Data Tidying

PSY 410: Data Science for Psychology

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What is tidy data?

Can you plot this?

participant	depression_pre	depression_post	anxiety_pre	anxiety_post
P1	18	12	24	20
P2	22	14	19	15
P3	15	11	28	22

. . .

Not easily. The columns mix variables (depression vs anxiety) with time points (pre vs post). ggplot doesn't know what to put on each axis.

. . .

By the end of today, you'll be able to reshape this into a form that works — and understand *why* it needs reshaping.

The tidyverse philosophy

> "Tidy datasets are all alike, but every messy dataset is messy in its own way." — Hadley Wickham

The tools we've learned (ggplot2, dplyr) expect data in a specific format: **tidy data**.

The three rules of tidy data

1. Each **variable** is a column
2. Each **observation** is a row
3. Each **value** is a cell

. . .

Simple in theory, surprisingly complex in practice.

Tidy data visualized

Table 2: Is this tidy?

participant	pre_test	post_test
P1	45	62
P2	52	58
P3	48	71

. . .

No! Time (pre/post) is a variable, but it's spread across columns.

The tidy version

Table 3: Now it's tidy!

participant	time	score
P1	pre	45
P1	post	62
P2	pre	52
P2	post	58
P3	pre	48
P3	post	71

Now: participant, time, and score are all columns.

Why does it matter?

Tidy data works with tidyverse tools:

```
# Easy to visualize
ggplot(data, aes(x = time, y = score, color = participant)) +
  geom_point()

# Easy to analyze
data |>
  group_by(time) |>
  summarize(mean = mean(score))
```

Wide vs. Long

Wide format

- Variables spread across columns
- One row per subject
- Humans like to read this

Long format

- Variables in a single column
- Multiple rows per subject
- R likes to work with this

Most real data needs reshaping.

Common untidy patterns

Pattern 1: Column headers are values

```
wide_scores <- tibble(
  student = c("Alice", "Bob", "Carol"),
  fall_2024 = c(85, 78, 92),
  spring_2025 = c(88, 82, 95),
  fall_2025 = c(91, 85, 94)
)
wide_scores
```

```
# A tibble: 3 x 4
  student fall_2024 spring_2025 fall_2025
  <chr>       <dbl>       <dbl>     <dbl>
1 Alice          85          88        91
2 Bob            78          82        85
3 Carol          92          95        94
```

The semester names are **values**, not variable names.

Pattern 2: Multiple variables in one column

```r
messy_data <- tibble(
  id = 1:3,
  age_sex = c("25_M", "32_F", "28_F")
)
messy_data
```

```
# A tibble: 3 x 2
     id age_sex
  <int> <chr>
1     1 25_M
2     2 32_F
3     3 28_F
```

Age and sex are crammed into one column.

Pattern 3: Variables in rows and columns

```r
weather <- tibble(
  id = c("MX001", "MX001", "MX002", "MX002"),
  year = c(2020, 2020, 2020, 2020),
  month = c(1, 2, 1, 2),
  element = c("tmax", "tmax", "tmin", "tmin"),
  value = c(85, 87, 32, 35)
)
weather
```

```
# A tibble: 4 x 5
  id     year month element value
  <chr> <dbl> <dbl> <chr>   <dbl>
1 MX001  2020     1 tmax       85
2 MX001  2020     2 tmax       87
3 MX002  2020     1 tmin       32
4 MX002  2020     2 tmin       35
```

`element` contains variable names (tmax, tmin).

Psychology-specific patterns

Surveys often look like:

```r
survey_wide <- tibble(
  participant = 1:3,
  bdi_1 = c(2, 1, 3),
  bdi_2 = c(1, 0, 2),
  bdi_3 = c(3, 2, 2),
  bdi_4 = c(2, 1, 1)
)
survey_wide
```

```
# A tibble: 3 x 5
  participant bdi_1 bdi_2 bdi_3 bdi_4
        <int> <dbl> <dbl> <dbl> <dbl>
1           1     2     1     3     2
2           2     1     0     2     1
3           3     3     2     2     1
```

Each item is a column — wide format.

pivot_longer()

