Data Transformation I

PSY 410: Data Science for Psychology

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Data transformation

A question you can't answer yet

You collected survey data from 500 participants. You only want women over 25 who passed the attention check.

. . .

How do you get to *just those rows?*

. . .

That's what `filter()` does. And it's just the beginning — today we learn four verbs that turn raw data into exactly what you need.

The dplyr verbs

Verb	What it does
`filter()`	Pick **rows** by their values
`arrange()`	Reorder **rows**
`select()`	Pick **columns** by name
`mutate()`	Create new **columns**
`summarize()`	Collapse to a **summary**

Today: `filter()`, `arrange()`, `select()`, `mutate()`

Our dataset: flights

```r
# All 336,776 flights departing NYC in 2013
glimpse(flights)
```

```
Rows: 336,776
Columns: 19
$ year           <int> 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2~
$ month          <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ day            <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ dep_time       <int> 517, 533, 542, 544, 554, 554, 555, 557, 557, 558, 558, ~
$ sched_dep_time <int> 515, 529, 540, 545, 600, 558, 600, 600, 600, 600, 600, ~
$ dep_delay      <dbl> 2, 4, 2, -1, -6, -4, -5, -3, -3, -2, -2, -2, -2, -2, -
1~
$ arr_time       <int> 830, 850, 923, 1004, 812, 740, 913, 709, 838, 753, 849,~
$ sched_arr_time <int> 819, 830, 850, 1022, 837, 728, 854, 723, 846, 745, 851,~
$ arr_delay      <dbl> 11, 20, 33, -18, -25, 12, 19, -14, -8, 8, -2, -3, 7, -
1~
$ carrier        <chr> "UA", "UA", "AA", "B6", "DL", "UA", "B6", "EV", "B6", "~
$ flight         <int> 1545, 1714, 1141, 725, 461, 1696, 507, 5708, 79, 301, 4~
$ tailnum        <chr> "N14228", "N24211", "N619AA", "N804JB", "N668DN", "N394~
$ origin         <chr> "EWR", "LGA", "JFK", "JFK", "LGA", "EWR", "EWR", "LGA",~
$ dest           <chr> "IAH", "IAH", "MIA", "BQN", "ATL", "ORD", "FLL", "IAD",~
$ air_time       <dbl> 227, 227, 160, 183, 116, 150, 158, 53, 140, 138, 149, 1~
$ distance       <dbl> 1400, 1416, 1089, 1576, 762, 719, 1065, 229, 944, 733, ~
$ hour           <dbl> 5, 5, 5, 5, 6, 5, 6, 6, 6, 6, 6, 6, 6, 6, 6, 5, 6, 6, 6~
$ minute         <dbl> 15, 29, 40, 45, 0, 58, 0, 0, 0, 0, 0, 0, 0, 0, 0, 59, 0~
$ time_hour      <dttm> 2013-01-01 05:00:00, 2013-01-01 05:00:00, 2013-01-
01 0~
```

Understanding the data

- `year`, `month`, `day` — departure date
- `dep_time`, `arr_time` — actual times (HHMM format)
- `dep_delay`, `arr_delay` — delays in minutes (negative = early)
- `carrier` — airline code
- `origin`, `dest` — airport codes
- `air_time`, `distance` — in minutes and miles

filter()

filter() picks rows

```r
# All flights on January 1st
filter(flights, month == 1, day == 1)
```

```
# A tibble: 842 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     1      517            515         2      830            819
 2  2013     1     1      533            529         4      850            830
 3  2013     1     1      542            540         2      923            850
 4  2013     1     1      544            545        -1     1004           1022
 5  2013     1     1      554            600        -6      812            837
 6  2013     1     1      554            558        -4      740            728
 7  2013     1     1      555            600        -5      913            854
 8  2013     1     1      557            600        -3      709            723
 9  2013     1     1      557            600        -3      838            846
10  2013     1     1      558            600        -2      753            745
# i 832 more rows
# i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>
```

Comparison operators

Operator	Meaning
`==`	equal to
`!=`	not equal to
`<`, `>`	less than, greater than
`<=`, `>=`	less/greater than or equal

Warning

Use == for comparison, not =!

