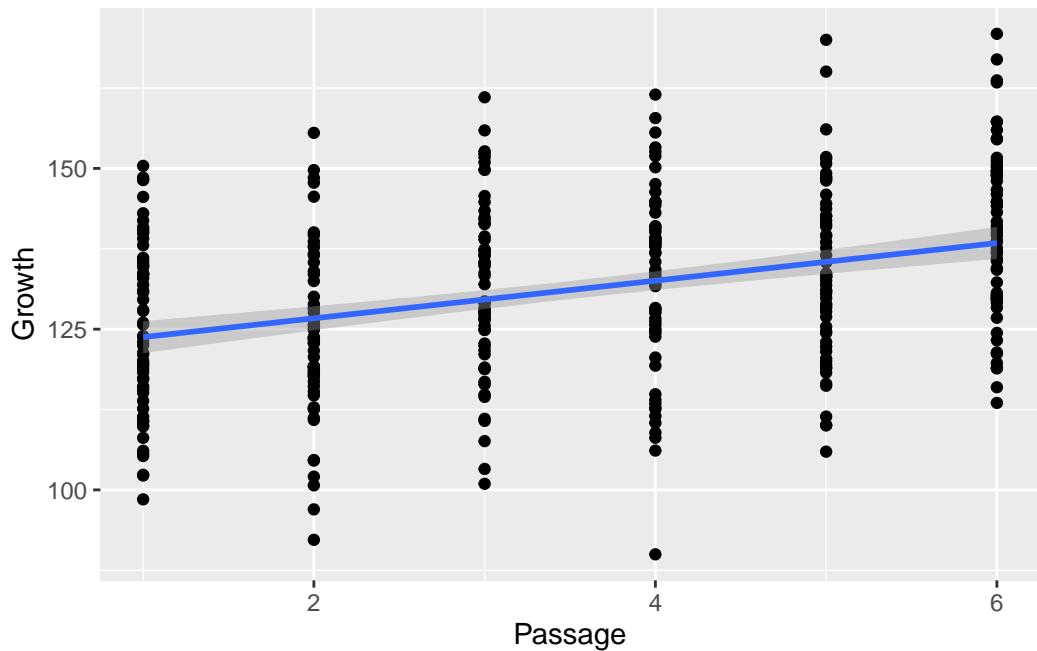
9.4.1 Linear regression

We will analyse the relation between independent variable (IV) Passage and dependent variable (DV) Growth.

9.4.1.1 Graphical exploration

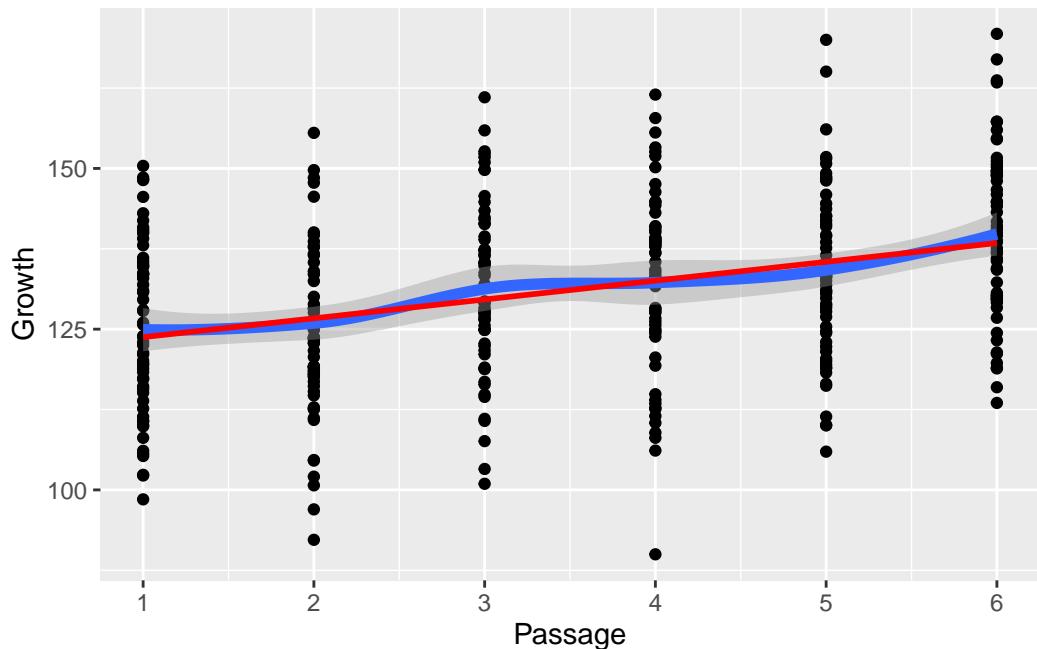
```
ggplot(rawdata,aes(Passage,Growth))+  
  geom_point() +  
  geom_smooth(method=lm)
```

```
`geom_smooth()` using formula = 'y ~ x'
```



```
ggplot(rawdata,aes(Passage,Growth))+  
  geom_point() +  
  scale_x_continuous(breaks=seq(0,10,1)) +  
  geom_smooth(linewidth=2) +  
  geom_smooth(method=lm,se=F,color='red')
```

```
`geom_smooth()` using method = 'loess' and formula = 'y ~ x'  
`geom_smooth()` using formula = 'y ~ x'
```



