R Tutorial at the WZB

6 - Recap / Transforming data with R II

Markus Konrad

November 29, 2018

Today's schedule

1. Review of last weeks' tasks and recap
2. Data aggregation and summarization

WZB
Wissenschaftszentrum Berlin für Sozialforschung

Review of last weeks' tasks and recap

Solutions and review of previous tasks

Solutions for all previous tasks are online at https://wzbsocialsciencecenter.github.io/wzb_r_tutorial/

Any problems, questions?

Recap

I prepared a small quiz for you…

Transforming data with R II

What we've learned so far

We already got to know several dplyr "verbs" for transforming data:

- `filter()` for filtering (subsetting) rows (observations) according to some criteria
- `distinct()` for selecting only unique rows
- `arrange()` for ordering rows
- `select()` for selecting only certain columns (variables)
- `rename()` for giving new names to columns
- `mutate()` and `transmute()` for adding new columns

Today: Combining several verbs in one step and learning new verbs for **grouping and summarizing data**.

Combining several dplyr verbs

Applying several steps is cumbersome this way:

```
air_june <- filter(airquality, Month == 6)
air_june <- select(air_june, -Month)   # we don't need Month any more
head(air_june)
```

```
##   Ozone Solar.R Wind Temp Day
## 1    NA     286  8.6   78   1
## 2    NA     287  9.7   74   2
## 3    NA     242 16.1   67   3
## 4    NA     186  9.2   84   4
## 5    NA     220  8.6   85   5
## 6    NA     264 14.3   79   6
```

You can always nest functions:

```
air_june <- select(filter(airquality, Month == 6), -Month)
```

→ makes code harder to read (you have to read "inside-out")

Combining several dplyr verbs

A common approach to chain several data transformation steps is to use the **pipe operator:**

```
step_one() %>% step_two() %>% ... %>% last_step()
```

→ the output of one function is passed as input to the next function

```
air_june <- filter(airquality, Month == 6) %>% select(-Month)
```

Notice how `select()` has only one parameter, since it implicitely operates on the output of `filter()`.

For long complex data transformations, each step is usually written on a separate line:

```
air_june <- airquality %>%
  filter(Month == 6) %>%
  select(-Month) %>%
  arrange(desc(Wind))
```

Aggregates with `group_by()` and `summarise()`

`summarise()` can be used to create summary statistics on aggregate data:

```
summarise(airquality, mean_ozone = mean(Ozone, na.rm = TRUE))
```

```
##   mean_ozone
## 1   42.12931
```

→ summary of the whole data frame

Aggregates with `group_by()` and `summarise()`

It is more useful in combination with `group_by()`, which forms groups based on the variables you pass:

```
group_by(airquality, Month) %>% summarise(mean_ozone = mean(Ozone, na.rm = T
```

```
## # A tibble: 5 x 2
##   Month mean_ozone
##   <int>      <dbl>
## 1     5       23.6
## 2     6       29.4
## 3     7       59.1
## 4     8       60.0
## 5     9       31.4
```

→ summary per group, i.e. per month

Aggregates with `group_by()` and `summarise()`

You can pass several aggregate values as arguments:

```
group_by(airquality, Month) %>%
  summarise(mean_ozone = mean(Ozone, na.rm = TRUE),
            sd_ozone = sd(Ozone, na.rm = TRUE),
            n = n(),                          # number of obs. per group
            n_nonNA = sum(!is.na(Ozone)))   # number of non-NA Ozone obs.
```

```
## # A tibble: 5 x 5
##   Month mean_ozone sd_ozone     n n_nonNA
##   <int>      <dbl>    <dbl> <int>   <int>
## 1     5       23.6     22.2    31      26
## 2     6       29.4     18.2    30       9
## 3     7       59.1     31.6    31      26
## 4     8       60.0     39.7    31      26
## 5     9       31.4     24.1    30      29
```

- any function passed to `summarize` will operate on each group's observations
- `n()` counts the number of observations in each group

Some more complex examples with the `flights` data

We'll use a subset `fl_sub` for some more grouping and summarizing examples.

```
library(nycflights13)

fl_sub <- select(flights, origin, dest, distance, arr_delay)
head(fl_sub)
```

```
## # A tibble: 6 x 4
##   origin dest  distance arr_delay
##   <chr>  <chr>    <dbl>     <dbl>
## 1 EWR    IAH       1400        11
## 2 LGA    IAH       1416        20
## 3 JFK    MIA       1089        33
## 4 JFK    BQN       1576       -18
## 5 LGA    ATL        762       -25
## 6 EWR    ORD        719        12
```

- `origin` and `dest` are the origin and destination airports
- `distance` is the flight distance in miles
- `arr_delay` is the arrival delay in minutes

WZB Wissenschaftszentrum Berlin für Sozialforschung

Relationship between the distance and average delay

We want to find out what's the **relationship between distance and average delay per destination airport**. We want to **exclude small destination airports (<= 20 connections) and outlier Honolulu**. Which data transformation steps are necessary?

