# Data Handling: Import, Cleaning and Visualisation

## Lecture 10:

## Data Analysis and Basic Statistics with R

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# Recap: Data Preparation

# The dataset is imported, now what?

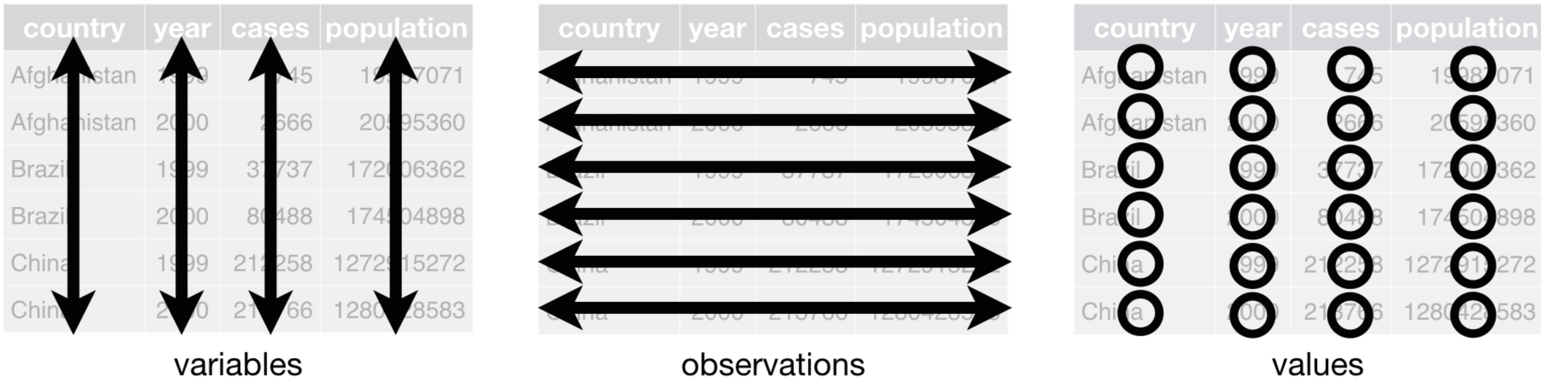
- In practice: still a long way to go.
- Parsable, but messy data: Inconsistencies, data types, missing observations, wide format.
- **Goal** of data preparation: Dataset is ready for analysis.
- **Key conditions**:
  1. Data values are consistent/clean within each variable.
  2. Variables are of proper data types.
  3. Dataset is in 'tidy' (in long format)!

# Some vocabulary

Following Wickham (2014):

- **Dataset**: Collection of **values** (numbers and strings).
- Every value belongs to a **variable** and an **observation**
- **Variable**: Contains all values that measure the same underlying attribute across units.
- **Observation**: Cointains all values measured on the same unit (e.g., a person).

# Tidy data




*Tidy data. Source: Wickham and Grolemund (2017), licensed under the Creative Commons Attribution-Share Alike 3.0 United States license)*

# Data Analysis with R

# Merging (Joining) datasets

- Combine data of two datasets in one dataset.
  - Why?
- Needed: Unique identifiers for observations ('keys').

# Merging (joining) datasets: example

```
# load packages
library(tidyverse)

# initiate data frame on persons personal spending
df_c <- data.frame(id = c(1:3,1:3),
                   money_spent= c(1000, 2000, 6000, 1500, 3000, 5500),
                   currency = c("CHF", "CHF", "USD", "EUR", "CHF", "USD"),
                   year=c(2017,2017,2017,2018,2018,2018))
df_c
```

```
##   id money_spent currency year
## 1  1        1000      CHF 2017
## 2  2        2000      CHF 2017
## 3  3        6000      USD 2017
## 4  1        1500      EUR 2018
## 5  2        3000      CHF 2018
## 6  3        5500      USD 2018
```

# Merging (joining) datasets: example

```
# initiate data frame on persons' characteristics
df_p <- data.frame(id = 1:4,
                   first_name = c("Anna", "Betty", "Claire", "Diane"),
                   profession = c("Economist", "Data Scientist", "Data Scientist", '
df_p
```

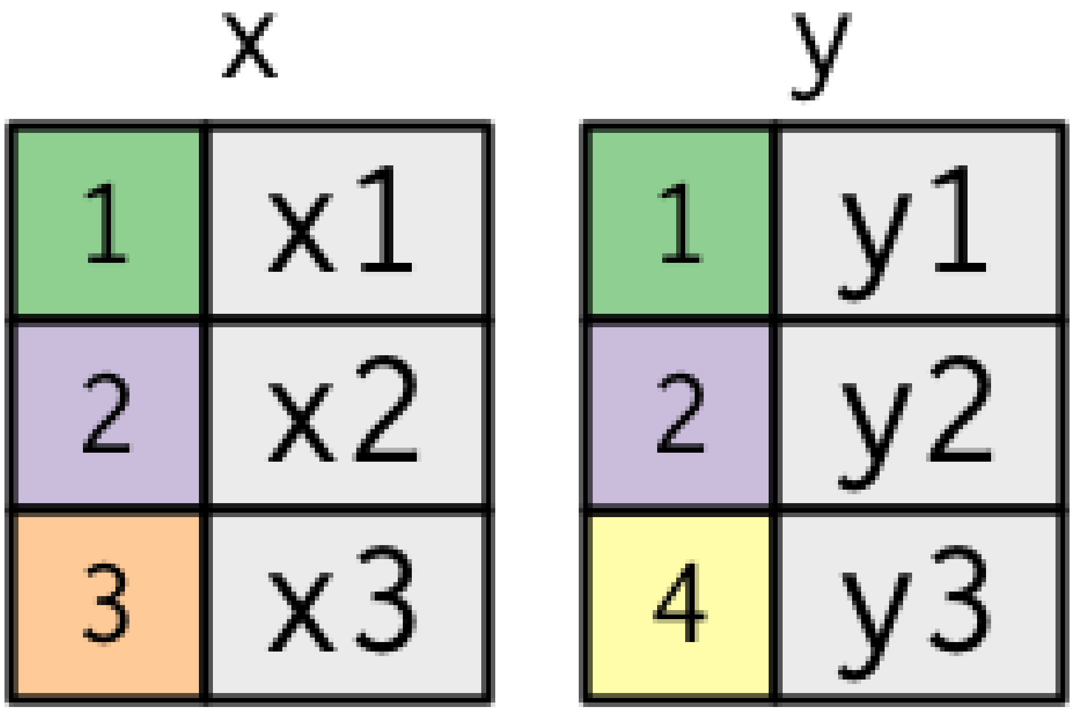
```
##   id first_name     profession
## 1  1       Anna      Economist
## 2  2      Betty Data Scientist
## 3  3     Claire Data Scientist
## 4  4      Diane      Economist
```