9.4.1.2 Modelling

This takes 2 steps, building the model and computing p-values.

```
# model
(regressionOut<-lm(Growth~Passage,data=rawdata))
```

```
Call:
lm(formula = Growth ~ Passage, data = rawdata)

Coefficients:
(Intercept)      Passage
120.834        2.927
```

```
# model and p.value for slope, not recommended
tidy(regressionOut)
```

```
# A tibble: 2 x 5
  term      estimate std.error statistic   p.value
  <chr>      <dbl>     <dbl>     <dbl>      <dbl>
1 (Intercept) 121.       1.63      74.2  1.77e-219
2 Passage      2.93      0.418      7.00  1.26e- 11
```

```
# computation of SSQs and p-values, use this!
(anova_out<-anova(regressionOut))
```

Analysis of Variance Table

```
Response: Growth
  Df Sum Sq Mean Sq F value    Pr(>F)
Passage     1   8996   8996.2  49.022 1.257e-11 ***
Residuals  358  65698    183.5
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova_out$`Pr(>F)` #|> na.omit()
```

```
[1] 1.257266e-11          NA
```

```
tidy(anova_out)
```

```
# A tibble: 2 x 6
  term      df  sumsq meansq statistic  p.value
  <chr>    <int> <dbl>  <dbl>     <dbl>    <dbl>
1 Passage     1   8996.   8996.     49.0  1.26e-11
2 Residuals  358  65698.   184.      NA     NA
```

```
# summary(regressionOut)
# str(regressionOut)
```

9.4.1.3 Adjusting

To take out the variance due to Passage effects, we can use the residuals and shift them to the original mean:

```
rawdata <-
  mutate(rawdata,
        growthAdj = regressionOut$residuals+mean(Growth))

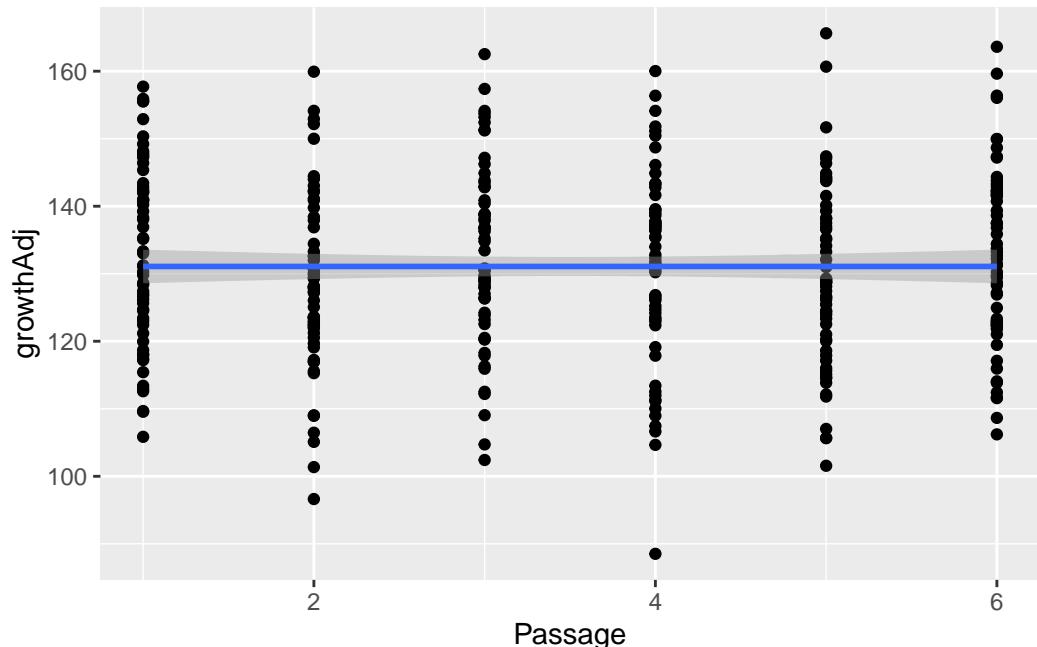
  summarise(rawdata,
            across(contains('growth'),
```

```
~meansd(.x,roundDig =4)))
```

```
# A tibble: 1 x 2
  Growth      growthAdj
  <chr>       <chr>
1 131.1 ± 14.4 131.1 ± 13.5
```

```
ggplot(rawdata,aes(Passage,growthAdj))+  
  geom_point() +  
  geom_smooth(method = 'lm')
```

```
`geom_smooth()` using formula = 'y ~ x'
```



```
lm(growthAdj~Passage,data=rawdata) |> tidy()
```

