Lecture 4: R Basics II: Vectors, Tables, and Tidy Thinking

EC7422: Data Science for Economic Analysis

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Today

- From single values to vectors
- From vectors to tables
- Table access and column work
- Keys, factors, tidy data
- Checks and quick plots

Review: lecture 3 in one minute

- Expressions evaluate to values
- Assignment binds names to objects
- Types affect behavior
- Logic and `if / else` control decisions
- Functions package reusable work

- Vectors
- From Vectors To Tables
- Subsetting Tables
- Working With Table Columns
- Categories
- Tidy Data
- Basic Checks
- Quick Inspection Plots

A vector stores many values of one type

```r
scores <- c(45, 62, 78)
scores
```

```
[1] 45 62 78
```

- One name for many values
- Values stay in order
- One object in memory

A vector is the basic way R stores values. In fact, also singletons are really vectors of length one.

Mixed values are coerced

If you try to mix values, R will force them to a common type:

```
survey_answers <- c(1, 2, "3")
survey_answers
```

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

```
typeof(survey_answers)
```

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

- One vector, one type
- Coercion can be silent and cause bugs

When mixed values are combined, they are coerced to a common type according to a hierarchy. R tries to preserve information, but sometimes the coercion can hide a mistake.

Logical operators evaluate each pair of elements

```
scores >= 60
```

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

```
scores >= 60 & scores < 75
```

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

- Same operators as before
- One result per element: a logical vector

```
typeof(scores >= 60)
```

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

The operators are familiar from lecture 3, but the result is now a logical vector rather than one single logical value.

Be wary of recycling

```
1 c(1, 2, 3) > c(1, 3)
```

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

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

- Shorter vector may repeat
- Sometimes warning
- Sometimes silent

Recycling can be convenient, but it can also hide a mistake. Length mismatches deserve suspicion.

“Vectorized” functions operate element by element

```r
trial <- c(1, NA, 3)
is.na(trial)
```

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

```r
!is.na(trial)
```

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

- Same `is.na()`
- One result per element
- Useful before filtering

Not all functions take vector inputs. The missingness tools from lecture 3 become more useful once many values are handled at once. This pattern shows up constantly in data cleaning.

Use `%in%` to check membership

```
1 cities <- c("stockholm", "uppsala", "umea")
2 cities %in% c("stockholm", "malmo", "uppsala")
```

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

- Membership in a reference set
- One result per element

Often clearer than many `|`:

```
1 cities == "stockholm" | cities == "malmo" | cities == "uppsala"
```

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

`%in%` is especially useful when checking whether values belong to an allowed set of categories, identifiers, or years.

`ifelse()` builds a new vector

The `if / else` pattern requires `condition` to be a single logical value. If you want to apply the same logic to many values, `ifelse()` is the vectorized alternative:

```
1 ifelse(scores >= 60, "pass", "retry")
```

```
[1] "retry" "pass"  "pass"
```

- Condition checked element by element
- Output has matching length
- Useful for quick categories

Subset by position with `[]`

```
1 years <- c(2021, 2022, 2023, 2024)
2 years[1]
```

```
[1] 2021
```

- Position-based subsetting
- One element or several
- Fundamental operator in R

Use `:` to create a sequence of integers:

```
1 2:4
```

```
[1] 2 3 4
```

```
1 years[2:4]
```

```
[1] 2022 2023 2024
```

Subset by logical vector with `[]`

Use a same-length logical vector to keep matching elements:

```
1 years[c(TRUE, FALSE, TRUE, FALSE)]
```

```
[1] 2021 2023
```

Subset by condition with `[]`

Or let a condition evaluate to a logical vector on the fly:

```
scores[scores >= 60]
```

```
[1] 62 78
```

```
years[years >= 2023]
```

```
[1] 2023 2024
```

This is what we use to filter table rows!

Vectors can replace loops

```
out <- numeric(length(scores))
for (i in seq_along(scores)) {
  out[i] <- scores[i]^2
}
out
```

```
[1] 2025 3844 6084
```

```
scores^2
```

```
[1] 2025 3844 6084
```

- Same result
- Loop is explicit
- Vector form is shorter and often faster

The point is not that loops are wrong. The point is that many operations in R already know how to work element by element on a whole vector, so the shorter vector form is often easier to read and write.

