DATA MANIPULATION WITH DPLYR

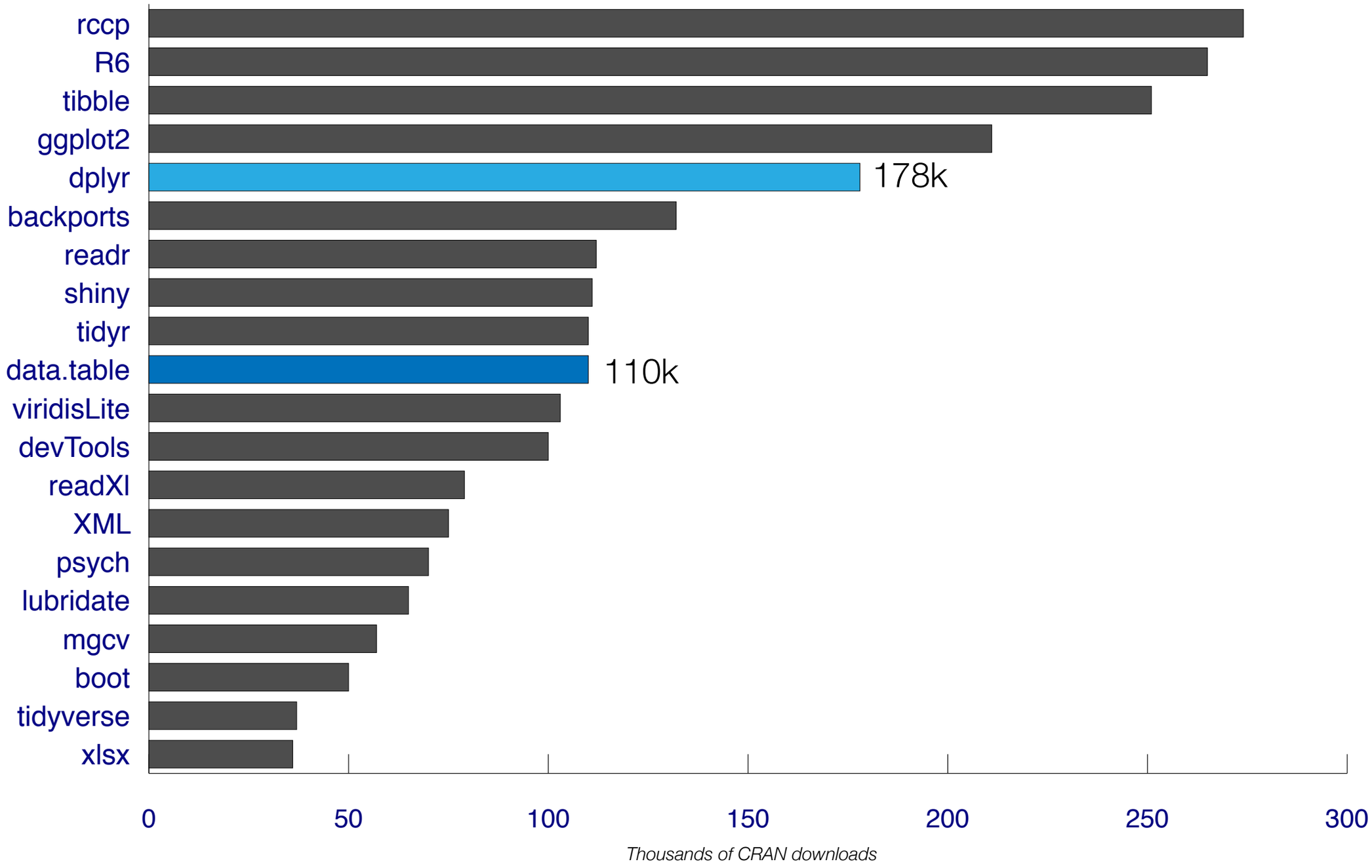
DPLYR RATIONALE

- Data science means manipulating data
- R is a flexible environment

IT STARTS WITH DATA MANIPULATION

POPULAR R LIBRARIES

Top 20 CRAN downloads (direct and indirect) September 2017



source: http://makemeanalyst.com/20-most-popular-r-packages/

DPLYR Vs DATA.TABLE

dplyr advantages

- SQL like syntax..
- Popular

data.table advantages

- Extremely fast
- Perhaps more robust..

CHEAT SHEETS

Available from: https://www.rstudio.com/wp-content/uploads/2015/02/data-wrangling-cheatsheet.pdf

Data Wrangling
with dplyr and tidyr
Cheat Sheet

RStudio

Tidy Data - A foundation for wrangling in R

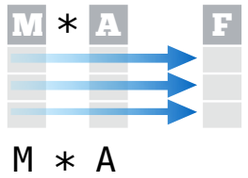
In a tidy data set:

Each **variable** is saved in its own **column**

&

Each **observation** is saved in its own **row**

Tidy data complements R's **vectorized operations**. R will automatically preserve observations as you manipulate variables. No other format works as intuitively with R.