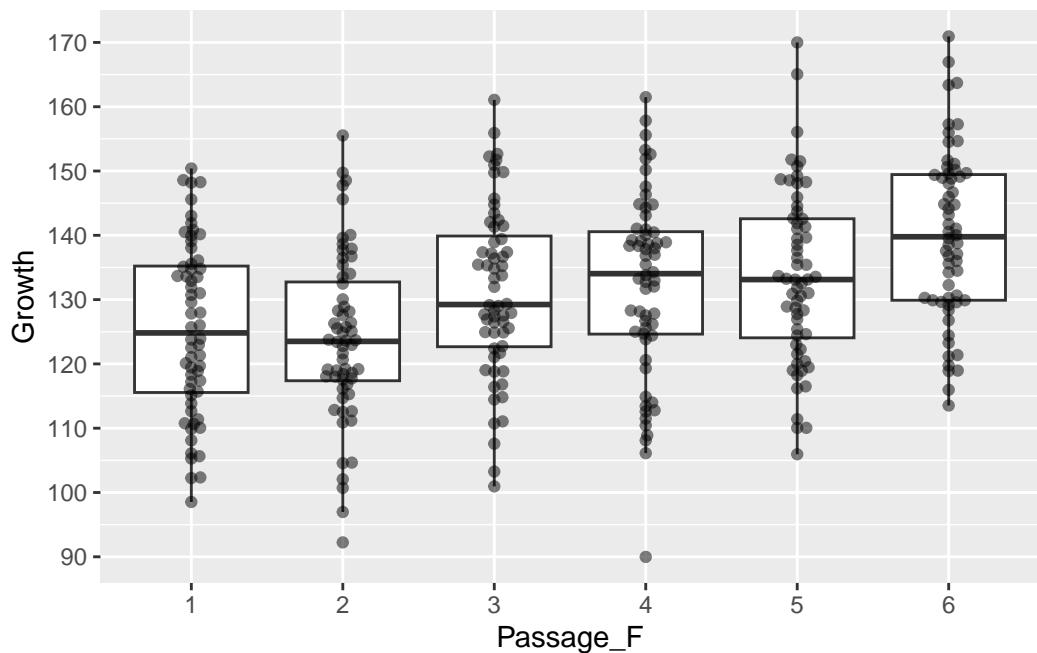
```
# A tibble: 2 x 5
  term      estimate std.error statistic   p.value
  <chr>        <dbl>     <dbl>      <dbl>     <dbl>
1 (Intercept) 1.31e+ 2      1.63    8.05e+ 1 2.04e-231
2 Passage      6.80e-15     0.418   1.63e-14 1.00e+ 0
```