The most common tidying operation

`pivot_longer()` takes wide data and makes it long:

```r
wide_scores |>
  pivot_longer(
    cols = fall_2024:fall_2025,  # Which columns to pivot
    names_to = "semester",        # New column for old column names
    values_to = "score"           # New column for values
  )
```

```
# A tibble: 9 x 3
  student semester    score
  <chr>   <chr>       <dbl>
1 Alice   fall_2024      85
2 Alice   spring_2025    88
3 Alice   fall_2025      91
4 Bob     fall_2024      78
5 Bob     spring_2025    82
6 Bob     fall_2025      85
7 Carol   fall_2024      92
8 Carol   spring_2025    95
9 Carol   fall_2025      94
```

Breaking it down

```r
pivot_longer(
  cols = ...,         # Columns to reshape (use select helpers!)
  names_to = "...",   # Name for the new "names" column
  values_to = "..."   # Name for the new "values" column
)
```

Selecting columns to pivot

Use any of the `select()` helpers:

```r
# By name
pivot_longer(cols = c(fall_2024, spring_2025, fall_2025))

# By range
pivot_longer(cols = fall_2024:fall_2025)

# By pattern
```

```r
pivot_longer(cols = starts_with("fall"))
pivot_longer(cols = contains("202"))

# Everything except
pivot_longer(cols = -student)
```

Psychology example: Survey items

```r
survey_wide |>
  pivot_longer(
    cols = starts_with("bdi"),
    names_to = "item",
    values_to = "response"
  )
```

```
# A tibble: 12 x 3
   participant item  response
         <int> <chr>    <dbl>
 1           1 bdi_1        2
 2           1 bdi_2        1
 3           1 bdi_3        3
 4           1 bdi_4        2
 5           2 bdi_1        1
 6           2 bdi_2        0
 7           2 bdi_3        2
 8           2 bdi_4        1
 9           3 bdi_1        3
10           3 bdi_2        2
11           3 bdi_3        2
12           3 bdi_4        1
```

Now each response is its own row!

Extracting information from names

What if column names contain useful info? We want to extract the time point (t1, t2, t3).

```r
# Scores at different time points
experiment_wide <- tibble(
  id = 1:3,
  score_t1 = c(100, 95, 110),
  score_t2 = c(105, 100, 115),
  score_t3 = c(108, 102, 120)
)
experiment_wide
```

```
# A tibble: 3 x 4
     id score_t1 score_t2 score_t3
  <int>    <dbl>    <dbl>    <dbl>
1     1      100      105      108
2     2       95      100      102
3     3      110      115      120
```

names_prefix argument

```r
experiment_wide |>
  pivot_longer(
    cols = starts_with("score"),
    names_to = "time",
    names_prefix = "score_",  # Remove this prefix from names
    values_to = "score"
  )
```

```
# A tibble: 9 x 3
     id time  score
  <int> <chr> <dbl>
1     1 t1      100
2     1 t2      105
3     1 t3      108
4     2 t1       95
5     2 t2      100
6     2 t3      102
7     3 t1      110
8     3 t2      115
9     3 t3      120
```

names_pattern argument

For more complex parsing:

```r
# Column names like "bdi_1", "anxiety_1", etc.
multi_scale <- tibble(
  id = 1:2,
  bdi_1 = c(2, 1), bdi_2 = c(1, 2),
  anxiety_1 = c(3, 2), anxiety_2 = c(2, 3)
)
multi_scale
```

```
# A tibble: 2 x 5
     id bdi_1 bdi_2 anxiety_1 anxiety_2
  <int> <dbl> <dbl>     <dbl>     <dbl>
1     1     2     1         3         2
2     2     1     2         2         3
```

names_pattern argument

For more complex parsing:

```r
multi_scale |>
  pivot_longer(
    cols = -id,
    names_to = c("scale", "item"),
    names_pattern = "(.+)_(.+)",  # Regex: anything_anything
    values_to = "response"
  )
```

```
# A tibble: 8 x 4
     id scale   item  response
  <int> <chr>   <chr>    <dbl>
1     1 bdi     1            2
2     1 bdi     2            1
3     1 anxiety 1            3
4     1 anxiety 2            2
5     2 bdi     1            1
6     2 bdi     2            2
7     2 anxiety 1            2
8     2 anxiety 2            3
```

Pivoting to calculate scale scores

```
# Calculate BDI total from long format
survey_wide |>
  pivot_longer(
    cols = starts_with("bdi"),
    names_to = "item",
    values_to = "response"
  ) |>
  group_by(participant) |>
  summarize(bdi_total = sum(response))
```

```
# A tibble: 3 x 2
  participant bdi_total
        <int>     <dbl>
1           1         8
2           2         4
3           3         8
```

Pair coding break

Your turn: 10 minutes

We defined `survey_wide` earlier in this deck:

```
survey_wide
```

```
# A tibble: 3 x 5
  participant bdi_1 bdi_2 bdi_3 bdi_4
        <int> <dbl> <dbl> <dbl> <dbl>
1           1     2     1     3     2
2           2     1     0     2     1
3           3     3     2     2     1
```

With a partner, figure out: Which participant has the highest mean BDI score?