# Merging (joining) Datasets: Example

```
df_merged <- merge(df_p, df_c, by="id")
df_merged
```

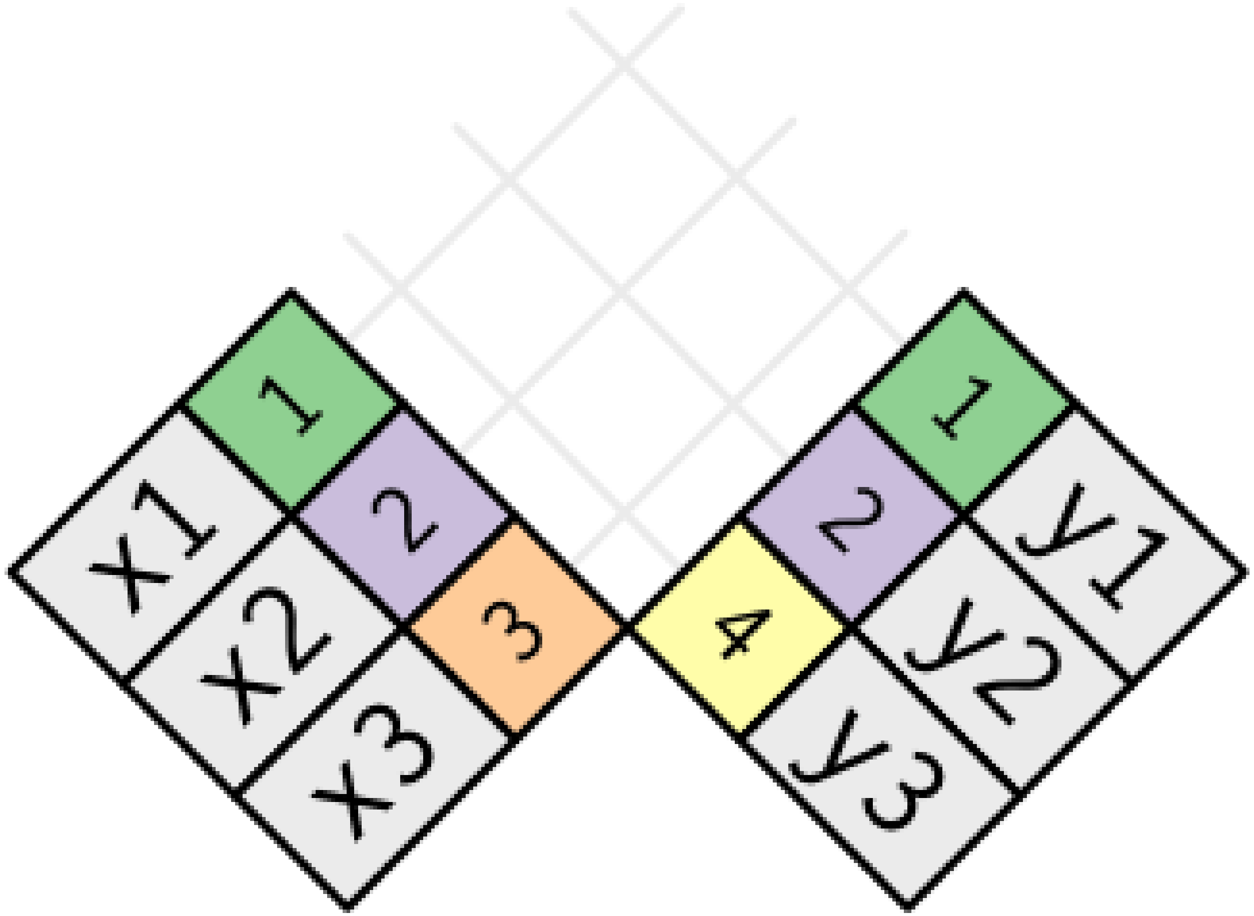
```
##   id first_name     profession money_spent currency year
## 1  1       Anna      Economist        1000      CHF 2017
## 2  1       Anna      Economist        1500      EUR 2018
## 3  2      Betty Data Scientist        2000      CHF 2017
## 4  2      Betty Data Scientist        3000      CHF 2018
## 5  3     Claire Data Scientist        6000      USD 2017
## 6  3     Claire Data Scientist        5500      USD 2018
```

# Merging (joining) datasets: concept




*Join setup. Source: Wickham and Grolemund (2017), licensed under the [Creative Commons Attribution-Share Alike 3.0 United States](#) license.*