9.4.2 ANOVA

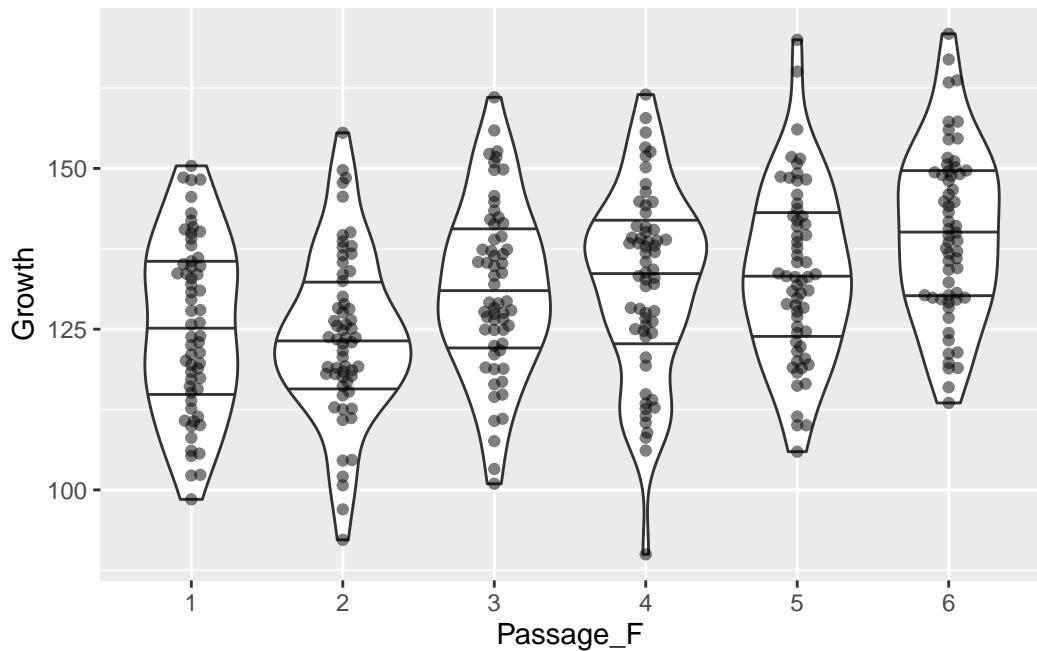
In the linear regression, we had Passage as a continuous IV, estimating a global ‘universal’ effect supposed to be constant. Now we look at Passage_F and model a discrete IV, allowing for specific effects, and thereby comparing means between groups.

9.4.2.1 Graphical exploration

```
ggplot(rawdata,aes(x = Passage_F, y = Growth))+  
  geom_boxplot(outlier.alpha = 0)+  
  geom_beeswarm(alpha=.5)+  
  scale_y_continuous(breaks=seq(0,1000,10))
```



```
ggplot(rawdata,aes(x = Passage_F, y = Growth))+  
  geom_violin(draw_quantiles = c(.25,.5,.75))+  
  geom_beeswarm(alpha=.5)
```



9.4.2.2 Modelling

```
(AnovaOut<-lm(Growth~Passage_F,data=rawdata))
```

Call:
`lm(formula = Growth ~ Passage_F, data = rawdata)`

Coefficients:

| | (Intercept) | Passage_F2 | Passage_F3 | Passage_F4 | Passage_F5 | Passage_F6 |
|--|-------------|------------|------------|------------|------------|------------|
| | 125.440 | -1.467 | 5.824 | 6.801 | 8.156 | 14.520 |

```
tidy(AnovaOut)
```

```
# A tibble: 6 x 5
  term      estimate std.error statistic p.value
  <chr>      <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept) 125.       1.74      71.9  2.20e-213
2 Passage_F2   -1.47     2.47     -0.595 5.52e- 1
3 Passage_F3    5.82     2.47      2.36  1.87e- 2
4 Passage_F4    6.80     2.47      2.76  6.11e- 3
5 Passage_F5    8.16     2.47      3.31  1.04e- 3
6 Passage_F6   14.5      2.47      5.89  9.03e- 9
```

```
# summary(AnovaOut)
(t <- anova(AnovaOut))
```

Analysis of Variance Table

```
Response: Growth
          Df Sum Sq Mean Sq F value    Pr(>F)
Passage_F    5 10134  2026.71   11.113 5.852e-10 ***
Residuals 354 64561   182.38
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
t$`Pr(>F)`
```

```
[1] 5.851856e-10           NA
```

```
tidy(t)
```

```
# A tibble: 2 x 6
  term      df  sumsq meansq statistic  p.value
  <chr>     <int> <dbl>  <dbl>     <dbl>    <dbl>
1 Passage_F     5 10134.  2027.     11.1  5.85e-10
2 Residuals    354 64561.  182.      NA     NA
```

9.4.2.3 Post-hoc analyses

The p-value from our model only tests the global Null hypothesis of no differences between any group (all means are the same / all groups come from the same population). Post-hoc tests are used to figure out which groups are different. Those tests need to take multiple testing into account. Try to limit selection of tests!

```
# possible in a loop, but nominal p
t.test(rawdata$Growth[which(rawdata$Passage==1)],
       rawdata$Growth[which(rawdata$Passage==2)],
       var.equal = T)
```

Two Sample t-test

```
data: rawdata$Growth[which(rawdata$Passage == 1)] and rawdata$Growth[which(rawdata$Passage == 2)]
t = 0.60679, df = 118, p-value = 0.5452
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-3.321297 6.255936
sample estimates:
mean of x mean of y
125.4396 123.9723
```

```
# all pairwise group combinations
pt_out<-pairwise.t.test(x=rawdata$Growth,
                         g=rawdata$Passage_F,
                         p.adjust.method='none')
pt_out
```

