FE8828 Programming Web Applications in Finance

Week 3

Data Manipulation and EDA/2

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Lecture 7: Data Manipulation and EDA/2

Joins

left_/right_/anti_/full_join

Sample data:

- data_day1

Date	Position_id	Buy/Sell	Quantity	Risk Factor	Traded Price
2018-11-07	00010001	B	100	DCE_IO_1901	505.3
2018-11-07	00010002	B	100	DCE_IO_1901	506.8

- data_day2

Date	Position_id	Buy/Sell	Quantity	Risk Factor	Traded Price
2018-11-07	00010001	B	100	DCE_IO_1901	505.3
2018-11-07	00010002	B	100	DCE_IO_1901	506.8
2018-11-08	00010003	S	-100	DCE_IO_1901	507.9

Positions are additive (to close a position, we won't change the original position but to do a new reverse trade). Suppose we have two days of position data.

left_/right_/anti_/full_join

In order to find the new positions. We will use:

```
# order matters, data_day2 needs to be placed first.
# anti_join is like "data_day2 - data_day1"
anti_join(data_day2, data_day1, by = "position_id")
```

In order to find old positions, we will use:

```
# inner_join ignores order
# find the common positions
inner_join(data_day2, data_day1, by = "position_id")
left_join(data_day1, data_day2, by = "position_id") # produce the same result
right_join(data_day1, data_day2, by = "position_id") # produce the same result
left_join(data_day2, data_day1, by = "position_id") # produce all items in data_day2
```

left_join / right_join

They can be used to do mapping table (aka. vlookup)

Table `Product`:

type_code	type_name
1	orange
2	banana

Table `Transaction`:

type_code	quantity	customer_id
1	1	A
2	3	B
3	4	C
2	2	D
1	6	B

Table `Customer`:

customer_id	customer_phone
A	+123
B	+456
C	+789

Use `left_join` to create a full report

```
left_join(Transaction, Product, by = "type_code") %>%
left_join(Customer, by = "customer_id")
```

type_code	quantity	customer_id	type_name	customer_phone
1	1	A	orange	+123
2	3	B	banana	+456
3	4	C	NA	+789
2	2	D	banana	NA
1	6	B	orange	+456

full_join and anti_join

- full_join(a, b): Find all combinations between table a and b.
- anti_join(a, b): Find those in a but not in b.

```
# From something simple
df <- full_join(data_frame(a = 1:2), data_frame(a = 2:4), by = "a")
```

a
1
2
3
4

```
df <- anti_join(data_frame(a = 1:2), data_frame(a = 2:4), by = "a")
```

a
1

```
# All possible combination between job and education
x <- full_join(distinct(bank, job) %>% mutate(dummy = 1),
               distinct(bank, education) %>% mutate(dummy = 1),
               by = "dummy") %>%
     select(-dummy)
y <- distinct(bank, job, education)

nrow(x)
## [1] 48
nrow(y)
```

```
## [1] 48

df1 <- anti_join(x, y, by = c("job", "education"))
df2 <- anti_join(y, x, by = c("job", "education"))
```

- Empty result

job education —- ———-

- Empty result

job education —- ———-

Join is a set operation

- `full_join` is `*`
- `anti_join` is `-`
- `inner_joins` is `-`, `/`
- `left_join/right_join` is either just the same, or `*`, `/`.

group_by / summarize

group_by is the way leading to analyze the data at high-dimension. group_by is used together with summarize

```
group_by(df, ...) ... is the list of variables
summarize(df, new_field = some_func_can_process_bulk_data())
```

Functions can process bulk data:

- sum/mean/median/sd: basic statistics
- min(x), quantile(x, 0.25), max(x): min/max/quantile
- n()/n_distinct(): count and count distint
- ntile: a rough divide into a few groups
- first(x), last(x), nth(x, 2)
- …

group_by / summarize: Examples

```
# Add paramter na.rm, if there is NA among the data.
df <- data.frame(a = c(1, 3, 4, NA))
```

a
1
3
4
NA

```
summarise(df, total = sum(a))
```

total
NA

```
summarise(df, total = sum(a, na.rm = TRUE))
```

total
8

```
summarise(df, total = mean(a))
```

total
NA

```
summarise(df, total = mean(a, na.rm = TRUE))
```

total
2.666667

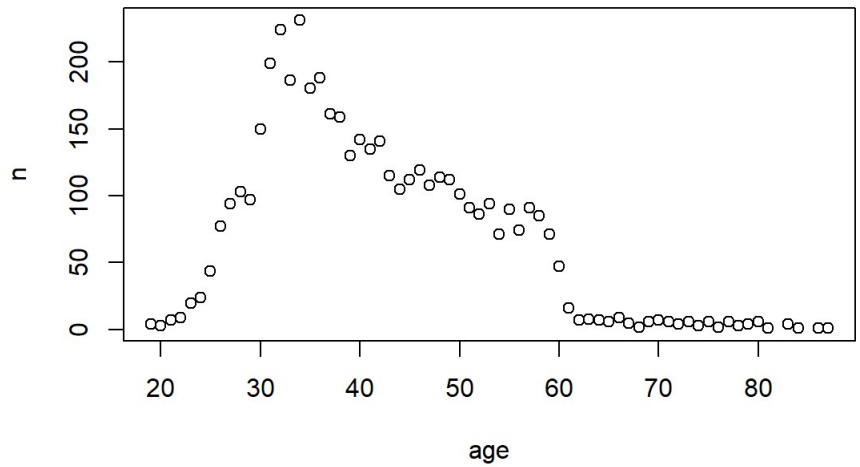
group_by / summarize: Examples

```
# count number of people in each age group
group_by(bank, age) %>% summarise(n = n())
```

age	n
19	4
20	3
21	7
22	9
23	20
24	24
…	

group_by / summarize: Examples

```
group_by(bank, age) %>% summarise(n = n()) %>% plot
```



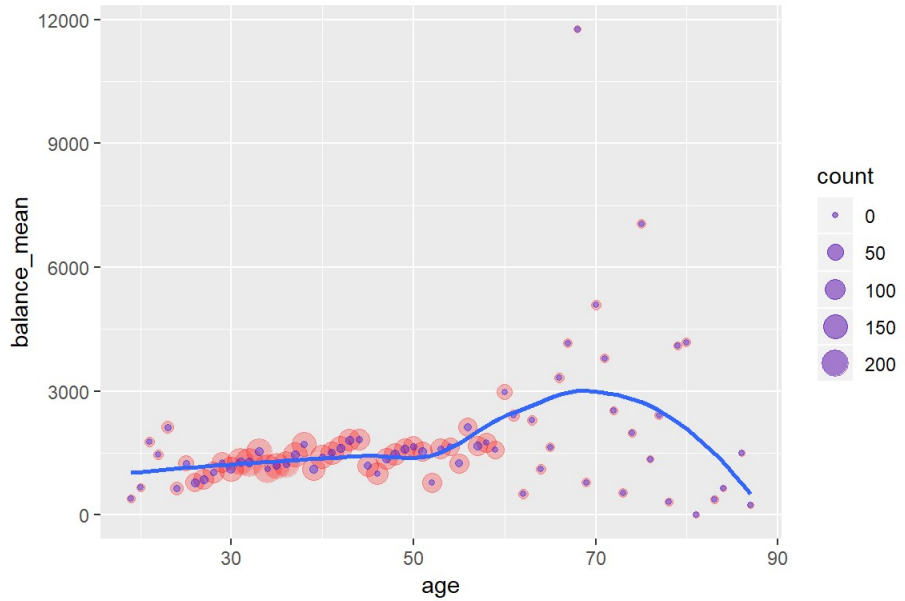
group_by / summarize: Examples

```
bank_age <- group_by(bank, age) %>%
          summarise(balance_mean = mean(balance),
                    count = n(),
                    default_count = sum(ifelse(default == "no", 0, 1)))
```