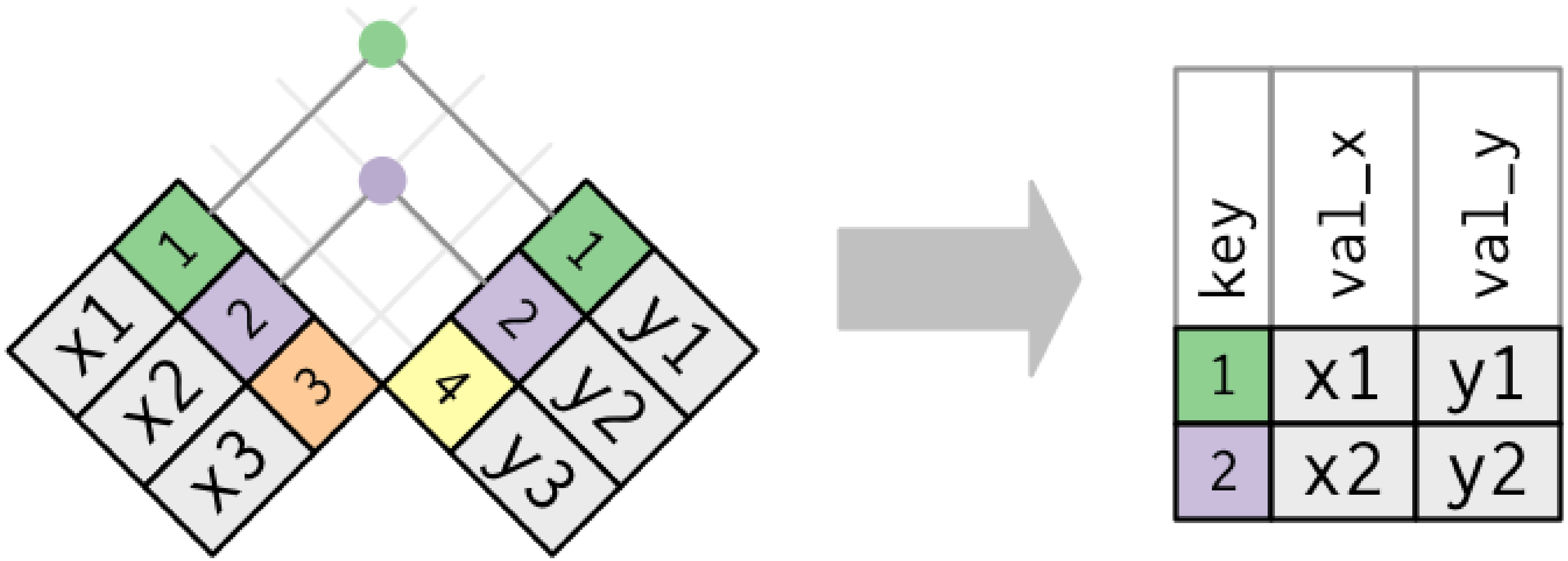
# Merging (joining) datasets: concept




*Join setup. Source: Wickham and Grolemund (2017), licensed under the [Creative Commons Attribution-Share Alike 3.0 United States](#) license.*

# Merging (joining) datasets: concept

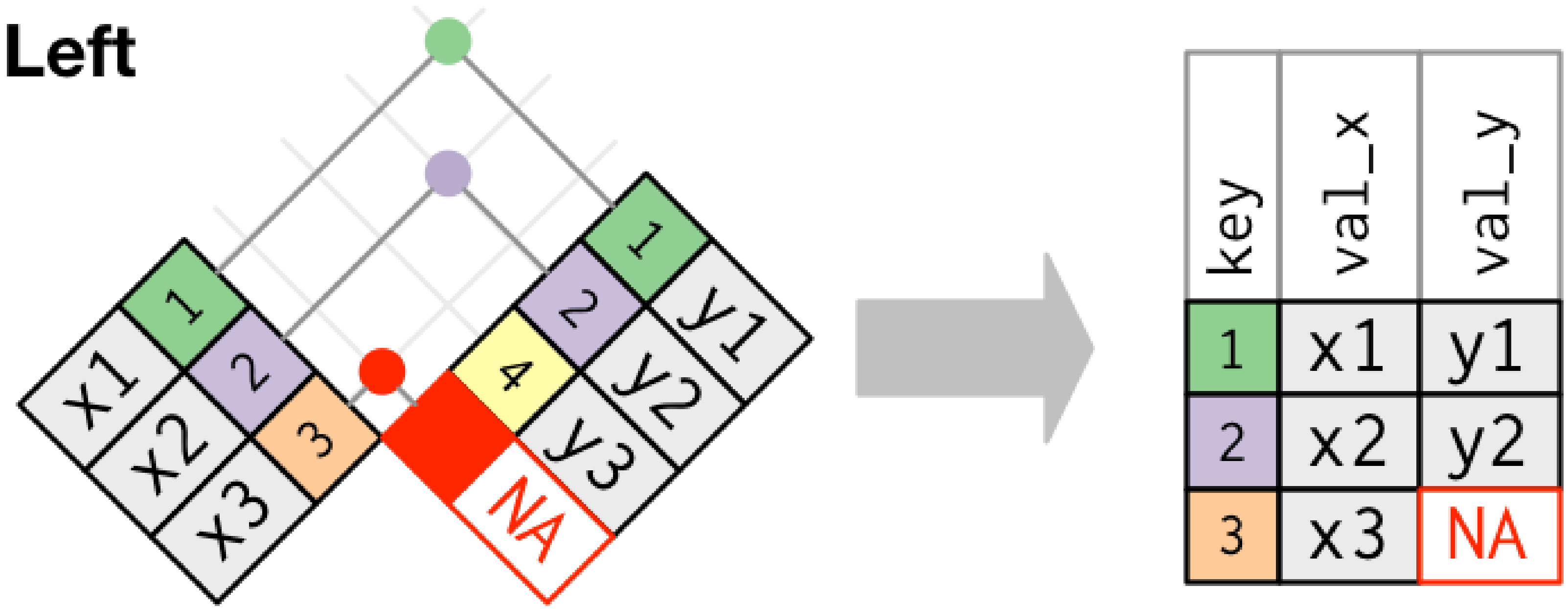
## Merge: Inner join




*Inner join. Source: Wickham and Grolemund (2017), licensed under the [Creative Commons Attribution-Share Alike 3.0 United States](#) license.*