Pairwise comparisons using t tests with pooled SD

```
data: rawdata$Growth and rawdata$Passage_F
```

| | 1 | 2 | 3 | 4 | 5 |
|---|---------|---------|---------|---------|---------|
| 2 | 0.55215 | - | - | - | - |
| 3 | 0.01871 | 0.00331 | - | - | - |
| 4 | 0.00611 | 0.00088 | 0.69214 | - | - |
| 5 | 0.00104 | 0.00011 | 0.34487 | 0.58296 | - |
| 6 | 9e-09 | 3e-10 | 0.00048 | 0.00189 | 0.01025 |

P value adjustment method: none

```
pairwise.t.test(x=rawdata$Growth,g=rawdata$Passage,
                 p.adjust.method='fdr')
```

Pairwise comparisons using t tests with pooled SD

```
data: rawdata$Growth and rawdata$Passage
```

| | 1 | 2 | 3 | 4 | 5 |
|---|---------|---|---|---|---|
| 2 | 0.62460 | - | - | - | - |

```
3 0.02552 0.00621 - - -
4 0.01018 0.00259 0.69214 - -
5 0.00259 0.00057 0.43109 0.62460 -
6 6.8e-08 4.5e-09 0.00178 0.00405 0.01538
```

P value adjustment method: fdr

```
pairwise.t.test(x=rawdata$Growth,g=rawdata$Passage,
                 p.adjust.method='bonferroni')
```

Pairwise comparisons using t tests with pooled SD

data: rawdata\$Growth and rawdata\$Passage

| | 1 | 2 | 3 | 4 | 5 |
|---|---------|---------|--------|--------|--------|
| 2 | 1.0000 | - | - | - | - |
| 3 | 0.2807 | 0.0497 | - | - | - |
| 4 | 0.0917 | 0.0133 | 1.0000 | - | - |
| 5 | 0.0155 | 0.0017 | 1.0000 | 1.0000 | - |
| 6 | 1.4e-07 | 4.5e-09 | 0.0071 | 0.0283 | 0.1538 |

P value adjustment method: bonferroni

```
# comparison against reference group 1
pt_out$p.value[,1]
```

| | 2 | 3 | 4 | 5 | 6 |
|--|--------------|--------------|--------------|--------------|--------------|
| | 5.521460e-01 | 1.871115e-02 | 6.110172e-03 | 1.036173e-03 | 9.031123e-09 |

```
# comparison against reference group 6
pt_out$p.value[5,]
```

| | 1 | 2 | 3 | 4 | 5 |
|--|--------------|--------------|--------------|--------------|--------------|
| | 9.031123e-09 | 3.001066e-10 | 4.757018e-04 | 1.889098e-03 | 1.025037e-02 |

```
# comparison for selection
c(pt_out$p.value[1,1],pt_out$p.value[3,2],
  pt_out$p.value[5,1])
```

```
[1] 5.521460e-01 8.842382e-04 9.031123e-09
```

```
# comparison against next level  
diag(pt_out$p.value)
```

```
[1] 0.55214600 0.00331248 0.69214393 0.58295615 0.01025037
```

```
# adjusting for multiple testing for selected comparisons  
p.adjust(diag(pt_out$p.value),method='fdr')
```

```
[1] 0.69214393 0.01656240 0.69214393 0.69214393 0.02562592
```

```
formatP(p.adjust(pt_out$p.value[,1],method='fdr'))
```