age	balance_mean	count	default_count
19	393.5000	4	0
20	661.3333	3	0
21	1774.2857	7	0
22	1455.3333	9	0
23	2117.9500	20	1
24	634.6250	24	1
25	1240.0682	44	1
26	788.5584	77	3
27	851.7766	94	4
28	1025.0971	103	1
…			

group_by / summarize: Examples

```
# If combined with ggplot, to be learnt in next session
bank_age %>%
  ggplot(aes(x = age, y = balance_mean)) +
  geom_point(aes(size = count), alpha = 1/4, color = "red") +
  geom_point(aes(size = default_count), alpha = 1/3, color = "blue") +
  geom_smooth(se = FALSE)
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Group filter

```
# Find the maximum and minimum balance on each age.
df <- bank %>%
  group_by(age) %>%
  filter(min_rank(balance) == 1 | min_rank(desc(balance)) == 1) %>%
  arrange(age, balance)
```

age	job	marital	education	default	balance	housing	loan	contact	day	month	du
19	student	single	unknown	no	0	no	no	cellular	11	feb	
19	student	single	unknown	no	1169	no	no	cellular	6	feb	
20	student	single	secondary	no	291	no	no	telephone	11	may	
20	student	single	secondary	no	1191	no	no	cellular	12	feb	
21	student	single	secondary	no	6	no	no	unknown	9	may	
21	student	single	secondary	no	6844	no	no	cellular	14	aug	
22	student	single	unknown	no	47	no	no	cellular	3	jul	
22	admin.	single	secondary	no	4111	no	yes	cellular	19	aug	
23	technician	single	secondary	no	-306	yes	no	unknown	4	jun	
23	student	single	secondary	no	9216	no	no	cellular	5	jun	

...

Count for condition

TRUE => 1, FALSE => 0

```
# Generate a report for balance and job
d1 <- group_by(bank, job) %>%
  summarise(`balance > 500` = sum(balance > 500))
d2 <- group_by(bank, job) %>%
  summarise(`balance <= 500` = sum(balance <= 500))
# df collects all jobs, in case some jobs are missing from either d1 or d2
# This is a typical example for collecting data.
df <- distinct(bank, job) %>% arrange(job)
df <- left_join(df, d1, by = "job")
df <- left_join(df, d2, by = "job")
df <- mutate(df, total = `balance > 500` + `balance <= 500`)
```

job	balance > 500	balance <= 500	total
admin.	226	252	478
blue-collar	423	523	946
entrepreneur	74	94	168
housemaid	42	70	112
management	521	448	969
retired	127	103	230
self-employed	89	94	183
services	154	263	417
student	41	43	84

job	balance > 500	balance <= 500	total
technician	353	415	768
unemployed	63	65	128
unknown	21	17	38

`group_by` and `summarise/summarize`: Further explain

- `group_by` is a like folding a paper without tearing it later.
- `summarise` tears the paper to do individual pieces.
- Therefore, `group_by` can be used with other verbs, `mutate`, `filter`, which will work within the group.
- `summarise` can be used without group_by, then it will apply to entire data as one whole group.

group_by

```
# mutate with group_by
df <- group_by(data.frame(a = 1:10), quantile = ntile(a, 2)) %>%
  mutate(b = a / sum(a))
```

a	quantile	b
1	1	0.0666667
2	1	0.1333333
3	1	0.2000000
4	1	0.2666667
5	1	0.3333333
6	2	0.1500000
7	2	0.1750000
8	2	0.2000000
9	2	0.2250000
10	2	0.2500000

group_by / 2