> 💡 Tip
>
> You'll need `pivot_longer()` followed by `group_by()` + `summarize()`. The column names start with `"bdi"` — that's a hint.

Before we move on

Upload your code to Canvas for participation credit. Paste what you have into today's in-class submission — it doesn't need to work perfectly.

pivot_wider()

The opposite operation

Sometimes you need to go from long to wide:

```r
long_data <- tibble(
  participant = rep(1:3, each = 2),
  time = rep(c("pre", "post"), 3),
  score = c(45, 62, 52, 58, 48, 71)
)
long_data
```

```
# A tibble: 6 x 3
  participant time  score
        <int> <chr> <dbl>
1           1 pre      45
2           1 post     62
3           2 pre      52
4           2 post     58
5           3 pre      48
6           3 post     71
```

pivot_wider() syntax

```r
long_data |>
  pivot_wider(
    names_from = time,   # Column to get new column names from
    values_from = score  # Column to get values from
  )
```

```
# A tibble: 3 x 3
  participant   pre  post
        <int> <dbl> <dbl>
1           1    45    62
2           2    52    58
3           3    48    71
```

When to use pivot_wider()

- Creating summary tables for reports
- Some analyses need wide format
- Merging data that was collected differently
- Human-readable output

Multiple value columns

```r
# Long data with multiple measures
long_multi <- tibble(
  id = rep(1:2, each = 2),
  time = rep(c("pre", "post"), 2),
  score = c(45, 62, 52, 58),
  rt = c(500, 480, 520, 490)
)
long_multi
```

```
# A tibble: 4 x 4
     id time  score    rt
  <int> <chr> <dbl> <dbl>
1     1 pre      45   500
2     1 post     62   480
3     2 pre      52   520
4     2 post     58   490
```

Multiple value columns

```r
long_multi |>
  pivot_wider(
    names_from = time,
    values_from = c(score, rt)  # Multiple columns!
  )
```

```
# A tibble: 2 x 5
     id score_pre score_post rt_pre rt_post
  <int>     <dbl>      <dbl>  <dbl>   <dbl>
1     1        45         62    500     480
2     2        52         58    520     490
```

Separating and uniting

separate_wider_delim()

Split one column into multiple:

```r
tibble(
  id = 1:3,
  age_sex = c("25_M", "32_F", "28_F"))|>
  separate_wider_delim(
    cols = age_sex,
    delim = "_",
    names = c("age", "sex")
  )
```

```
# A tibble: 3 x 3
     id age   sex
  <int> <chr> <chr>
1     1 25    M
2     2 32    F
3     3 28    F
```

separate_wider_regex()

For complex patterns:

```r
tibble(
  code = c("A123", "B456", "C789")
) |>
  separate_wider_regex(
    cols = code,
    patterns = c(letter = "[A-Z]", number = "[0-9]+")
  )
```

```
# A tibble: 3 x 2
  letter number
  <chr>  <chr>
1 A      123
2 B      456
3 C      789
```

unite()

The opposite — combine columns:

```r
tibble(
  year = c(2024, 2024, 2025),
  month = c(1, 6, 1),
  day = c(15, 20, 10)
) |>
  unite(
    col = "date",        # New column name
    year, month, day,    # Columns to combine
    sep = "-"            # Separator
  )
```

```
# A tibble: 3 x 1
  date
  <chr>
1 2024-1-15
2 2024-6-20
3 2025-1-10
```

Real-world examples

Example 1: Repeated measures experiment

```
# Data as you might receive it from SPSS
wide_rm <- tibble(
  subject = 1:4,
  cond_a_time1 = c(450, 520, 480, 510),
  cond_a_time2 = c(420, 490, 460, 480),
  cond_b_time1 = c(480, 540, 500, 530),
  cond_b_time2 = c(440, 510, 470, 500)
)
wide_rm
```

```
# A tibble: 4 x 5
  subject cond_a_time1 cond_a_time2 cond_b_time1 cond_b_time2
    <int>        <dbl>        <dbl>        <dbl>        <dbl>
1       1          450          420          480          440
2       2          520          490          540          510
3       3          480          460          500          470
4       4          510          480          530          500
```