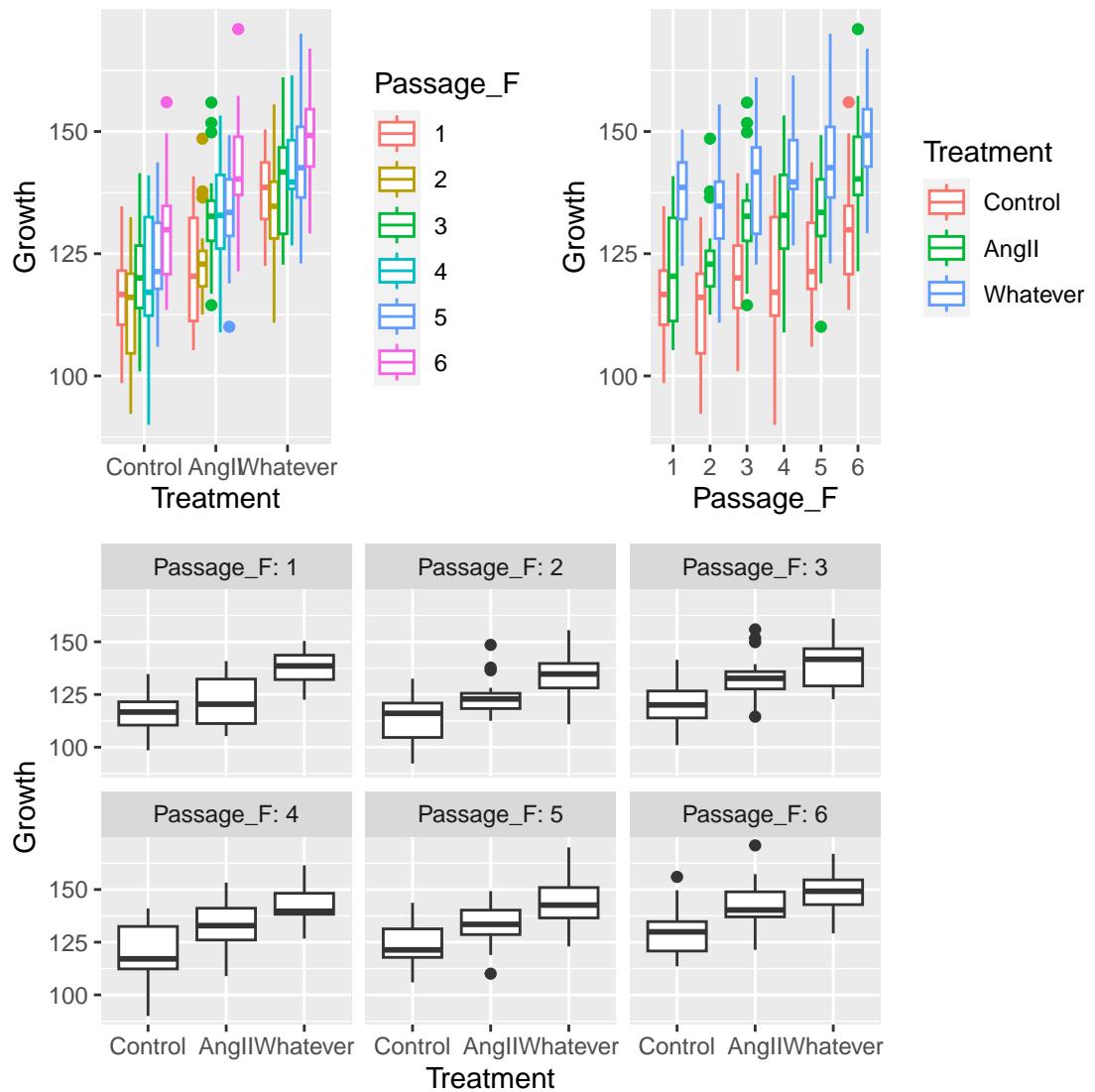
```
[1] "0.552" "0.023" "0.010" "0.003" "0.001"
```

9.4.3 LM with continuous AND categorical IV

Traditionally you may think of *regression OR ANOVA*, but they are no different and can be combined. This is called a general linear model. Multivariable models may contain interactions between independent variables V $IV1*IV2$.

9.4.3.1 Graphical exploration

```
p0 <- ggplot(rawdata,aes(Treatment,Growth))+  
  geom_boxplot()  
p1 <- ggplot(rawdata,aes(Treatment,Growth, color=Passage_F))+  
  geom_boxplot()  
p2 <- ggplot(rawdata,aes(color=Treatment,Growth, x=Passage_F))+  
  geom_boxplot()  
p3 <- ggplot(rawdata,aes(Treatment,Growth))+  
  geom_boxplot()  
  facet_wrap(facets = vars(Passage_F), labeller='label_both')  
# from patchwork  
(p1+p2)/p3
```



9.4.3.2 Modelling

Models with (*) and without (+) interaction are build and tested.

```
lmOut_interaction<-lm(Growth~Passage*Treatment,data=rawdata)
Anova(lmOut_interaction,type = 3)
```

Anova Table (Type III tests)

| Response: Growth | Sum Sq | Df | F value | Pr(>F) |
|------------------|--------|----|---------|--------|
|------------------|--------|----|---------|--------|

```

(Intercept)      285160    1 2448.5613 < 2.2e-16 ***
Passage          2723     1   23.3855 1.981e-06 ***
Treatment        5635     2   24.1924 1.419e-10 ***
Passage:Treatment 335     2    1.4376    0.2389
Residuals       41227  354
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

#
lmOut_additive<-lm(Growth~Passage+Treatment,data=rawdata)
Anova(lmOut_additive,type=2)