1. Group flights by destination with `group_by()`.
2. For each group, compute average distance, average delay and number of flights with `summarise()`.
3. Exclude observations according to mentioned criteria with `filter()`.

WZB
Wissenschaftszentrum Berlin für Sozialforschung

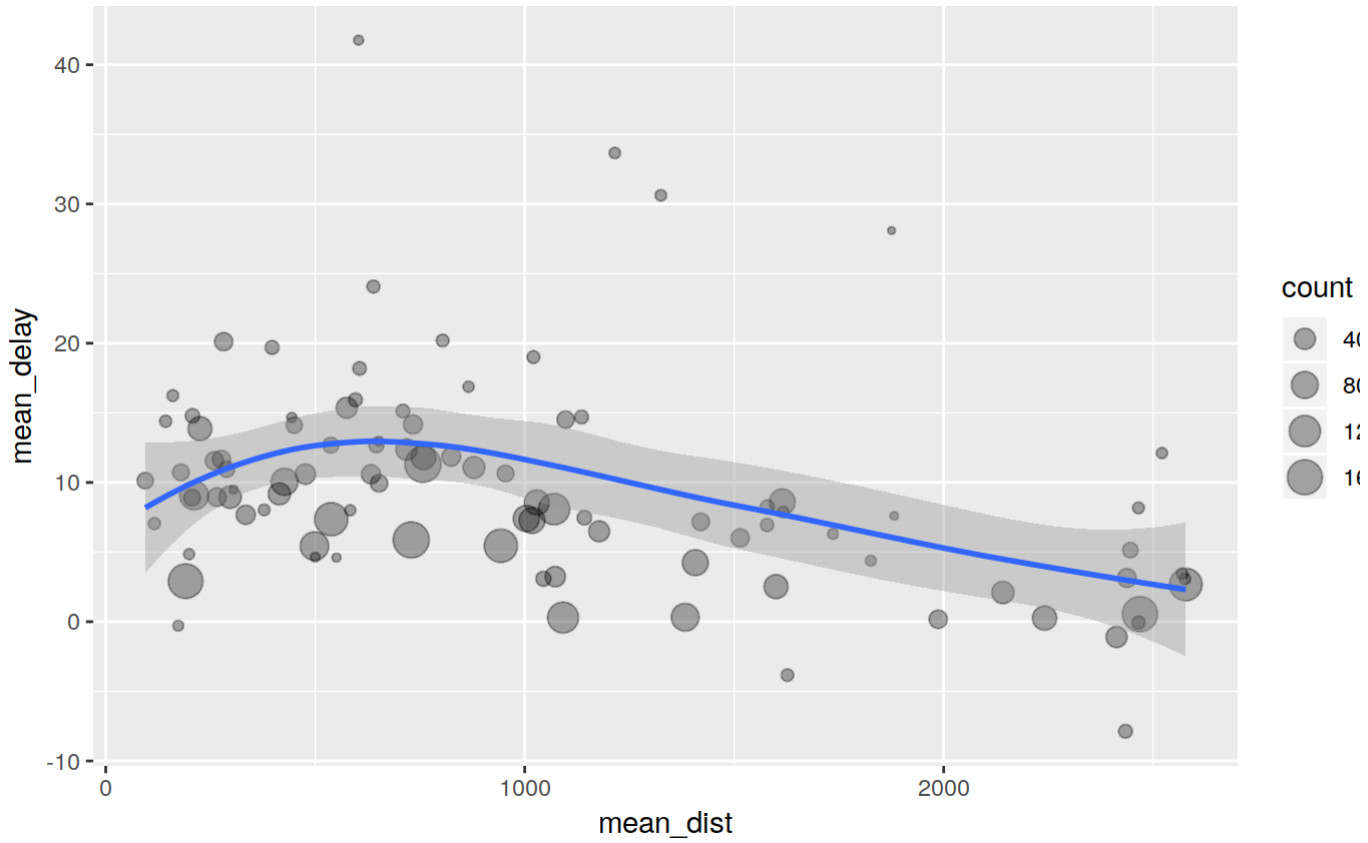
Relationship between the distance and average delay