Filter examples

```r
# Flights to Los Angeles
filter(flights, dest == "LAX")

# Flights with arrival delay over 2 hours
filter(flights, arr_delay > 120)

# Flights by United Airlines
filter(flights, carrier == "UA")
```

Multiple conditions

Conditions separated by `,` are combined with AND:

```r
# January 1st flights (both must be true)
filter(flights, month == 1, day == 1)
```

Equivalent to:

```r
filter(flights, month == 1 & day == 1)
```

Logical operators

Operator	Meaning
`&`	AND (both true)
`|`	OR (either true)
`!`	NOT (negation)

Using OR

```r
# Flights in November OR December
filter(flights, month == 11 | month == 12)
```

```
# A tibble: 55,403 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013    11     1        5           2359         6      352            345
 2  2013    11     1       35           2250       105      123           2356
 3  2013    11     1      455            500        -5      641            651
 4  2013    11     1      539            545        -6      856            827
 5  2013    11     1      542            545        -3      831            855
 6  2013    11     1      549            600       -11      912            923
 7  2013    11     1      550            600       -10      705            659
 8  2013    11     1      554            600        -6      659            701
 9  2013    11     1      554            600        -6      826            827
10  2013    11     1      554            600        -6      749            751
# i 55,393 more rows
# i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>
```

A useful shortcut: %in%

```
# Same as above, but cleaner
filter(flights, month %in% c(11, 12))
```

```
# A tibble: 55,403 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013    11     1        5           2359         6      352            345
 2  2013    11     1       35           2250       105      123           2356
 3  2013    11     1      455            500        -5      641            651
 4  2013    11     1      539            545        -6      856            827
 5  2013    11     1      542            545        -3      831            855
 6  2013    11     1      549            600       -11      912            923
 7  2013    11     1      550            600       -10      705            659
 8  2013    11     1      554            600        -6      659            701
 9  2013    11     1      554            600        -6      826            827
10  2013    11     1      554            600        -6      749            751
# i 55,393 more rows
# i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>
```

`%in%` checks if the value is in the vector.

filter() with psychology data

Imagine a survey dataset:

```r
# Exclude participants who failed attention check
filter(survey, attention_check == "correct")

# Keep only complete responses
filter(survey, !is.na(total_score))

# Adults only
filter(survey, age >= 18)

# Specific conditions
filter(survey, condition %in% c("treatment", "control"))
```

Missing values: NA

`NA` means "not available" — a missing value.

```r
x <- c(1, 2, NA, 4)
x > 2
```

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

Any operation with `NA` returns `NA` (it's unknown!).

Checking for NA

Use `is.na()` to check for missing values:

```r
x <- c(1, 2, NA, 4)
is.na(x)
```

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

```r
# Keep rows where dep_delay is NOT missing
filter(flights, !is.na(dep_delay))
```

Pair coding break

Your turn: 10 minutes

With a partner, using the `flights` dataset:

1. Find all **United Airlines** (`"UA"`) flights
2. that were **more than 2 hours late** arriving
3. and were flying **to Los Angeles** (`"LAX"`)

How many flights match? Which origin airport had the most?

> Tip
>
> You'll need `filter()` with multiple conditions. Think about which operators you need.

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.

arrange()

arrange() reorders rows

```r
# Sort by departure delay (smallest first)
arrange(flights, dep_delay)
```

```
# A tibble: 336,776 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013    12     7     2040           2123       -43       40           2352
 2  2013     2     3     2022           2055       -33     2240           2338
 3  2013    11    10     1408           1440       -32     1549           1559
 4  2013     1    11     1900           1930       -30     2233           2243
 5  2013     1    29     1703           1730       -27     1947           1957
 6  2013     8     9      729            755       -26     1002            955
 7  2013    10    23     1907           1932       -25     2143           2143
 8  2013     3    30     2030           2055       -25     2213           2250
 9  2013     3     2     1431           1455       -24     1601           1631
10  2013     5     5      934            958       -24     1225           1309
# i 336,766 more rows
# i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>
```