Tidying repeated measures

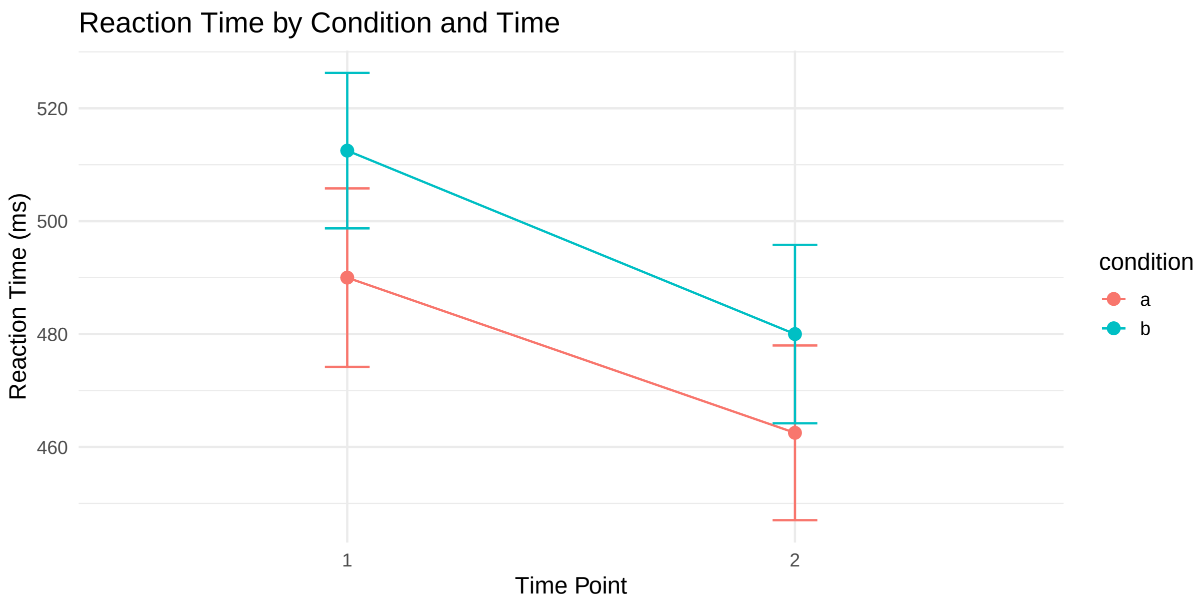
```
tidy_rm <- wide_rm |>
  pivot_longer(
    cols = -subject,
    names_to = c("condition", "time"),
    names_pattern = "cond_(.+)_time(.+)",
    values_to = "rt"
  )
tidy_rm
```

```
# A tibble: 16 x 4
   subject condition time     rt
     <int> <chr>     <chr> <dbl>
 1       1 a         1       450
 2       1 a         2       420
```

3	1	b	1	480
4	1	b	2	440
5	2	a	1	520
6	2	a	2	490
7	2	b	1	540
8	2	b	2	510
9	3	a	1	480
10	3	a	2	460
11	3	b	1	500
12	3	b	2	470
13	4	a	1	510
14	4	a	2	480
15	4	b	1	530
16	4	b	2	500

Now we can analyze it!

```r
tidy_rm |>
  ggplot(aes(x = time, y = rt, color = condition, group = condition)) +
  stat_summary(fun = mean, geom = "point", size = 3) +
  stat_summary(fun = mean, geom = "line") +
  stat_summary(fun.data = mean_se, geom = "errorbar", width = 0.1) +
  labs(
    title = "Reaction Time by Condition and Time",
    x = "Time Point",
    y = "Reaction Time (ms)"
  ) +
  theme_minimal(base_size = 14)
```



Example 2: Questionnaire with subscales

```
# Raw questionnaire data
quest <- tibble(
  pid = 1:3,
  anx_1 = c(3, 2, 4), anx_2 = c(2, 3, 3), anx_3 = c(4, 2, 5),
  dep_1 = c(2, 1, 3), dep_2 = c(3, 2, 4), dep_3 = c(2, 1, 3)
)

quest
```

```
# A tibble: 3 x 7
    pid anx_1 anx_2 anx_3 dep_1 dep_2 dep_3
  <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1     1     3     2     4     2     3     2
2     2     2     3     2     1     2     1
3     3     4     3     5     3     4     3
```