A list can hold different kinds of objects

```r
student_record <- list(name = "Alice", age = 24, passed = TRUE)
student_record
```

```
$name
[1] "Alice"

$age
[1] 24

$passed
[1] TRUE
```

```r
typeof(student_record)
```

```
[1] "list"
```

- Flexible container
- Mixed object types allowed

Lists are more flexible than atomic vectors because their elements do not all need the same type.

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Start with three column vectors

A table is really just a collection of equal-length vectors. Let's build one:

```
municipality_code <- c("0180", "1280")
year <- c(2023, 2023)
unemployment_rate <- c(6.2, 7.1)
```

Collect them in a list

```r
table_list <- list(
  municipality_code,
  year,
  unemployment_rate
)
table_list
```

```
[[1]]
[1] "0180" "1280"

[[2]]
[1] 2023 2023

[[3]]
[1] 6.2 7.1
```

Give the columns names

```r
table_list <- list(
  municipality_code = municipality_code,
  year = year,
  unemployment_rate = unemployment_rate
)
table_list
```

```
$municipality_code
[1] "0180" "1280"

$year
[1] 2023 2023

$unemployment_rate
[1] 6.2 7.1
```

The ingredients of a simple table are just equal-length vectors. Before there is any table syntax, there are already ordinary vectors in memory.

Data frames

`data.frame()` is the built-in way of doing this

```r
table_df <- data.frame(
  municipality_code,
  year,
  unemployment_rate
)
table_df
```

```
  municipality_code year unemployment_rate
1              0180 2023               6.2
2              1280 2023               7.1
```

Note how the naming is implicit.

A `data.frame` is built by combining equal-length vectors into one tabular object. Unlike `list()`, `data.frame()` requires compatible lengths — it will recycle shorter vectors only if their length evenly divides the longest, and error otherwise.

Under the hood

`data.frame` is just a named equal-length list:

```
1 typeof(table_df)
```

```
[1] "list"
```

```
1 str(table_df)
```

```
'data.frame':   2 obs. of  3 variables:
 $ municipality_code: chr  "0180" "1280"
 $ year             : num  2023 2023
 $ unemployment_rate: num  6.2 7.1
```

```
1 str(table_list)
```

```
List of 3
 $ municipality_code: chr [1:2] "0180" "1280"
 $ year             : num [1:2] 2023 2023
 $ unemployment_rate: num [1:2] 6.2 7.1
```

The difference is that `data.frame` has a different `class`. The special class `data.frame` adds table behavior to an underlying list. For example, the class comes with its own print method (`print.data.frame`) that shows the list in a tabular format.

A matrix is something else

Matrices are also rectangular, but they hold one common type:

```
1 as.matrix(table_df)
```

```
     municipality_code year   unemployment_rate
[1,] "0180"            "2023" "6.2"
[2,] "1280"            "2023" "7.1"
```

```
1 typeof(as.matrix(table_df))
```

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

- Still rows and columns, but stored as a single vector
- One common type for all cells

A matrix is closer to one atomic vector with dimensions than to a list of column vectors. That is why matrices are useful for numeric linear algebra.

The municipal panel from Lecture 1

```r
panel_df <- read.csv("../lecture_1/lecture_1_demo_panel.csv")
head(panel_df)
```

```
  municipality_code municipality_name year unemployment_rate
1               114    Upplands Väsby 2016              11.9
2               115        Vallentuna 2016               6.1
3               117         Österåker 2016               7.2
4               120            Värmdö 2016               7.3
5               123          Järfälla 2016              13.7
6               125             Ekerö 2016               5.6
```

Inspect before doing anything else

```r
str(panel_df)
```

```
'data.frame':   2320 obs. of  4 variables:
 $ municipality_code: int  114 115 117 120 123 125 126 127 128 136 ...
 $ municipality_name: chr  "Upplands Väsby" "Vallentuna" "Österåker" "Värmdö" ...
 $ year             : int  2016 2016 2016 2016 2016 2016 2016 2016 2016 2016 ...
 $ unemployment_rate: num  11.9 6.1 7.2 7.3 13.7 5.6 12 17.7 9.7 11.9 ...
```

Also try `View(panel_df)` in VsCode for an interactive viewer.