Descending order

```
# Most delayed flights first
arrange(flights, desc(dep_delay))
```

```
# A tibble: 336,776 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     9      641            900      1301     1242           1530
 2  2013     6    15     1432           1935      1137     1607           2120
 3  2013     1    10     1121           1635      1126     1239           1810
 4  2013     9    20     1139           1845      1014     1457           2210
 5  2013     7    22      845           1600      1005     1044           1815
 6  2013     4    10     1100           1900       960     1342           2211
 7  2013     3    17     2321            810       911      135           1020
 8  2013     6    27      959           1900       899     1236           2226
 9  2013     7    22     2257            759       898      121           1026
10  2013    12     5      756           1700       896     1058           2020
# i 336,766 more rows
# i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>
```

Multiple sort columns

```r
# Sort by month, then by day, then by departure time
arrange(flights, month, day, dep_time)
```

```
# A tibble: 336,776 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     1      517            515         2      830            819
 2  2013     1     1      533            529         4      850            830
 3  2013     1     1      542            540         2      923            850
 4  2013     1     1      544            545        -1     1004           1022
 5  2013     1     1      554            600        -6      812            837
 6  2013     1     1      554            558        -4      740            728
 7  2013     1     1      555            600        -5      913            854
 8  2013     1     1      557            600        -3      709            723
 9  2013     1     1      557            600        -3      838            846
10  2013     1     1      558            600        -2      753            745
# i 336,766 more rows
# i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>
```

arrange() use cases

```r
# Psychology examples:
# Find participants with highest scores
arrange(data, desc(total_score))

# Sort by condition, then by participant ID
arrange(data, condition, participant_id)

# Find earliest responses
arrange(data, response_time)
```

Quick mental model

You've now seen three verbs. Each answers a different question:

Verb	Question it answers
`filter()`	Which **rows** do I keep?
`arrange()`	What **order** should they be in?
`select()`	Which **columns** do I need?
`mutate()`	What **new columns** should I create?

We've done the first two. Now let's pick our columns.

select()

select() picks columns

```r
# Just these three columns
select(flights, year, month, day)
```

```
# A tibble: 336,776 x 3
    year month   day
   <int> <int> <int>
 1  2013     1     1
 2  2013     1     1
 3  2013     1     1
 4  2013     1     1
 5  2013     1     1
 6  2013     1     1
 7  2013     1     1
 8  2013     1     1
 9  2013     1     1
10  2013     1     1
# i 336,766 more rows
```

Select a range

```r
# All columns from year to day
select(flights, year:day)
```

```
# A tibble: 336,776 x 3
    year month   day
   <int> <int> <int>
 1  2013     1     1
 2  2013     1     1
 3  2013     1     1
 4  2013     1     1
 5  2013     1     1
 6  2013     1     1
 7  2013     1     1
 8  2013     1     1
 9  2013     1     1
10  2013     1     1
# i 336,766 more rows
```

Select helpers

Helper	What it does
`starts_with("x")`	Columns starting with "x"
`ends_with("x")`	Columns ending with "x"
`contains("x")`	Columns containing "x"
`everything()`	All remaining columns

Using select helpers

```r
# All delay-related columns
select(flights, contains("delay"))
```

```
# A tibble: 336,776 x 2
   dep_delay arr_delay
       <dbl>     <dbl>
 1         2        11
 2         4        20
 3         2        33
 4        -1       -18
 5        -6       -25
 6        -4        12
 7        -5        19
 8        -3       -14
 9        -3        -8
10        -2         8
# i 336,766 more rows
```

Using select helpers

```
# All time columns
select(flights, ends_with("time"))
```

```
# A tibble: 336,776 x 5
   dep_time sched_dep_time arr_time sched_arr_time air_time
      <int>          <int>    <int>          <int>    <dbl>
 1      517            515      830            819      227
 2      533            529      850            830      227
 3      542            540      923            850      160
 4      544            545     1004           1022      183
 5      554            600      812            837      116
 6      554            558      740            728      150
 7      555            600      913            854      158
 8      557            600      709            723       53
 9      557            600      838            846      140
10      558            600      753            745      138
# i 336,766 more rows
```