```
# filter with group_by
df <- group_by(bank, age) %>% filter(balance == max(balance))
```

age	job	marital	education	default	balance	housing	loan	contact	day	month
22	admin.	single	secondary	no	4111	no	yes	cellular	19	aug
78	housemaid	married	secondary	no	499	no	no	telephone	16	mar
23	student	single	secondary	no	9216	no	no	cellular	5	jun
46	management	married	secondary	no	12186	no	no	unknown	20	jun
64	retired	married	unknown	no	2923	no	no	cellular	12	mar
77	retired	married	tertiary	no	7802	no	no	telephone	4	may
39	management	single	tertiary	no	12437	no	no	telephone	18	nov
28	student	single	secondary	no	11555	no	no	cellular	8	apr
81	retired	married	secondary	no	1	no	no	cellular	19	aug
33	housemaid	single	tertiary	no	23663	yes	no	cellular	16	apr
40	self-employed	married	tertiary	no	13669	no	no	cellular	15	oct
31	housemaid	single	primary	no	26965	no	no	cellular	21	apr
30	management	single	tertiary	no	19358	no	no	cellular	19	nov
67	blue-collar	married	secondary	no	16353	no	no	cellular	27	oct

age	job	marital	education	default	balance	housing	loan	contact	day	month
49	retired	single	primary	no	25824	no	no	unknown	17	jun

…

summarize/summarise

```
# summarise with group_by
df <- group_by(data.frame(a = 1:10), quantile = ntile(a, 2)) %>%
  summarise(b = sum(a))
```

quantile	b
1	15
2	40

```
# summarise without a group_by. It will treat entire df as a whole.
df <- summarise(bank,
                with_housing = sum(housing == "yes") / n(),
                age_min = min(age),
                duration_mean = mean(duration))
```

with_housing	age_min	duration_mean
0.5660252	19	263.9613

group_by/ungroup

`ungroup()` removes group definition, restores the "ungrouped"" data frame back to entire data. Because `group_by` will leave a trace

```
# wrong
df_wrong <- group_by(bank, age) %>%
  filter(balance == max(balance)) %>%
  summarize(balance = mean(balance)) %>%
  head(n = 3)

# correct
df_correct <- group_by(bank, age) %>%
  filter(balance == max(balance)) %>%
  ungroup %>%
  summarize(balance = mean(balance))
```

age	balance
19	1169
20	1191
21	6844

balance
13541.21

group_by/ungroup

```
# We can't remove age
# R will prompt for "Adding missing grouping variables: `age`"
df1 <- group_by(bank, age) %>%
  filter(balance == max(balance)) %>%
  select(-age) %>% head(n = 3)
## Adding missing grouping variables: `age`

# We can remove age with ungroup
df2 <- group_by(bank, age) %>%
  filter(balance == max(balance)) %>%
  ungroup %>%
  select(-age) %>% head(n = 3)
```

age	job	marital	education	default	balance	housing	loan	contact	day	month	du
22	admin.	single	secondary	no	4111	no	yes	cellular	19	aug	
78	housemaid	married	secondary	no	499	no	no	telephone	16	mar	
23	student	single	secondary	no	9216	no	no	cellular	5	jun	

job	marital	education	default	balance	housing	loan	contact	day	month	durati
admin.	single	secondary	no	4111	no	yes	cellular	19	aug	
housemaid	married	secondary	no	499	no	no	telephone	16	mar	
student	single	secondary	no	9216	no	no	cellular	5	jun	4

rowwise

Sometimes, we need to use `rowwise()` which is a special `group_by` which makes every one row a group. `rowwise()` use case, it applies to complex logic that can't be applied as a group.

```
df <- data.frame(throw_dices = 1:10)
df <- rowwise(df) %>% mutate( mean = mean(sample(1:6, throw_dices, replace = TRUE)))
```

throw_dices	mean
1	6.000000
2	4.500000
3	3.666667
4	4.250000
5	5.000000
6	2.666667
7	3.857143
8	3.125000
9	4.444444
10	3.600000

bind_rows

- bind_rows is the + operator for data frames.