The first step with a new table should be inspection rather than immediate filtering or plotting. Printing a few rows, checking structure, and looking at variable names usually reveals the row meaning, key candidates, and suspicious column types quickly.

Ask five questions first

- What is one observation/row?
- What is the key?
- Which columns:
  - → identify?
  - → measure?
  - → label?

Count rows and columns

```
1 nrow(panel_df)
```

```
[1] 2320
```

```
1 ncol(panel_df)
```

```
[1] 4
```

Check the variable names

```r
names(panel_df)
```

```
[1] "municipality_code" "municipality_name" "year"
[4] "unemployment_rate"
```

What is the key?

A database concept: the key is a set of columns that **uniquely** identifies one observation

- `municipality_code + year`
- Not municipality name, that is a label

The key is the combination of columns that uniquely identifies one observation. Here that combination is municipality code and year.

Identifier versus label

- Code = identifier
- Name = label
- Identifier for matching
- Label for humans

Leading zeroes matter

```r
str(panel_df)
```

```
'data.frame':   2320 obs. of  4 variables:
 $ municipality_code: int  114 115 117 120 123 125 126 127 128 136 ...
 $ municipality_name: chr  "Upplands Väsby" "Vallentuna" "Österåker" "Värmdö" ...
 $ year             : int  2016 2016 2016 2016 2016 2016 2016 2016 2016 2016 ...
 $ unemployment_rate: num  11.9 6.1 7.2 7.3 13.7 5.6 12 17.7 9.7 11.9 ...
```

```r
panel_df <- read.csv(
  "../lecture_1/lecture_1_demo_panel.csv",
  colClasses = c(municipality_code = "character")
)
str(panel_df)
```

```
'data.frame':   2320 obs. of  4 variables:
 $ municipality_code: chr  "0114" "0115" "0117" "0120" ...
 $ municipality_name: chr  "Upplands Väsby" "Vallentuna" "Österåker" "Värmdö" ...
 $ year             : int  2016 2016 2016 2016 2016 2016 2016 2016 2016 2016 ...
 $ unemployment_rate: num  11.9 6.1 7.2 7.3 13.7 5.6 12 17.7 9.7 11.9 ...
```

read.csv guesses that “municipality_code” is numeric because it only contains numbers. But if its an identifier the leading zeroes matter and we need to make sure to tell R to read it as character. That is what the

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A table column is just a vector

`$` pulls the column out, then `[]` subsets that vector like before

```
1 panel_df$year[1]
```

```
[1] 2016
```

```
1 panel_df$year[1:5]
```

```
[1] 2016 2016 2016 2016 2016
```

This is the key bridge. After a column has been extracted from the table, subsetting works exactly like it does on any other vector.

On data.frame: `[]` keeps table, `[[]]`, `$` pulls vector

`[]` returns a one-column table

```
1 head(panel_df["year"])
```

```
  year
1 2016
2 2016
3 2016
4 2016
5 2016
6 2016
```

`[[]]` returns the vector inside

```
1 head(panel_df[["year"]])
```

```
[1] 2016 2016 2016 2016 2016 2016
```

This distinction is about returned shape more than about internal storage. Keeping the table shape is useful when further table operations should still work on the result as a table.

Subsetting both rows and columns with `[]`

```r
panel_df[1:3, c("municipality_name", "year")]
```

```
  municipality_name year
1    Upplands Väsby 2016
2        Vallentuna 2016
3         Österåker 2016
```

- First slot = rows
- Second slot = columns

Filter with logic

Works just like vector filtering, but keeps the table shape:

```
panel_df[
  panel_df$year == 2023 &
  panel_df$municipality_name %in% c("Stockholm", "Uppsala", "Kiruna"),
  c("municipality_name", "year", "unemployment_rate")
]
```

```
     municipality_name year unemployment_rate
2047         Stockholm 2023              10.5
2062           Uppsala 2023               9.9
2320            Kiruna 2023               5.3
```

Filtering keeps row meaning

```r
panel_df[
  panel_df$municipality_code %in% c("0180", "0380", "1280") &
  panel_df$year %in% c(2022, 2023),
]
```

	municipality_code	municipality_name	year	unemployment_rate
1757	0180	Stockholm	2022	10.5
1772	0380	Uppsala	2022	10.2
1857	1280	Malmö	2022	18.0
2047	0180	Stockholm	2023	10.5
2062	0380	Uppsala	2023	9.9
2147	1280	Malmö	2023	17.7