# Merging (joining) datasets: concept

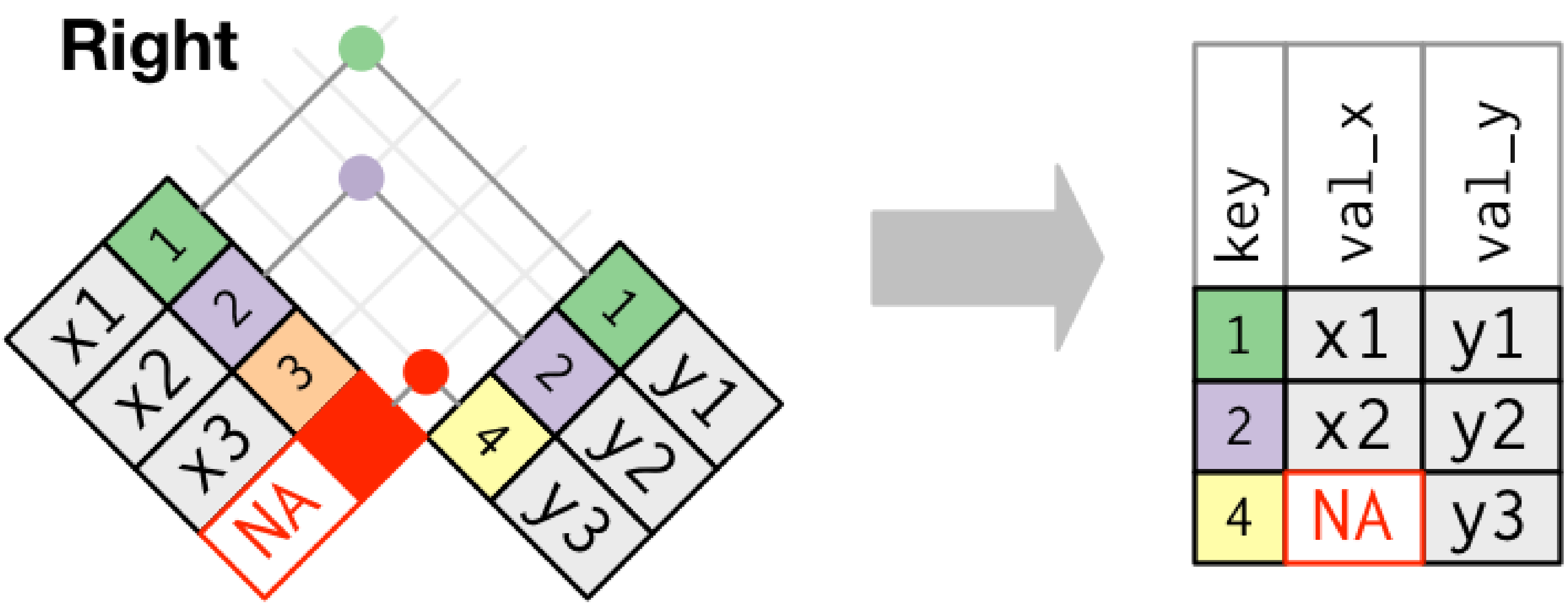
## Merge all x: Left join




*Outer join. Source: Wickham and Grolemund (2017), licensed under the [Creative Commons Attribution-Share Alike 3.0 United States](#) license.*