```
# add empty data frame is the same.
df1 <- bind_rows(data.frame(a = 3:4), data.frame())
```

a
3
4

```
df2 <- bind_rows(data.frame(), data.frame(a = 3:4))
```

a
3
4

bind_rows: Use case

I usually use bind_rows to collect results. For example,

```
new_positions <- data.frame()
closed_positions <- data.frame()

for (i in length(dates)-1) {
  old_date <- dates[i]
  new_date <- dates[i+1]

  new_data <- filter(position, date == new_date)
  old_data <- filter(position, date == old_date)

  new_positions <- bind_rows(new_positions,
                             anti_join(new_data, old_data, by = "position_id"))
}

# new_positions contains all new positions on their day 1
```

bind_rows: Use case

If row order matters, bind_row can be used to re-order/splice and recombine.

```
# Get head and tail
# Note: use { } to use the .
df <- arrange(bank, age) %>%
      { bind_rows(head(., n = 5), tail(., n = 5)) }
```

age	job	marital	education	default	balance	housing	loan	contact	day	month	dura
19	student	single	primary	no	103	no	no	cellular	10	jul	
19	student	single	unknown	no	0	no	no	cellular	11	feb	
19	student	single	secondary	no	302	no	no	cellular	16	jul	
19	student	single	unknown	no	1169	no	no	cellular	6	feb	
20	student	single	secondary	no	502	no	no	cellular	30	apr	
83	retired	divorced	primary	no	0	no	no	telephone	31	may	
83	retired	divorced	primary	no	1097	no	no	telephone	5	mar	
84	retired	divorced	primary	no	639	no	no	telephone	18	may	
86	retired	married	secondary	no	1503	no	no	telephone	18	mar	
87	retired	married	primary	no	230	no	no	cellular	30	oct	

bind_rows: Use case

```
# summary
df1 <- summarise_if(bank, is.numeric, mean)
```

age	balance	day	duration	campaign	pdays	previous
41.1701	1422.658	15.91528	263.9613	2.79363	39.76664	0.5425791

```
# add summary to the records
df2<- tail(bind_rows(bank, summarise_if(bank, is.numeric, mean)), n = 1)
```

	age	job	marital	education	default	balance	housing	loan	contact	day	mo
4522	41.1701	NA	NA	NA	NA	1422.658	NA	NA	NA	15.91528	NA

bind_rows: Use case

```
# bind_rows can match column names and type.
# let's adjust the column order.
# As due-deligence, better to check the result.
# I remember earlier version of dplyr doesn't do match.
df <- tail(bind_rows(bank, summarise_if(bank, is.numeric, mean) %>%
  select(balance, day, everything())), n = 1)
```

	age	job	marital	education	default	balance	housing	loan	contact	day	mo
4522	41.1701	NA	NA	NA	NA	1422.658	NA	NA	NA	15.91528	NA

bind_cols

- bind_cols is to extend the data frame in width.

Use cases

- It's a lazyman's `left_join` or `select`
- It copies the columns
- I usually find it useful to generate data frame for reports.

```
dt1 <- bind_cols(select(bank, job), select(bank, education))
dt1[1:3,]
```

job	education
unemployed	primary
services	secondary
management	tertiary

bind_cols

```
dt2 <- bind_cols(dt1, dt1)
dt2[1:3,]
```

job	education	job1	education1
unemployed	primary	unemployed	primary
services	secondary	services	secondary
management	tertiary	management	tertiary

bind_cols: Use cases

```
d1 <- filter(bank, month == "sep") %>%
  summarize(duration = mean(duration)) %>%
  rename(`Duration Sep` = duration)
d2 <- filter(bank, month == "oct") %>%
  summarize(duration = mean(duration)) %>%
  rename(`Duration Oct` = duration)
d3 <- filter(bank, month == "nov") %>%
  summarize(duration = mean(duration)) %>%
  rename(`Duration Nov` = duration)

df <- bind_cols(d1, d2, d3)
```

Duration Sep	Duration Oct	Duration Nov
215.7308	272.8	272.0668

Exercise

1. How to know the row number of the wrong date

```
df <- data.frame(dt = c("2018-10-01", "2018-31-12", "2018-03-17", "2018-02-29", "2018-09-
```

dt

2018-10-01

2018-31-12

2018-03-17

2018-02-29

2018-09-30

Output:

```
## Wrong dates on rows: 2, 4
```

Exercise

2. How to get sub-total and total on mean of age and balance, group by job and education?

job	education	mean(Age)	median(Balance)
services	primary	…	…
services			
services	+	…	…
…			
+	+	…	…

Exercise

3. To evaluate a portfolio of options for its total value.