- Fewer rows
- Same observation
- Note `,` at the end to keep all columns

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Assigning to a new column

We can create a new column by assigning to a name that doesn't exist yet:

```
panel_df$high_unemployment <- panel_df$unemployment_rate > 8
head(panel_df[c("municipality_name", "unemployment_rate", "high_unemployment")])
```

```
  municipality_name unemployment_rate high_unemployment
1    Upplands Väsby              11.9              TRUE
2        Vallentuna               6.1             FALSE
3         Österåker               7.2             FALSE
4            Värmdö               7.3             FALSE
5          Järfälla              13.7              TRUE
6             Ekerö               5.6             FALSE
```

The `unemployment_rate` column is a vector, and the comparison (`> 8`) is vectorized. The operation evaluates to a logical vector of the same length as the original column, and the result stays aligned row by row with the

`ifelse()` can build categories

```r
panel_df$period <- ifelse(panel_df$year >= 2020, "recent", "older")
head(panel_df[c("year", "period")])
```

```
  year period
1 2016  older
2 2016  older
3 2016  older
4 2016  older
5 2016  older
6 2016  older
```

`ifelse()` is often useful for creating quick derived categories from existing columns. Because the output is a vector of the same length, it can be added back to the table as a new column.

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`factor()` creates categorical data

A factor is a vector of integer levels with attached labels

```
kon <- c(1L, 2L, 1L, 1L, 2L)
typeof(kon)
```

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

```
kon <- kon |>
  factor(
    levels = c(1, 2),
    labels = c("Male", "Female")
  )
typeof(kon)
```

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

```
class(kon)
```

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

```
str(kon)
```

```
 Factor w/ 2 levels "Male","Female": 1 2 1 1 2
```

```
kon
```

```
[1] Male   Female Male   Male   Female
Levels: Male Female
```

A factor in a table

```r
sex_demo <- data.frame(
  id = 1:4,
  sex_code = c(1, 2, 1, 2)
)
sex_demo$sex <- factor(
  sex_demo$sex_code,
  levels = c(1, 2),
  labels = c("Male", "Female")
)
sex_demo
```

```
  id sex_code    sex
1  1        1   Male
2  2        2 Female
3  3        1   Male
4  4        2 Female
```

What a factor stores

- Numeric codes
- Human labels
- Explicit categories

Factors attach labels to stored codes. Factors look like labeled text when printed, but internally they store integer codes plus a set of levels. This saves lots of memory and is useful for various reasons. But factors

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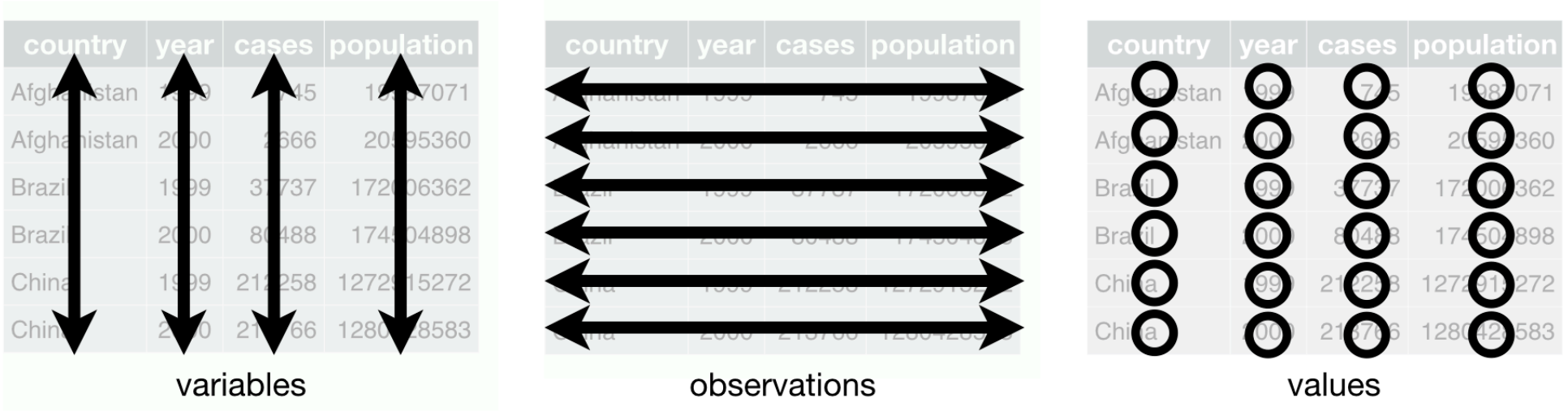
Tidy data

Tidy data is a standard way of organizing tables that makes them easier to work with. The tidy data principles are simple but powerful, and they apply to almost any kind of data.