Example 2: Questionnaire with subscales

```r
# Tidy and calculate subscales
quest |>
  pivot_longer(
    cols = -pid,
    names_to = c("scale", "item"),
    names_pattern = "(.+)_(.+)",
    values_to = "response"
  ) |>
  group_by(pid, scale) |>
  summarize(subscale_mean = mean(response), .groups = "drop") |>
  pivot_wider(names_from = scale, values_from = subscale_mean)
```

Example 2: Questionnaire with subscales

```
# A tibble: 3 x 3
    pid   anx   dep
  <int> <dbl> <dbl>
1     1  3     2.33
2     2  2.33  1.33
3     3  4     3.33
```

Example 3: Multilevel/nested data

```r
# Students nested in classrooms
students <- tibble(
  classroom = rep(c("A", "B"), each = 3),
  student = 1:6,
  pretest = c(70, 75, 72, 68, 71, 69),
  posttest = c(80, 82, 78, 75, 79, 77)
)

students
```

```
# A tibble: 6 x 4
  classroom student pretest posttest
  <chr>       <int>   <dbl>    <dbl>
1 A               1      70       80
2 A               2      75       82
3 A               3      72       78
```

```
4 B                 4      68        75
5 B                 5      71        79
6 B                 6      69        77
```

Example 3: Multilevel/nested data

```r
# Tidy for analysis
students |>
  pivot_longer(
    cols = c(pretest, posttest),
    names_to = "time",
    values_to = "score"
  )
```

```
# A tibble: 12 x 4
   classroom student time     score
   <chr>       <int> <chr>    <dbl>
 1 A               1 pretest     70
 2 A               1 posttest    80
 3 A               2 pretest     75
 4 A               2 posttest    82
 5 A               3 pretest     72
 6 A               3 posttest    78
 7 B               4 pretest     68
 8 B               4 posttest    75
 9 B               5 pretest     71
10 B               5 posttest    79
11 B               6 pretest     69
12 B               6 posttest    77
```

pivot_longer() trips everyone up the first time

Pitfall 1: Forgetting what's a variable

Ask yourself: What are my **variables**?

- Participant ID? Variable
- Time point? Variable (not separate columns!)
- Score? Variable
- Item number? Depends on your analysis

Pitfall 2: Over-pivoting

Not everything needs to be long:

```
# Maybe this is fine as-is?
tibble(
  id = 1:3,
  age = c(25, 32, 28),
  gender = c("M", "F", "F"),
  score = c(85, 92, 88)
)
```

Age, gender, and score are **different variables** — keep them as columns.

General tidying strategy

1. **Identify** the variables (what are you measuring?)
2. **Look** at your current structure (what's a row? column?)
3. **Determine** what operations you need
4. **Test** with a small subset first
5. **Verify** you haven't lost data

Get a head start

Try it yourself

We created `wide_rm` earlier — a repeated measures dataset:

On your own:

1. Pivot it to long format, extracting **condition** and **time** from the column names
2. Calculate **mean RT by condition and time**
3. Sketch (on paper or in ggplot) what you'd expect the plot to look like

This is very close to what Assignment 3 will ask you to do.

Wrapping up

The tidyr toolkit

Function	What it does
`pivot_longer()`	Wide → Long
`pivot_wider()`	Long → Wide
`separate_*()`	Split columns
`unite()`	Combine columns

The tidy data mantra

1. Each **variable** is a column
2. Each **observation** is a row
3. Each **value** is a cell

When in doubt, ask: "What would make this easiest to plot/analyze?"

Before next class

Read:

- R4DS Ch 7: Data import
- R4DS Ch 20: Spreadsheets

Practice:

- Reshape a dataset you've worked with
- Try tidying some messy example data
- Practice `pivot_longer()` — it's the most common

Key takeaways

1. **Tidy data** has a specific structure that works with tidyverse
2. **pivot_longer()** is your most-used tidying function
3. **pivot_wider()** is useful for tables and some analyses
4. **Think about your variables** before reshaping
5. **Column names contain information** — extract it with `names_pattern`

The one thing to remember

If your data isn't tidy, your analysis can't start. `pivot_longer()` is the bridge.

Next time: Data Import