Reorder columns

```
# Move air_time and distance to the front
select(flights, air_time, distance, everything())
```

```
# A tibble: 336,776 x 19
   air_time distance  year month   day dep_time sched_dep_time dep_delay
      <dbl>    <dbl> <int> <int> <int>    <int>          <int>     <dbl>
 1      227     1400  2013     1     1      517            515         2
 2      227     1416  2013     1     1      533            529         4
 3      160     1089  2013     1     1      542            540         2
 4      183     1576  2013     1     1      544            545        -1
 5      116      762  2013     1     1      554            600        -6
 6      150      719  2013     1     1      554            558        -4
 7      158     1065  2013     1     1      555            600        -5
 8       53      229  2013     1     1      557            600        -3
 9      140      944  2013     1     1      557            600        -3
10      138      733  2013     1     1      558            600        -2
# i 336,766 more rows
# i 11 more variables: arr_time <int>, sched_arr_time <int>, arr_delay <dbl>,
#   carrier <chr>, flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>
```

Exclude columns

Use - to remove columns:

```r
# Remove year column
select(flights, -year)
```

```
# A tibble: 336,776 x 18
   month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1     1     1      517            515         2      830            819
 2     1     1      533            529         4      850            830
 3     1     1      542            540         2      923            850
 4     1     1      544            545        -1     1004           1022
 5     1     1      554            600        -6      812            837
 6     1     1      554            558        -4      740            728
 7     1     1      555            600        -5      913            854
 8     1     1      557            600        -3      709            723
 9     1     1      557            600        -3      838            846
10     1     1      558            600        -2      753            745
# i 336,766 more rows
# i 11 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>
```

Exclude columns

```r
# Remove multiple columns
select(flights, -year, -month, -day)
select(flights, -(year:day))  # same thing
```

select() in psychology

```r
# Select demographic columns
select(survey, starts_with("demo_"))

# Select all BDI items
select(survey, contains("bdi"))

# Remove identifying information
select(survey, -name, -email, -ip_address)

# Reorder for analysis
select(survey, participant_id, condition, starts_with("outcome"))
```

The pattern so far

Notice: every verb has the same shape.

```r
# verb(data, what_you_want)
filter(flights, month == 1)
arrange(flights, dep_delay)
select(flights, year, month, day)
```

Data goes first. Then you describe what you want. This consistency is by design.

mutate()

mutate() creates new columns

```r
# Calculate total delay
mutate(flights, total_delay = dep_delay + arr_delay)
```

```
# A tibble: 336,776 x 20
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     1      517            515         2      830            819
 2  2013     1     1      533            529         4      850            830
 3  2013     1     1      542            540         2      923            850
 4  2013     1     1      544            545        -1     1004           1022
 5  2013     1     1      554            600        -6      812            837
 6  2013     1     1      554            558        -4      740            728
 7  2013     1     1      555            600        -5      913            854
 8  2013     1     1      557            600        -3      709            723
 9  2013     1     1      557            600        -3      838            846
10  2013     1     1      558            600        -2      753            745
# i 336,766 more rows
# i 12 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>, total_delay <dbl>
```

Multiple new columns

```
mutate(flights,
       # Create new variables
       total_delay = dep_delay + arr_delay,
       speed = distance / air_time * 60,  # mph
       # Can reference columns you just created!
       delay_per_mile = total_delay / distance
)
```

```
# A tibble: 336,776 x 22
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     1      517            515         2      830            819
 2  2013     1     1      533            529         4      850            830
 3  2013     1     1      542            540         2      923            850
 4  2013     1     1      544            545        -1     1004           1022
 5  2013     1     1      554            600        -6      812            837
 6  2013     1     1      554            558        -4      740            728
 7  2013     1     1      555            600        -5      913            854
 8  2013     1     1      557            600        -3      709            723
 9  2013     1     1      557            600        -3      838            846
10  2013     1     1      558            600        -2      753            745
# i 336,766 more rows
# i 14 more variables: arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>, total_delay <dbl>, speed <dbl>,
#   delay_per_mile <dbl>
```

mutate() keeps all columns

`mutate()` adds new columns while keeping existing ones.