# Merging (joining) datasets: concept

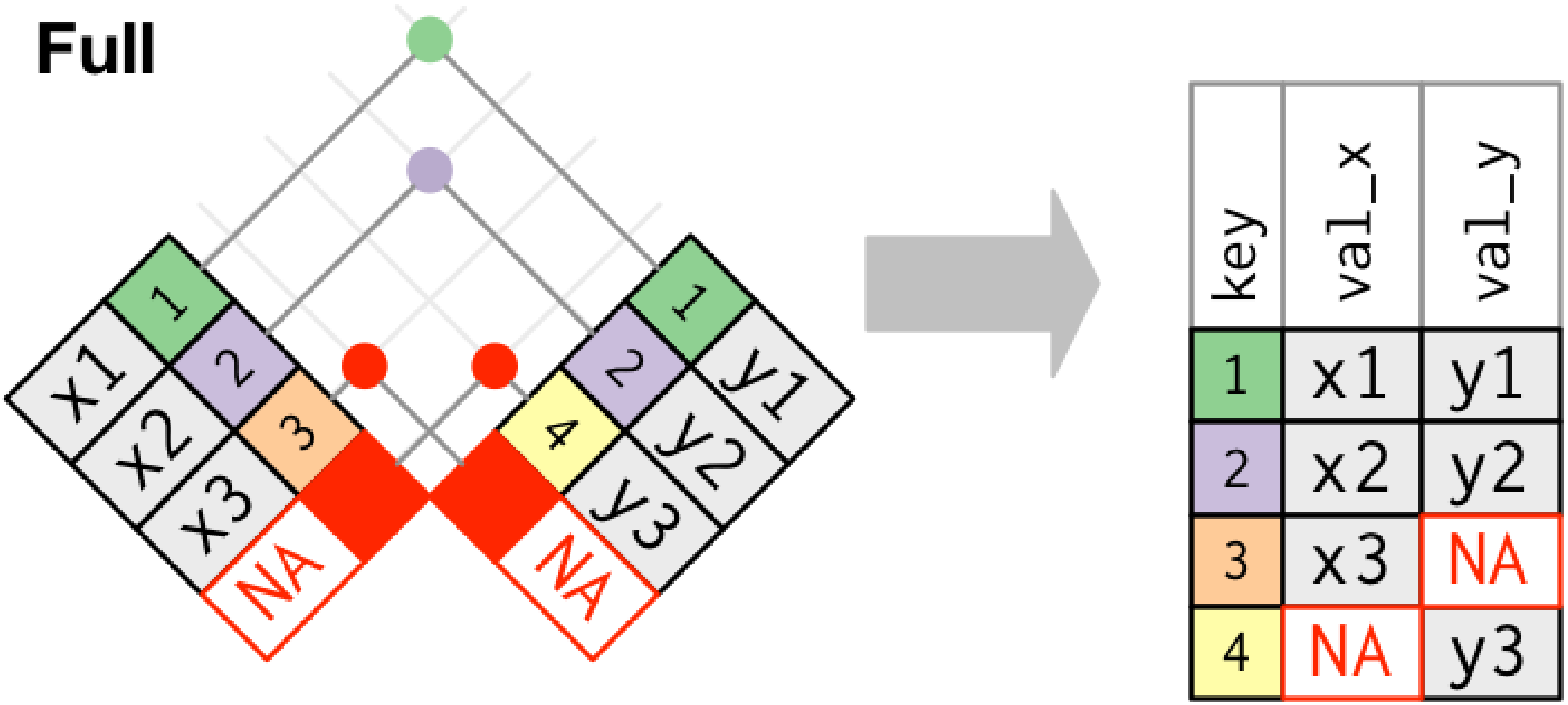
## Merge all y: Right join




*Outer join. Source: Wickham and Grolemund (2017), licensed under the [Creative Commons Attribution-Share Alike 3.0 United States](#) license.*

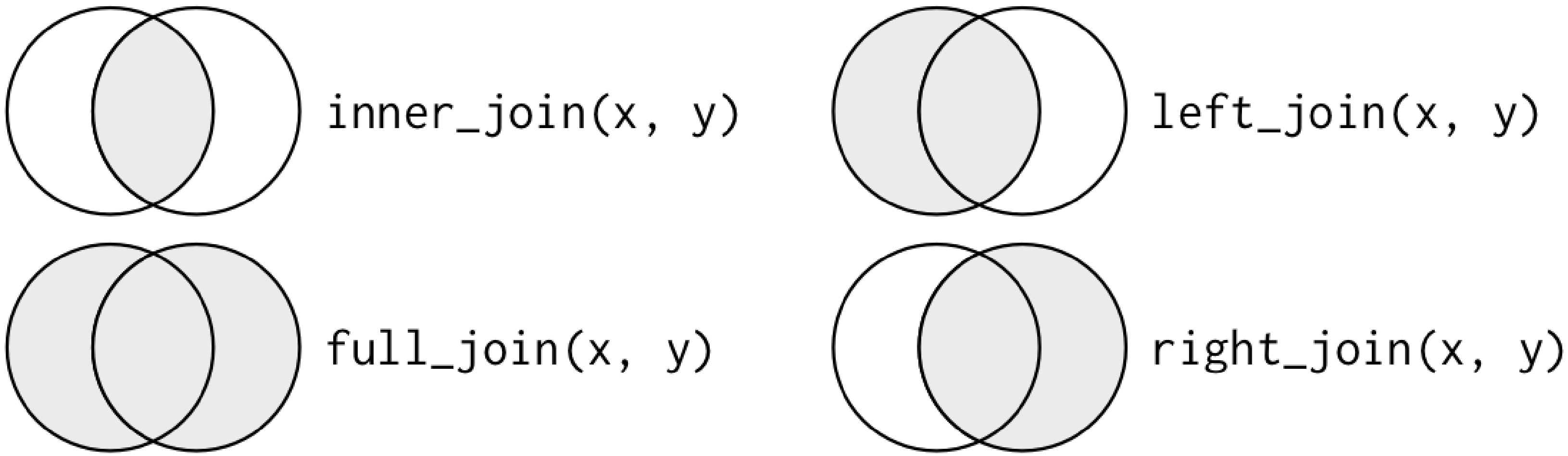
# Merging (joining) datasets: concept

## Merge all x and all y: Full join




*Outer join. Source: Wickham and Grolemund (2017), licensed under the [Creative Commons Attribution-Share Alike 3.0 United States](#) license.*

# Merging (joining) datasets: concept




*Join Venn Diagramm. Source: Wickham and Grolemund (2017), licensed under the [Creative Commons Attribution-Share Alike 3.0 United States](#) license.*

# Merging (joining) datasets: R

Overview by Wickham and Grolemund (2017):

| dplyr (tidyverse) | base::merge |
|---|---|
| `inner_join(x, y)` | `merge(x, y)` |
| `left_join(x, y)` | `merge(x, y, all.x = TRUE)` |
| `right_join(x, y)` | `merge(x, y, all.y = TRUE)`, |
| `full_join(x, y)` | `merge(x, y, all.x = TRUE, all.y = TRUE)` |

# Data Summaries: Selecting, Filtering, and Mutating

# Data summaries

- First step of analysis.
- Get overview over dataset.
- Show key aspects of data.
  - Inform your own statistical analysis.
  - Inform audience (helps understand advanced analytics parts)

# Data summaries: first steps

- **Select** subset of variables (e.g., for comparisons).
- **Filter** the dataset (some observations not needed in **this** analysis).
- **Mutate** the dataset: additional values needed

# Select, filter, mutate in R (tidyverse)

- `select()`
- `filter()`
- `mutate()`

# Data Summaries: Aggregate Statistics

# Descriptive/aggregate statistics

- Overview of key characteristics of main variables used in analysis.
- Key characteristics:
    - mean
    - standard deviation
    - No. of observations
    - etc.