This picture gives the compact rule behind tidy data: columns correspond to variables, rows correspond to observations, and each cell contains one value. The rest of the section just makes that rule concrete with examples.

Tidy data rule

- One row per observation
- One column per variable
- One cell per value

Wide table: year in the column name

```r
wide_rates <- data.frame(
  municipality_code = c("0180", "0380", "1280"),
  unemployment_rate_2022 = c(10.5, 10.2, 18.0),
  unemployment_rate_2023 = c(10.5, 9.9, 17.7)
)
wide_rates
```

```
  municipality_code unemployment_rate_2022 unemployment_rate_2023
1              0180                   10.5                   10.5
2              0380                   10.2                    9.9
3              1280                   18.0                   17.7
```

Tidy table: year as a variable

```r
tidy_rates <- data.frame(
  municipality_code = c("0180", "0180", "0380", "0380", "1280", "1280"),
  year = c(2022, 2023, 2022, 2023, 2022, 2023),
  unemployment_rate = c(10.5, 10.5, 10.2, 9.9, 18.0, 17.7)
)
tidy_rates
```

```
  municipality_code year unemployment_rate
1              0180 2022              10.5
2              0180 2023              10.5
3              0380 2022              10.2
4              0380 2023               9.9
5              1280 2022              18.0
6              1280 2023              17.7
```

Same question, two table shapes

Both tables contain the same information, but one is easier to work with:

```
wide_rates[c("municipality_code", "unemployment_rate_2023")]
```

```
  municipality_code unemployment_rate_2023
1              0180                   10.5
2              0380                    9.9
3              1280                   17.7
```

```
tidy_rates[tidy_rates$year == 2023, c("municipality_code", "unemployment_rate")]
```

```
  municipality_code unemployment_rate
2              0180              10.5
4              0380               9.9
6              1280              17.7
```

Why tidy usually wins

- Same code across years
- Easier filtering
- Easier joining
- Easier plotting

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Check names and types

Before filtering or plotting, check the boring structure first:

```r
names(panel_df)[1:6]
```

```
[1] "municipality_code" "municipality_name" "year"
[4] "unemployment_rate" "high_unemployment" "period"
```

```r
str(panel_df)
```

```
'data.frame':   2320 obs. of  6 variables:
 $ municipality_code: chr  "0114" "0115" "0117" "0120" ...
 $ municipality_name: chr  "Upplands Väsby" "Vallentuna" "Österåker" "Värmdö" ...
 $ year             : int  2016 2016 2016 2016 2016 2016 2016 2016 2016 2016 ...
 $ unemployment_rate: num  11.9 6.1 7.2 7.3 13.7 5.6 12 17.7 9.7 11.9 ...
 $ high_unemployment: logi  TRUE FALSE FALSE FALSE TRUE FALSE ...
 $ period           : chr  "older" "older" "older" "older" ...
```

- Names reveal variable content
- Types reveal how R will treat the column

Check the range

Summary statistics catch implausible values quickly:

```
1 summary(panel_df$unemployment_rate)
```

```
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  5.00    9.80   12.20   12.49   14.80   23.40
```

- Minimum and maximum
- Center and spread
- Anything implausible?