Use `transmute()` to *only* keep new columns:

```r
transmute(flights,
          total_delay = dep_delay + arr_delay,
          speed = distance / air_time * 60
)
```

```
# A tibble: 336,776 x 2
   total_delay speed
         <dbl> <dbl>
 1          13  370.
 2          24  374.
 3          35  408.
 4         -19  517.
 5         -31  394.
 6           8  288.
 7          14  404.
 8         -17  259.
 9         -11  405.
10           6  319.
# i 336,766 more rows
```

Useful functions in mutate()

Arithmetic: `+`, `-`, `*`, `/`, `^`, `%%` (modulo), `%/%` (integer division)

Logs: `log()`, `log2()`, `log10()`

Offsets: `lead()`, `lag()` (for time series)

Cumulative: `cumsum()`, `cummean()`, `cummax()`

Ranking: `min_rank()`, `dense_rank()`, `row_number()`

Common transformations

```r
# Z-score (standardize)
mutate(data, score_z = (score - mean(score)) / sd(score))

# Log transform (for skewed data)
mutate(data, rt_log = log(reaction_time))

# Create categories from continuous
mutate(data, age_group = case_when(
  age < 30 ~ "young",
  age < 60 ~ "middle",
  TRUE ~ "older"
))
```

mutate() for psychology

```r
# Calculate scale scores (mean of items)
mutate(survey,
       bdi_total = (bdi_1 + bdi_2 + bdi_3 + bdi_4) / 4,
       # Or rowwise if you have many items:
       anxiety = rowMeans(select(., anx_1:anx_20), na.rm = TRUE)
)

# Create dummy codes
mutate(survey,
       female = if_else(gender == "female", 1, 0),
       treatment = if_else(condition == "treatment", 1, 0)
)

# Reverse code items
mutate(survey,
       item_5r = 8 - item_5  # For 1-7 scale
)
```

The pipe makes your code read like a sentence

The problem with nested functions

What if we want to:

1. Filter to January flights
2. Select departure time and delay
3. Arrange by delay

Nested approach:

```r
arrange(
  select(
    filter(flights, month == 1),
    dep_time, dep_delay
  ),
  dep_delay
)
```

This is hard to read!

Intermediate objects approach

```r
# Save each step
jan_flights <- filter(flights, month == 1)
jan_selected <- select(jan_flights, dep_time, dep_delay)
jan_arranged <- arrange(jan_selected, dep_delay)
```

Works, but clutters your environment with objects.

The pipe: |>

The pipe takes the result of one function and passes it as the first argument to the next:

```r
# Same result, much cleaner!
flights |>
  filter(month == 1) |>
  select(dep_time, dep_delay) |>
  arrange(dep_delay)
```

```
# A tibble: 27,004 x 2
   dep_time dep_delay
      <int>     <dbl>
 1     1900       -30
 2      1703       -27
 3      1354       -22
 4      2137       -22
 5       704       -21
 6      2050       -20
 7      2134       -20
 8      2050       -20
 9      2140       -19
10      1947       -18
# i 26,994 more rows
```

Reading piped code

Read `|>` as **"then"**:

```
flights |>                        # Start with flights, THEN
  filter(month == 1) |>           # filter to January, THEN
  select(dep_time, dep_delay) |>  # select these columns, THEN
  arrange(dep_delay)              # arrange by delay
```

Keyboard shortcut

The pipe is so common, there's a shortcut:

- **Windows/Linux:** Ctrl + Shift + M
- **Mac:** Cmd + Shift + M

. . .

Tip

In RStudio settings, make sure "Use native pipe operator" is enabled (Tools → Global Options → Code)

Note: |> vs %>%

You'll see both:

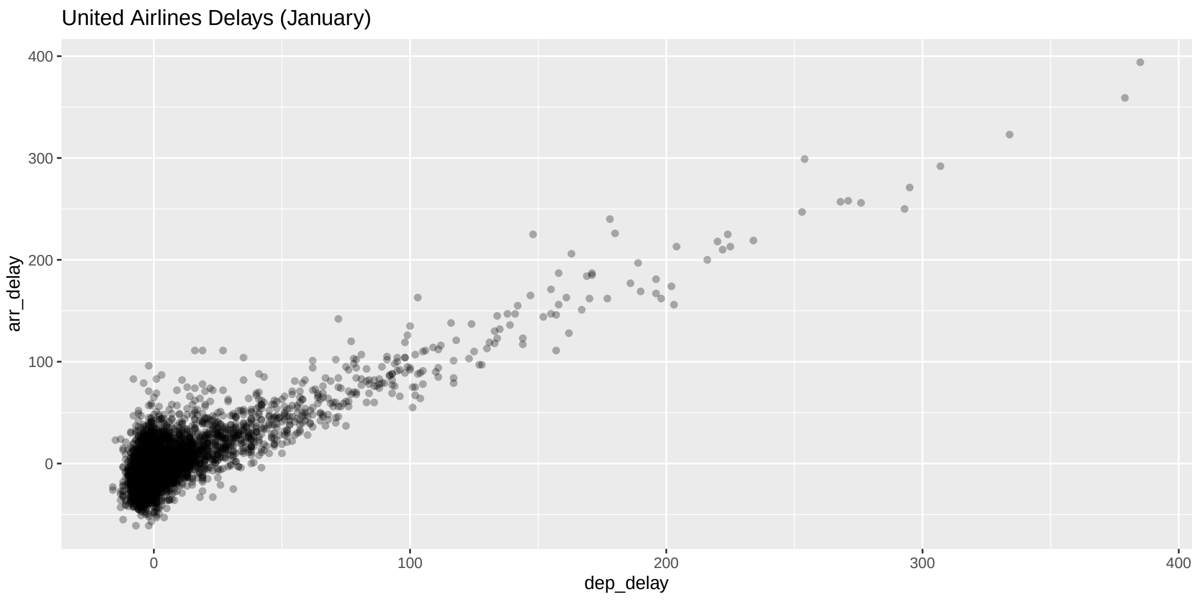
- `|>` — the **native** pipe (built into R 4.1+)
- `%>%` — the **magrittr** pipe (older, from tidyverse)

They work almost identically. We'll use `|>` since it's now standard.

Piping into ggplot

The pipe works beautifully with ggplot:

```r
flights |>
  filter(month == 1, carrier == "UA") |>
  ggplot(aes(x = dep_delay, y = arr_delay)) +
  geom_point(alpha = 0.3) +
  labs(title = "United Airlines Delays (January)")
```



Putting it together

A complete workflow

```r
# Which airlines have the longest delays in summer?
flights |>
  filter(month %in% c(6, 7, 8)) |>          # Summer months
  filter(!is.na(arr_delay)) |>              # Remove NAs
  mutate(delay_hours = arr_delay / 60) |>   # Convert to hours
  select(carrier, delay_hours) |>           # Keep relevant columns
  arrange(desc(delay_hours))                # Longest delays first
```

```
# A tibble: 84,124 x 2
   carrier delay_hours
   <chr>         <dbl>
 1 MQ             18.8
 2 MQ             16.5
 3 DL             14.9
 4 DL             14.2
 5 AA             13.4
 6 DL             13
 7 DL             12.8
 8 VX             11.3
 9 AA             10.8
10 VX             10.5
# i 84,114 more rows
```

Get a head start

Your turn!

Using the `flights` dataset:

1. Filter to American Airlines ("AA") flights to Los Angeles ("LAX")
2. Create a new variable `speed` (distance / air_time * 60)
3. Select carrier, origin, dest, and speed
4. Arrange by speed (highest first)
5. What's the fastest AA flight to LAX?

Wrapping up

The dplyr workflow

```
data |>
  filter(<conditions>) |>    # Pick rows
  select(<columns>) |>       # Pick columns
  mutate(<new vars>) |>      # Create columns
  arrange(<order>)           # Sort rows
```

The pipe (`|>`) connects these verbs into a readable workflow.

Before next class

Read:

- R4DS Ch 3: Data transformation (section 3.5)
- R4DS Ch 4: Workflow: code style

Practice:

- Transform `flights` in different ways
- Create new variables with `mutate()`
- Build multi-step pipelines

Key takeaways

1. **filter()** picks rows by condition
2. **arrange()** reorders rows (use `desc()` for descending)
3. **select()** picks columns (helpers like `contains()` are useful)
4. **mutate()** creates new columns
5. **The pipe** |> makes code readable and elegant

The one thing to remember

The pipe turns a wall of nested code into a sentence you can read aloud.

Next time: group_by() and summarize()