```
GBSOption(TypeFlag = "p", S = 3500, X = 3765,
          Time = 1/12, r = 0, b = 0, sigma = 0.3)@price
## [1] 300.0049
df <- data.frame(type = sample(c("c", "p"), 100, replace = TRUE),
                 strike = round(runif(100) * 100, 0),
                 underlying = round(runif(100) * 100, 0),
                 Time = 1,
                 r = 0.01,
                 b = 0,
                 sigma = 0.3)
```

tidyr: gather/spread

Wide format <=> Long format

- Wide format is more familiar to us. Column name is the data attribute.
- Long format is what we reformat the data that common attributes are gathered together as a single variable.
- Reference: Tidy data https://en.wikipedia.org/wiki/Tidy_data

Wide v.s. Long

Wide format

```
wfmt <- data_frame(date = seq(from = as.Date("2018-01-01"), by = "day", length.out = 5),
                   Copper_qty = round(runif(5) * 1000, 0),
                   Gold_qty = round(runif(5) * 1000, 0),
                   Silver_qty = round(runif(5) * 1000, 0))
```

date	Copper_qty	Gold_qty	Silver_qty
2018-01-01	433	170	454
2018-01-02	232	880	623
2018-01-03	502	183	202
2018-01-04	433	231	2
2018-01-05	133	394	259

Wide v.s. Long

Long format

```
library(tidyr)
df <- gather(wfmt, key, value, -date)
```

date	key	value
2018-01-01	Copper_qty	433
2018-01-02	Copper_qty	232
2018-01-03	Copper_qty	502
2018-01-04	Copper_qty	433
2018-01-05	Copper_qty	133
2018-01-01	Gold_qty	170
2018-01-02	Gold_qty	880
2018-01-03	Gold_qty	183
2018-01-04	Gold_qty	231
2018-01-05	Gold_qty	394
2018-01-01	Silver_qty	454
2018-01-02	Silver_qty	623
2018-01-03	Silver_qty	202

date	key	value
2018-01-04	Silver_qty	2
2018-01-05	Silver_qty	259

`spread/gather` convert for Wide format <=> Long format

```
gather(data, key, value, ...)
```

… is where you want to make as independent columns. You need to specify all columns that should be `gather`ed (or before `gather`, remove all columns that should *not* be `gather`ed).

```
mini_iris <- iris[1:3,]
df <- gather(mini_iris,
             key = flower_att,
             value = measurement,
             -Species)
```

Species	flower_att	measurement
setosa	Sepal.Length	5.1
setosa	Sepal.Length	4.9
setosa	Sepal.Length	4.7
setosa	Sepal.Width	3.5
setosa	Sepal.Width	3.0
setosa	Sepal.Width	3.2
setosa	Petal.Length	1.4
setosa	Petal.Length	1.4
setosa	Petal.Length	1.3

Species	flower_att	measurement
setosa	Petal.Width	0.2
setosa	Petal.Width	0.2
setosa	Petal.Width	0.2

spread/gather which columns to remove/add

```
lfmt <- gather(mini_iris,
               key = flower_att,
               value = measurement,
               Sepal.Length, Sepal.Width, Petal.Length, Petal.Width)
lfmt
```

Species	flower_att	measurement
setosa	Sepal.Length	5.1
setosa	Sepal.Length	4.9
setosa	Sepal.Length	4.7
setosa	Sepal.Width	3.5
setosa	Sepal.Width	3.0
setosa	Sepal.Width	3.2
setosa	Petal.Length	1.4
setosa	Petal.Length	1.4
setosa	Petal.Length	1.3
setosa	Petal.Width	0.2
setosa	Petal.Width	0.2
setosa	Petal.Width	0.2

spread

```
spread(lfmt, key, value)
```

Example: get row sum.