Check missing values

Then count missingness explicitly:

```
1 sum(is.na(panel_df$unemployment_rate))
```

```
[1] 0
```

- Missing values?
- Count first
- Investigate next

Check the key

```r
any(duplicated(panel_df[c("municipality_code", "year")]))
```

```
[1] FALSE
```

```r
head(panel_df[c("municipality_code", "year")])
```

```
  municipality_code year
1              0114 2016
2              0115 2016
3              0117 2016
4              0120 2016
5              0123 2016
6              0125 2016
```

Break the table on purpose

```
bad_panel <- panel_df[c(1, 2, 3, 4, 1), ]
bad_panel$unemployment_rate[2] <- NA
```

- One missing value
- One duplicated key

Check the broken example

```r
is.na(bad_panel$unemployment_rate)
```

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

```r
duplicated(bad_panel[c("municipality_code", "year")])
```

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

```r
any(duplicated(bad_panel[c("municipality_code", "year")]))
```

```
[1] TRUE
```

Filter out missing rows

```r
bad_panel[!is.na(bad_panel$unemployment_rate), ]
```

```
    municipality_code municipality_name year unemployment_rate
1                0114    Upplands Väsby 2016              11.9
3                0117         Österåker 2016               7.2
4                0120            Värmdö 2016               7.3
1.1              0114    Upplands Väsby 2016              11.9
    high_unemployment period
1                TRUE  older
3               FALSE  older
4               FALSE  older
1.1              TRUE  older
```

- Keep observed rows
- Drop missing values explicitly

Checklist for a new table

- Row meaning
- Key
- Unique key?
- Right types?
- Missing values?

This checklist separates structure questions from value questions. Both matter before any serious analysis starts.

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Why plot now?

Simple plots are useful long before polished visualization:

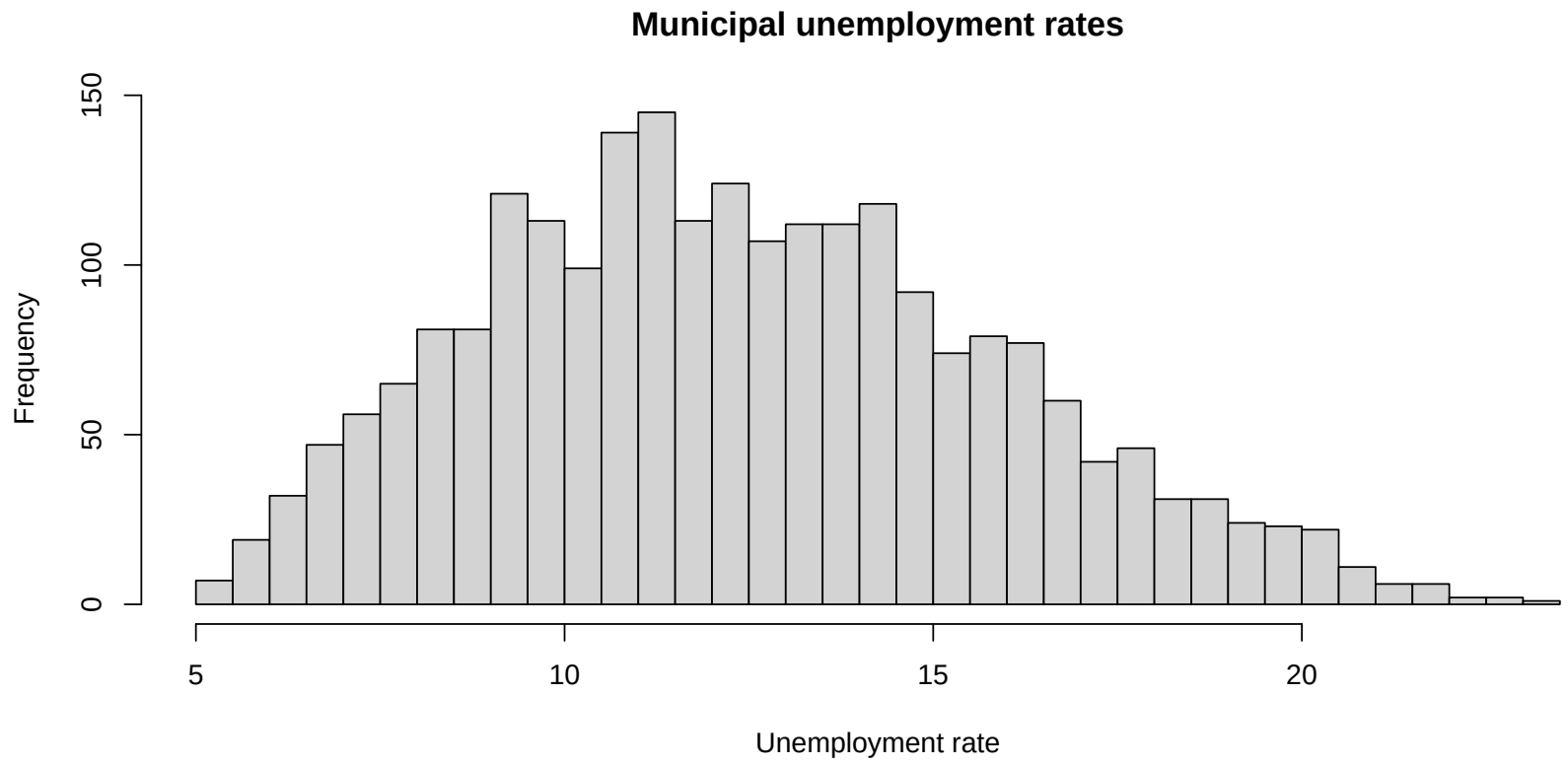
- Check data fast
- Use in problem sets
- Better design in lecture 10