# Aggregate statistics in R

1. Function to compute statistic (`mean()`).
2. Function to **apply** the statistics function to one or several colums in a tidy dataset.

- All values.
- By group (observation categories, e.g. by gender)

# Aggregate statistics in R

- `summarise()` (in `tidyverse`)
- `group_by()` (in `tidyverse`)
- `sapply()`, `apply()`, `lapply()`, etc. (in `base`)

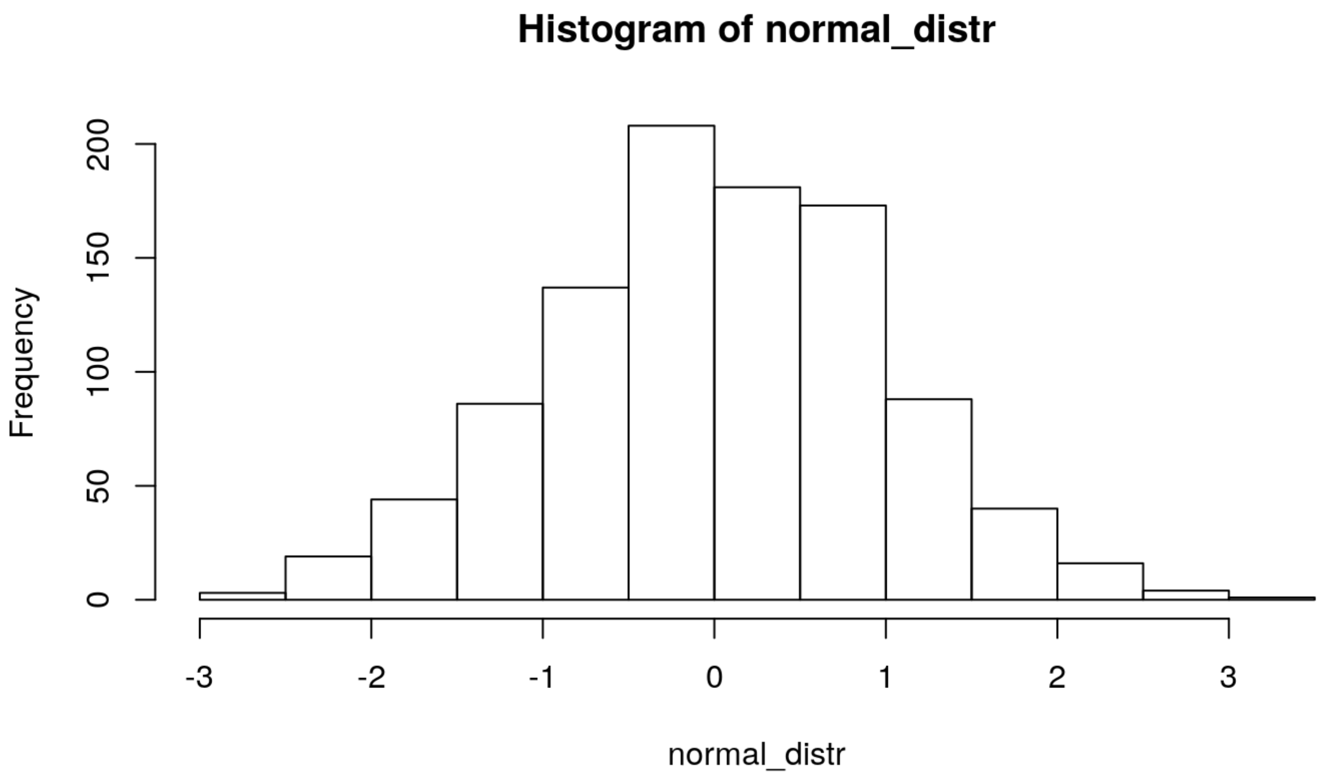
# Unterstanding Statistics and Probability with Code

# Random numbers and computation

## Can computers generate random numbers?!

# Random draws and distributions

```
normal_distr <- rnorm(1000)
hist(normal_distr)
```



# Illustration of variability

```r
# draw a random sample from a normal distribution with a large standard deviation
largevar <- rnorm(10000, mean = 5000, sd = 5)
# draw a random sample from a normal distribution with a small standard deviation
littlevar <- rnorm(10000, mean = 5000, sd = 1)
```

# Illustration of variability

```
# visualize the distributions of both samples with a density plot
plot(density(littlevar), col = "blue",
     xlim=c(min(largevar), max(largevar)), main="Income Distribution")
lines(density(largevar), col = "red")
```

# Skewness and kurtosis

```r
# install the R-package called "moments" with the following command (if not installe
# install.packages("moments")

# load the package
library(moments)
```

# Skewness

- Skewness refers to how symetric the frequency distribution of a variable is.
- For example, a distribution can be **'positively skewed'** meaning it has a **long tail on the right** and a lot of 'mass' (observations) on the left.