```
library(tidyr)
df <- wfmt %>%
      gather(key, value, -date) %>%
      group_by(date) %>%
      summarize(value1 = sum(value)) %>%
      rename(value = value1) %>%
      mutate(key = "Total") %>%
      spread(key = key, value = value) %>%
      inner_join(wfmt, ., by = "date")
```

date	Copper_qty	Gold_qty	Silver_qty	Total
2018-01-01	433	170	454	1057
2018-01-02	232	880	623	1735
2018-01-03	502	183	202	887
2018-01-04	433	231	2	666
2018-01-05	133	394	259	786

```
# although this works...
# It takes "Hard coding" of column names "Copper_qty Gold_qty Silver_qty".
df <- wfmt %>% mutate(total = Copper_qty + Gold_qty + Silver_qty)
```

date	Copper_qty	Gold_qty	Silver_qty	total

date	Copper_qty	Gold_qty	Silver_qty	total
2018-01-01	433	170	454	1057
2018-01-02	232	880	623	1735
2018-01-03	502	183	202	887
2018-01-04	433	231	2	666
2018-01-05	133	394	259	786

separate/unite

```
separate(data, col, into, sep = "[^[:alnum:]]+", remove = TRUE,
  convert = FALSE, extra = "warn", fill = "warn", ...)

#> # A tibble: 6 × 3
#>       country  year              rate
#> *       <chr> <int>             <chr>
#> 1 Afghanistan  1999      745/19987071
#> 2 Afghanistan  2000     2666/20595360
#> 3      Brazil  1999   37737/172006362
#> 4      Brazil  2000   80488/174504898
#> 5       China  1999 212258/1272915272
#> 6       China  2000 213766/1280428583

separate(df, rate, into = c("cases", "population"))
separate(df, rate, into = c("cases", "population"), convert = TRUE)

unite(df, century, year) # default sep is "_"
unite(df, century, year, sep = "") # seamless unite
```

Rules of Thumb for use list of data frame

- Use list to store app data, i.e. configuration.
  `conf <- list(use_calendar_days = TRUE, do_fx_conversion = FALSE, yea`
- User data frame to store repeating data of similar structure.
- Every data frame is better to have a id column, like **item_id**. It can be number or character. Make it unique. If **item_id** is a number, when insert new record to the data frame, we need to increment it somewhere. So, use a variable to keep it somewhere, or use `max(item_id) + 1` (It will do calculation for all ids. Performance still good with small data set)
- Delete is not good for enterprise. We need to leave an audit trail. And we can prevent from wrong operation. Add a column name with a common name, e.g. SYS_DEL. Its default value is FALSE, when you want to delete it, set it to TRUE. When extracting data, use `filter(df1, !SYS_DEL)`. The advanced version involves the user and datetime, i.e. SYS_DEL_USER, SYS_DEL_DATETIME.

```
| position_id | call_put | amount | strike | SYS_DEL |
| X123        |          |        |        |
```

CRUD in dplyr

Create:

- add new rows. bind_rows()

Read:

- You have known enough: filter/select/joins/… to get what you need.

Update:

- Use either data frame way or mutate.

```
# get all row numbers for students
# . refers to the output of the pipe %>%. .$nnn => df$nnn
row_nums <- mutate(bank, nnn = 1:n()) %>%
            filter(job == "student" & age < 22) %>%
            select(nnn) %>%
            .$nnn

bank1 <- bank
bank1[row_nums, "taxable"] <- "no"
bank1[setdiff(1:nrow(bank), row_nums), "taxable"] <- "yes"

# use dplyr
bank1 <- mutate(bank, taxable = ifelse(job == "student" & age < 22, "no", "yes"))
distinct(bank1, taxable)
```

Delete:

- Use filter to exclude the row(s).

- (Advanced version) Create a column `SYS_DEL` of logic type, described in detail in previous slide.

Assignment

1. Exploratory Data Work on the bank dataset. Find 10 findings from data. Use R Markdown.