```

Anova Table (Type II tests)

```

Response: Growth
  Sum Sq Df F value    Pr(>F)
Passage    8996   1 77.058 < 2.2e-16 ***
Treatment  24137   2 103.372 < 2.2e-16 ***
Residuals  41562 356
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

# for comparison, here is the univariable model
lmOut_uni<-lm(Growth~Treatment,data=rawdata)
aOut<-Anova(lmOut_uni,type=3)
a_uni <- anova(lmOut_uni)
a_uni$`Pr(>F)` 

```

```
[1] 5.549803e-31           NA
```

9.4.3.3 Post-hoc analyses

For multivariable models, pairwise.t.test() is not appropriate, Dunnet or Tukey tests (depending on hypothesis) are typical solutions.

```
summary(glht(model=lmOut_additive,linfct=mcp(Treatment='Dunnett')))
```

Simultaneous Tests for General Linear Hypotheses

Multiple Comparisons of Means: Dunnett Contrasts

```
Fit: lm(formula = Growth ~ Passage + Treatment, data = rawdata)
```

Linear Hypotheses:

| | Estimate | Std. Error | t value | Pr(> t) |
|-------------------------|----------|------------|---------|------------|
| AngII - Control == 0 | 10.409 | 1.395 | 7.462 | <1e-10 *** |
| Whatever - Control == 0 | 20.052 | 1.395 | 14.375 | <1e-10 *** |
| --- | | | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Adjusted p values reported -- single-step method)

```
summary(glht(model=lmOut_additive, linfct=mcp(Treatment='Tukey')))
```

Simultaneous Tests for General Linear Hypotheses

Multiple Comparisons of Means: Tukey Contrasts

```
Fit: lm(formula = Growth ~ Passage + Treatment, data = rawdata)
```

Linear Hypotheses:

| | Estimate | Std. Error | t value | Pr(> t) |
|-------------------------|----------|------------|---------|------------|
| AngII - Control == 0 | 10.409 | 1.395 | 7.462 | <1e-10 *** |
| Whatever - Control == 0 | 20.052 | 1.395 | 14.375 | <1e-10 *** |
| Whatever - AngII == 0 | 9.643 | 1.395 | 6.913 | <1e-10 *** |
| --- | | | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Adjusted p values reported -- single-step method)

```
DescTools:::DunnettTest(Growth~Passage_F, data=rawdata)
```

Dunnett's test for comparing several treatments with a control :
95% family-wise confidence level

```
$`1`  
    diff      lwr.ci      upr.ci      pval  
2-1 -1.467320 -7.6899251  4.755285  0.9648  
3-1  5.824059 -0.3985468 12.046664  0.0752 .
```

```
4-1  6.801105  0.5784996 13.023710  0.0263 *
5-1  8.156143  1.9335375 14.378748  0.0048 **
6-1 14.520106  8.2975011 20.742712 6.9e-08 ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
pairwise.t.test(rawdata$Growth,rawdata$Treatment,p.adjust.method = 'n')
```

```
Pairwise comparisons using t tests with pooled SD

data: rawdata$Growth and rawdata$Treatment

Control AngII
AngII   5.1e-11 -
Whatever < 2e-16 1.0e-09

P value adjustment method: none
```

```
mean(rawdata$Growth[which(rawdata$Passage==1 &
                           rawdata$Treatment=='Control'))]
```

```
[1] 116.4531
```

```
aOut$'Pr(>F)'
```

```
[1] 2.909117e-279  5.549803e-31          NA
```

```
aOut$`Sum Sq`
```

```
[1] 1754742.53   24136.66    50557.95
```

```
summary(lmOut_additive)
```

```

Call:
lm(formula = Growth ~ Passage + Treatment, data = rawdata)

Residuals:
    Min      1Q  Median      3Q     Max 
-32.407 -7.793 -0.281  7.255 32.283 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 110.6802   1.5280  72.432 < 2e-16 ***
Passage      2.9271   0.3334   8.778 < 2e-16 *** 
TreatmentAngII 10.4089   1.3949   7.462 6.59e-13 ***
TreatmentWhatever 20.0520   1.3949  14.375 < 2e-16 *** 
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 10.8 on 356 degrees of freedom
Multiple R-squared:  0.4436,    Adjusted R-squared:  0.4389 
F-statistic:  94.6 on 3 and 356 DF,  p-value: < 2.2e-16

```

```
(result<-tibble(predictor=rownames(aOut),
                 p=formatP(aOut$'Pr(>F)',ndigits=5)))
```

```
# A tibble: 3 x 2
  predictor     p
  <chr>       <chr>
1 (Intercept) "0.00001"
2 Treatment    "0.00001"
3 Residuals    "     NA"
```

```
broom::tidy(aOut)
```