# Skewness: R example

```r
# draw a random sample of simulated data from a normal distribution
# the sample is of size 1000 (hence, n = 1000)
sample <- rnorm(n = 1000)

# plot a histogram and a density plot of that sample
# note that the distribution is neither strongly positively nor negatively skewed
# (this is to be expected, as we have drawn a sample from a normal distribution!)
hist(sample)
```

# Skewness: R example

```r
# now compute the skewness
skewness(sample)
```

```
## [1] -0.06196048
```

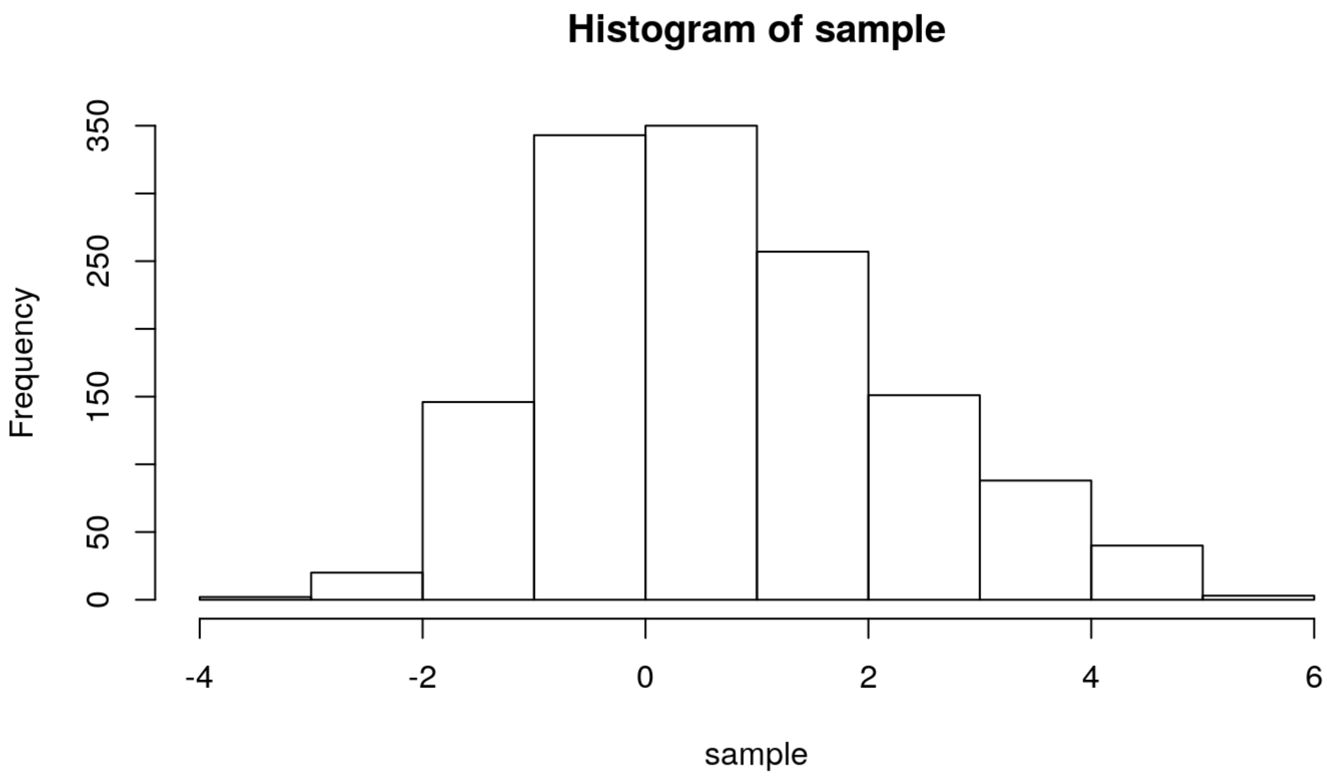
# Skewness: R example

```
# now we intentionally change our sample to be strongly positively skewed
# we do that by adding some outliers (observations with very high values) to the sam
sample <- c(sample, (rnorm(200) + 2), (rnorm(200) + 3))

# have a look at the distribution and re-calculate the skewness
hist(sample)
```

# Skewness: R example

```r
# have a look at the distribution and re-calculate the skewness
hist(sample)
```



# Kurtosis

- Kurtosis refers to how much 'mass' a distribution has in its 'tails'.
- Tells us something about whether a distribution tends to have a lot of outliers.

# Kurtosis: R example

```
# draw a random sample of simulated data from a normal distribution
# the sample is of size 1000 (hence, n = 1000)
sample <- rnorm(n = 1000)

# plot the density & compute the kurtosis
hist(sample)
```