Three quick plot patterns

- `hist(x)`
- `boxplot(x)`
- `plot(x, y)`

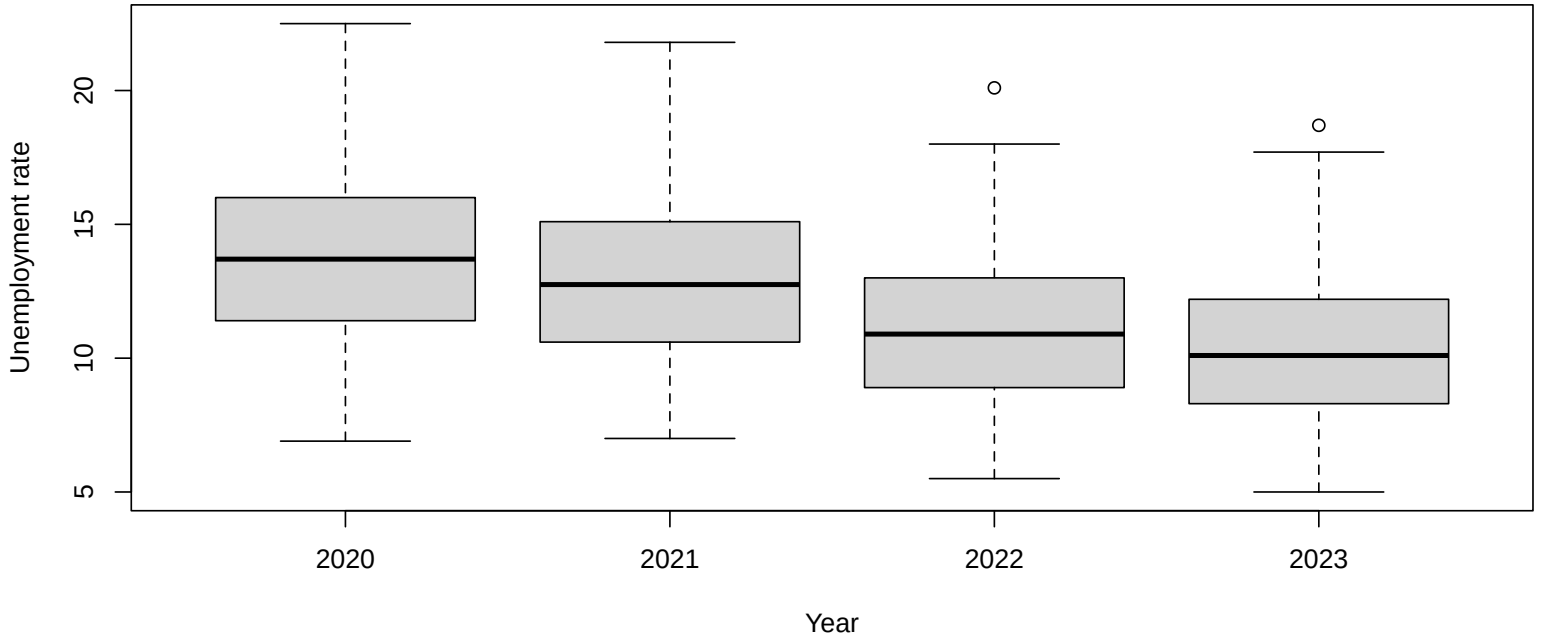
Histogram

```
hist(
  panel_df$unemployment_rate,
  breaks = 30,
  main = "Municipal unemployment rates",
  xlab = "Unemployment rate"
)
```