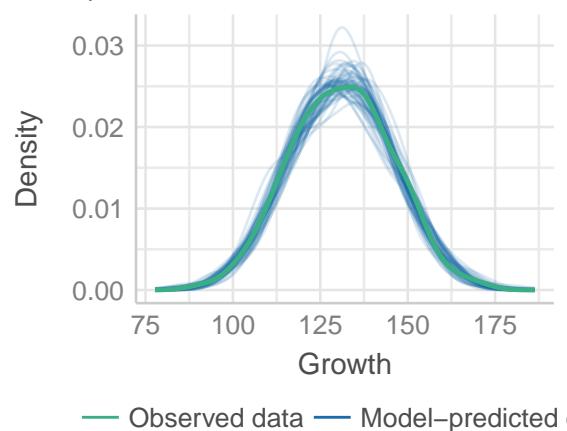
```
# A tibble: 3 x 5
  term        sumsq    df statistic   p.value
  <chr>      <dbl> <dbl>    <dbl>      <dbl>
1 (Intercept) 1754743.     1    12391.  2.91e-279
2 Treatment    24137.      2      85.2  5.55e- 31
3 Residuals    50558.     357      NA      NA
```

9.4.4 Model exploration with package performance

```
# x11() #interactive only!  
  
# from package performance  
check_model(lm0ut_additive)
```

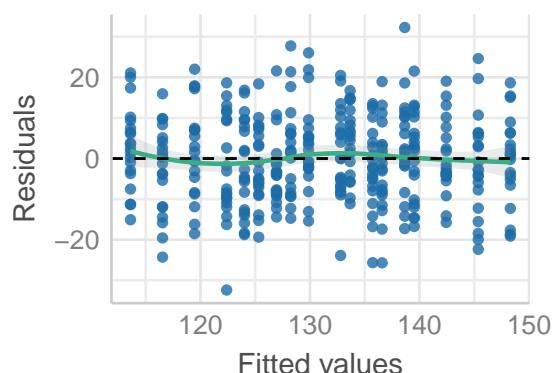
Posterior Predictive Check

Model-predicted lines should resemble observed data



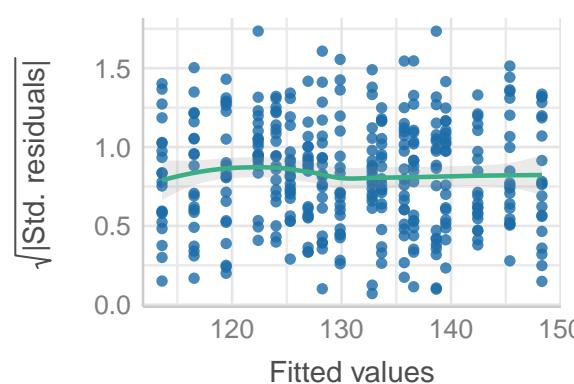
Linearity

Reference line should be flat and horizontal



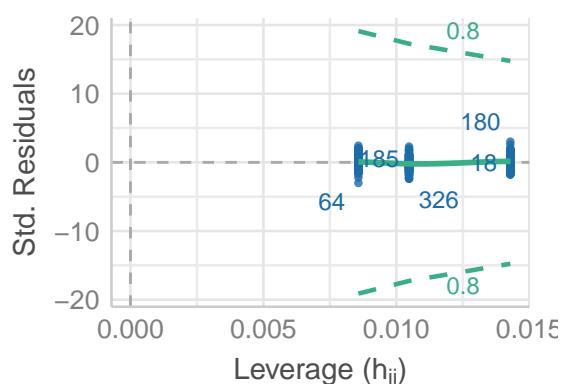
Homogeneity of Variance

Reference line should be flat and horizontal



Influential Observations

Points should be inside the contour lines



Collinearity

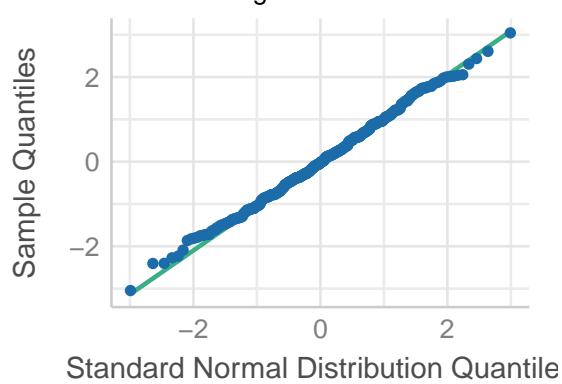
High collinearity (VIF) may inflate parameter uncertainty



● Low (< 5)

Normality of Residuals

Dots should fall along the line



10 Summary

In summary, this book has no content whatsoever.

1 + 1

[1] 2

References