We want to find out what's the **relationship between distance and average delay per destination airport**. We want to **exclude small destination airports (<= 20 connections) and outlier Honolulu**.

```
delays <- fl_sub %>%
  group_by(dest) %>%      # step 1
  summarise(count = n(),  # step 2
            mean_dist = mean(distance, na.rm = TRUE),
            mean_delay = mean(arr_delay, na.rm = TRUE)) %>%
  filter(count > 20, dest != "HNL")  # step 3
head(delays)
```

```
## # A tibble: 6 x 4
##   dest  count mean_dist mean_delay
##   <chr> <int>     <dbl>      <dbl>
## 1 ABQ     254     1826        4.38
## 2 ACK     265      199        4.85
## 3 ALB     439      143       14.4
## 4 ATL   17215      757.      11.3
## 5 AUS    2439     1514.       6.02
## 6 AVL     275      584.       8.00
```

Relationship between the distance and average delay



WZB
Wissenschaftszentrum Berlin für Sozialforschung

Grouping by multiple variables

We want to know what the **most popular flight connections** are, and also which connections have the **lowest or highest average delays**. We will **exclude rarely used connections with less than 100 flights**. Which data transformation steps are necessary?

1. Group by `origin` and `dest` to form groups of connections.
2. Summarise by counting the number of observations per connection and computing the mean delay.
3. Exclude observations according to mentioned criteria with `filter()`.

WZB
Wissenschaftszentrum Berlin für Sozialforschung

Grouping by multiple variables

We want to know what the **most popular flight connections** are, and also which connections have the **lowest or highest average delays**. We will **exclude rarely used connections with less than 100 flights**. Which data transformation steps are necessary?

```
connections <- fl_sub %>%
  group_by(origin, dest) %>%   # step 1
  summarise(n = n(),           # step 2
            mean_delay = mean(arr_delay, na.rm = TRUE)) %>%
  filter(n >= 100)             # step 3
head(connections)
```

```
## # A tibble: 6 x 4
## # Groups:   origin [1]
##   origin dest      n mean_delay
##   <chr>  <chr> <int>      <dbl>
## 1 EWR    ALB     439     14.4
## 2 EWR    ATL    5022     13.2
## 3 EWR    AUS     968     -0.474
## 4 EWR    AVL     265      8.80
## 5 EWR    BDL     443      7.05
## 6 EWR    BNA    2336     12.7
```

Grouping by multiple variables

Now we can obtain the top three connections by using `arrange()` and `head()`:

```
connections %>% arrange(desc(n)) %>% head(3)
```

```
## # A tibble: 3 x 4
## # Groups:   origin [2]
##   origin dest      n mean_delay
##   <chr>  <chr> <int>      <dbl>
## 1 JFK    LAX   11262     -0.481
## 2 LGA    ATL   10263     11.3
## 3 LGA    ORD    8857      1.83
```

Or the top three connections with the least delay time:

```
connections %>% arrange(mean_delay) %>% head(3)
```

```
## # A tibble: 3 x 4
## # Groups:   origin [2]
##   origin dest      n mean_delay
##   <chr>  <chr> <int>      <dbl>
## 1 EWR    SNA     825      -7.87
## 2 JFK    HNL     342      -6.92
## 3 JFK    STT     333      -6.37
```

Grouping by multiple variables

Or the top three connections with the most delay time:

```
connections %>% arrange(desc(mean_delay)) %>% head(3)
```

```
## # A tibble: 3 x 4
## # Groups:   origin [1]
##   origin dest      n mean_delay
##   <chr>  <chr> <int>      <dbl>
## 1 EWR    CAE     104       44.6
## 2 EWR    TYS     323       41.2
## 3 EWR    TUL     315       33.7
```

WZB Wissenschaftszentrum Berlin für Sozialforschung

Ungrouping

Once you group a data frame and assign it to an object, the grouping information is retained. You can see this in the additional information that is printed above the data (`Groups: ...`):

```
head(connections)
```

```
## # A tibble: 6 x 4
## # Groups:   origin [1]
##   origin dest      n mean_delay
##   <chr>  <chr> <int>      <dbl>
## 1 EWR    ALB     439     14.4
## 2 EWR    ATL    5022     13.2
## 3 EWR    AUS     968     -0.474
## 4 EWR    AVL     265      8.80
## 5 EWR    BDL     443      7.05
## 6 EWR    BNA    2336     12.7
```

Ungrouping

As long as a data frame is grouped, `summarise()` operates on the groups and not on the whole data frame:

```
connections %>% summarise(median_n_conn = median(n))
```

```
## # A tibble: 3 x 2
##   origin median_n_conn
##   <chr>          <dbl>
## 1 EWR            1080.
## 2 JFK            1130.
## 3 LGA             761
```

You can remove the grouping information via `ungroup()`. Now `summarise()` operates on the whole data frame:

```
connections %>% ungroup() %>% summarise(median_n_conn = median(n))
```

```
## # A tibble: 1 x 1
##   median_n_conn
##           <int>
## 1           997
```

Tasks

Tasks

See dedicated tasks sheet on the tutorial website.