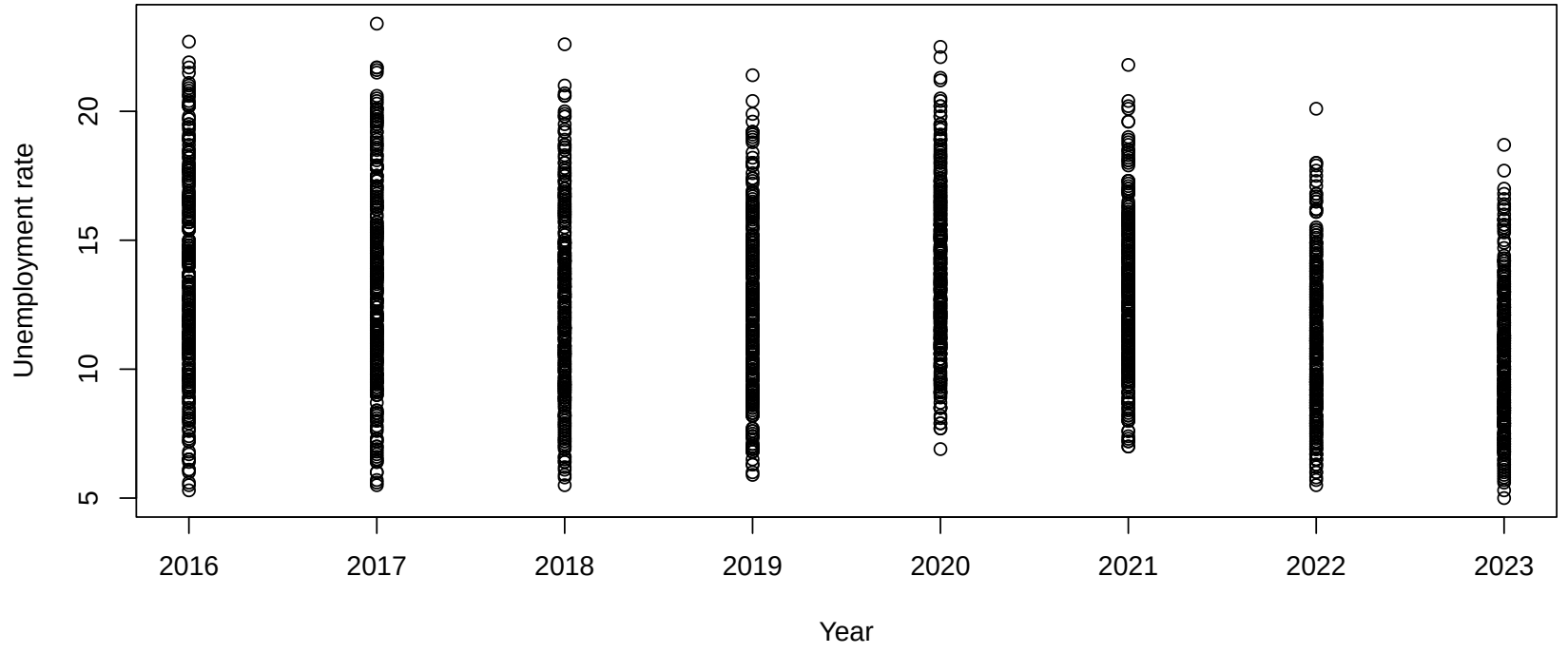
Quick boxplot

```r
recent_panel <- subset(panel_df, year >= 2020)
boxplot(
  formula = unemployment_rate ~ year,
  data = recent_panel,
  xlab = "Year",
  ylab = "Unemployment rate"
)
```



Quick scatterplot

```r
plot(
  x = panel_df$year,
  y = panel_df$unemployment_rate,
  xlab = "Year",
  ylab = "Unemployment rate"
)
```



Main takeaways

- Vectors support element-wise work
- Vectorization often avoids explicit repetition
- Tables are lists of equal-length vectors
- Keys and identifiers matter
- Tidy helps repeated work
- Check early
- Plot early

Next lecture: Independent Workflows, Debugging, and AI Support