# Kurtosis: R example

```r
# compute the kurtosis
kurtosis(sample)
```

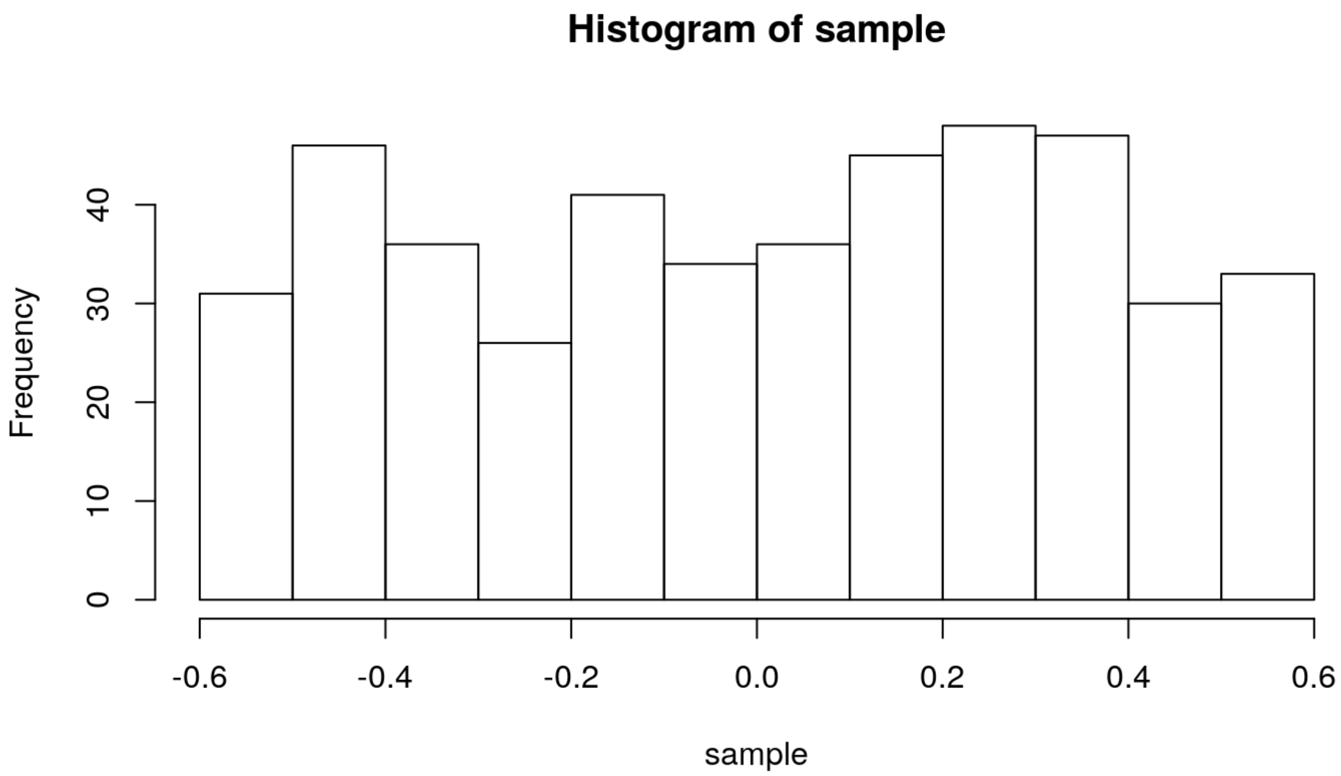
```
## [1] 3.144589
```

# Kurtosis: R example

```
# now lets remove observations from the extremes in this distribution
# we thus intentionally alter the distribution to have less mass in its tails
sample <- sample[ sample > -0.6 & sample < 0.6]
```

# Kurtosis: R example

```
# plot the distribution again and see how the tails have changed
hist(sample)
```



# Compute the skewness in R

## Skewness

```
# own implementation
sum((sample-mean(sample))^3) / ((length(sample)-1) * sd(sample)^3)
```

```
## [1] -0.09341458
```

```
# implementation in moments package
skewness(sample)
```

```
## [1] -0.09351786
```

# Compute the kurtosis in R

## Kurtosis

```r
# own implementation
sum((sample-mean(sample))^4) / ((length(sample)-1) * sd(sample)^4)
```

```
## [1] 1.806926
```

```r
# implementation in moments package
kurtosis(sample)
```

```
## [1] 1.810923
```

# The Law of Large Numbers (LLN)

- Important statistical property.
- Essentially describes how the behavior of **sample averages** is related to **sample size**.
- States that the **sample mean** can come arbitrarily close to the **population mean** by increasing the sample size $N$.

# The Law of Large Numbers (LLN): playing dice

- Roll a fair die, record result: either 1, 2, 3, 4, 5, or 6.
- Probability of each possible outcome is $1/6$.

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# The Law of Large Numbers (LLN): playing dice

- Roll a fair die, record result: either 1, 2, 3, 4, 5, or 6.
- Probability of each possible outcome is $1/6$.
- Expected value (average in the long run): $(1 + 2 + 3 + 4 + 5 + 6)/6 = 3.5$
- Proof?
  - Mathematically.
  - Or: Experiment/Simulation (with R).

# LLN in R

```r
# first we define the potential values a die can take
dvalues <- 1:6 # the : operater generates a regular sequence of numbers (from:to)
dvalues
```

```
## [1] 1 2 3 4 5 6
```

```r
# define the size of the sample n (how often do we roll the die...)
# for a start, we only roll the die ten times
n <- 10
# draw the random sample: 'roll the die n times and record each result'
results <- sample( x = dvalues, size = n, replace = TRUE)
# compute the mean
mean(results)
```

```
## [1] 3.9
```

# LLN in R

```r
n <- 100
# draw the random sample: 'roll the die n times and record each result'
results <- sample( x = dvalues, size = n, replace = TRUE)
# compute the mean
mean(results)
```

```
## [1] 3.48
```

# LLN in R

```
# essentially, what we are doing here is repeating the experiment above many times,
# each time increasing n
# define the set of sample sizes
ns <- seq(from = 10, to = 10000, by = 10)
# initiate an empty list to record the results
means <- list()
length(means) <- length(ns)
# iterate through each sample size: 'repeat the die experiment for each sample size
for (i in 1:length(ns)) {

     means[[i]] <- mean(sample( x = dvalues, size = ns[i], replace = TRUE))
}
```

# LLN in R

```r
# visualize the result: plot sample means against sample size
plot(ns, unlist(means),
     ylab = "Sample Mean",
     xlab = "Sample Size",
     pch = 16,
     cex = .6)
abline(h = 3.5, col = "red")
```

# Q&A

# References

Wickham, Hadley. 2014. "Tidy Data." **Journal of Statistical Software, Articles** 59 (10): 1–23. https://doi.org/10.18637/jss.v059.i10.

Wickham, Hadley, and Garrett Grolemund. 2017. Sebastopol, CA: O'Reilly. http://r4ds.had.co.nz/.