````
---
title: "FE8828 Assignment for Exploratory Data Analysis"
author: "Yang Ye <sub> <Email:yy@runchee.com> </sub>"
date: "Nov 15, 2017"
output: html_document
---

```{r setup, include=FALSE}
library(tidyverse)
library(lubridate)
library(bizdays)
# Use echo = TRUE for assignment is an exception, so code is visible.
knitr::opts_chunk$set(echo = TRUE, fig.align="center", collapse = TRUE, cache = TRUE)
bank <- read.csv("https://goo.gl/PBQnBt", sep = ";")
```

# Finding #1
This data contains `r nrow(data)` rows.

# Finding #2
```{r}
# Find the big age group
bank %>%
  group_by(age_group = (age %/% 10) * 10) %>%
  summarise(count = n()) %>%
  arrange(age_group) -> res

res

plot(res$age_group, res$count)
```

# Discover insights of data frame: bank
- Employment
- Social attributes.
- Count for sub-total / total, plot graph
````

Assignment

2. Book option trades

1.1 Copy the options data from https://www.nasdaq.com/symbol/goog/option-chain?dateindex=1

```
Gather data for "Dec 14, 2018" and store into following data frame format.

    | Expiry Date | Strike | Open Interest | Underlying | Call/Put | Bid | Ask
```

1.2 Count the total valuation of 1) call alone, 2) put alone, 3) call and put.
`Open Interest * (Bid + Ask) / 2`

1.3 Find those in the money and get their total `Open Interest`.

1.4. Plot the volatility curve, strike v.s. vol. For strike < current price, use puts' price; for strike > current price, use calls' price.

```
# GBSVolatility(price, TypeFlag, S, X, Time, r, b, tol, maxiter)
# Use Price to back-out implied volatility. Assume r = 0.03
# Example:

GBSVolatility(867.30, "c", 1135.67, 240,
              as.numeric((as.Date("2018-12-07") - as.Date("2018-11-10")))/365, r = 0.03, 
## [1] 1.059735e-16
GBSVolatility(256.50, "c", 1135.67, 880.00,
              as.numeric((as.Date("2018-12-07") - as.Date("2018-11-10")))/365, r = 0.03, 
## [1] 0.4889352
GBSVolatility(53.62, "c", 1135.67, 1120.00,
              as.numeric((as.Date("2018-12-07") - as.Date("2018-11-10")))/365, r = 0.03, 
## [1] 0.371771
```

Assignment

3. Bank

```
Data frame 1: Account
| AcountNo | Name |

Data frame 2: Transaction
| TransactionNo | Date | AccountNo | TransactionType | Amount | Currency |

Data frame 3: Currency to SGD
| Currency | Conversion | Date |
```

TransactionType can be: Withdraw/Deposit/Spend Write follow functions and combine them to form a small program

1. Create 10 accounts with initial random deposit and credit in SGD.
2. Create 3 currencies: CNY, USD, SGD. Download their conversion rate between 2018-07-01 and 2018-09-30.
3. Generate random transaction data for 10 accounts during 2018-07-01 and 2018-09-30. Make it more realistic, deposit is 1-2 times per month, a random number of 3000-5000, any of three currencies. Spend/Withdraw can be any times [0, 60] and any amount, any currencies. Deposit is positive, Withdraw/Spend is negative. Constraint: You can't withdraw more than the deposit, can't spend more than credit + deposit.
4. Generate report for transaction as month-end statement in SGD.

```
{ Client Name }
{ Month }

# Transaction History

Date | TransactionType | Amount | Currency | Deposit Balance | Credit Balance |
     |                 |        |          |                 |                |
     |                 |        |          |                 |                |
     |                 |        |          |                 |                |
-------------------------------------------------------------------------------
                        Month-End Balance | Deposit         | Credit         |

# Summary

TransactionType | Amount |
...
```

Submission:

R Markdown document, containing:

1. describing design
2. Code and explaination of result
3. Example running result.