Syntax - Helpful conventions for wrangling

dplyr::**tbl_df(iris)**

Converts data to tbl class. tbl's are easier to examine than data frames. R displays only the data that fits onscreen:

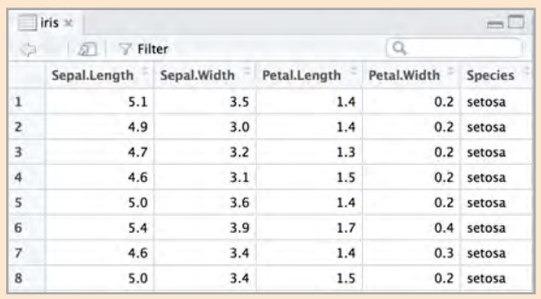
```
Source: local data frame [150 x 5]

   Sepal.Length Sepal.Width Petal.Length
1           5.1         3.5          1.4
2           4.9         3.0          1.4
3           4.7         3.2          1.3
4           4.6         3.1          1.5
5           5.0         3.6          1.4
..          ...         ...          ...
Variables not shown: Petal.Width (dbl),
  Species (fctr)
```

dplyr::**glimpse(iris)**

Information dense summary of tbl data.

utils::**View(iris)**

View data set in spreadsheet-like display (note capital V).



	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3.0	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5.0	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa
7	4.6	3.4	1.4	0.3	setosa
8	5.0	3.4	1.5	0.2	setosa

dplyr::**%>%**

Passes object on left hand side as first argument (or . argument) of function on righthand side.

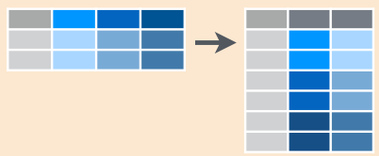
`x %>% f(y)` *is the same as* `f(x, y)`

`y %>% f(x, ., z)` *is the same as* `f(x, y, z )`

"Piping" with %>% makes code more readable, e.g.

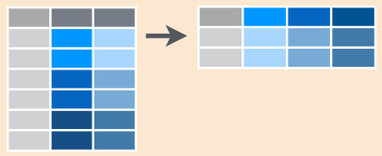
```
iris %>%
  group_by(Species) %>%
  summarise(avg = mean(Sepal.Width)) %>%
  arrange(avg)
```

Reshaping Data - Change the layout of a data set



tidyr::**gather(cases, "year", "n", 2:4)**

Gather columns into rows.



tidyr::**spread(pollution, size, amount)**

Spread rows into columns.

tidyr::**separate(storms, date, c("y", "m", "d"))**

Separate one column into several.

tidyr::**unite(data, col, ..., sep)**

Unite several columns into one.

dplyr::**data_frame(a = 1:3, b = 4:6)**

Combine vectors into data frame (optimized).

dplyr::**arrange(mtcars, mpg)**

Order rows by values of a column (low to high).

dplyr::**arrange(mtcars, desc(mpg))**

Order rows by values of a column (high to low).

dplyr::**rename(tb, y = year)**

Rename the columns of a data frame.

Subset Observations (Rows)

dplyr::**filter(iris, Sepal.Length > 7)**

Extract rows that meet logical criteria.

dplyr::**distinct(iris)**

Remove duplicate rows.

dplyr::**sample_frac(iris, 0.5, replace = TRUE)**

Randomly select fraction of rows.

dplyr::**sample_n(iris, 10, replace = TRUE)**

Randomly select n rows.

dplyr::**slice(iris, 10:15)**

Select rows by position.

dplyr::**top_n(storms, 2, date)**

Select and order top n entries (by group if grouped data).

Logic in R - ?Comparison, ?base::Logic

<	Less than	!=	Not equal to
>	Greater than	%in%	Group membership
==	Equal to	is.na	Is NA
<=	Less than or equal to	!is.na	Is not NA
>=	Greater than or equal to	&, |, !, xor, any, all	Boolean operators

Subset Variables (Columns)

dplyr::**select(iris, Sepal.Width, Petal.Length, Species)**

Select columns by name or helper function.

Helper functions for select - ?select

select(iris, contains("."))

Select columns whose name contains a character string.

select(iris, ends_with("Length"))

Select columns whose name ends with a character string.

select(iris, everything())

Select every column.

select(iris, matches(".t."))

Select columns whose name matches a regular expression.

select(iris, num_range("x", 1:5))

Select columns named x1, x2, x3, x4, x5.

select(iris, one_of(c("Species", "Genus")))

Select columns whose names are in a group of names.

select(iris, starts_with("Sepal"))

Select columns whose name starts with a character string.

select(iris, Sepal.Length:Petal.Width)

Select all columns between Sepal.Length and Petal.Width (inclusive).

select(iris, -Species)

Select all columns except Species.

devtools::install_github("rstudio/EDAWR") for data sets

Learn more with browseVignettes(package = c("dplyr", "tidyr")) • dplyr 0.4.0• tidyr 0.2.0 • Updated: 1/15

Summarise Data

dplyr::**summarise(iris, avg = mean(Sepal.Length))**
Summarise data into single row of values.

dplyr::**summarise_each(iris, funs(mean))**
Apply summary function to each column.

dplyr::**count(iris, Species, wt = Sepal.Length)**
Count number of rows with each unique value of variable (with or without weights).

Summarise uses **summary functions**, functions that take a vector of values and return a single value, such as:

dplyr::**first**
First value of a vector.

dplyr::**last**
Last value of a vector.

dplyr::**nth**
Nth value of a vector.

dplyr::**n**
# of values in a vector.

dplyr::**n_distinct**
# of distinct values in a vector.

IQR
IQR of a vector.

min
Minimum value in a vector.

max
Maximum value in a vector.

mean
Mean value of a vector.

median
Median value of a vector.

var
Variance of a vector.

sd
Standard deviation of a vector.

Group Data

dplyr::**group_by(iris, Species)**
Group data into rows with the same value of Species.

dplyr::**ungroup(iris)**
Remove grouping information from data frame.

iris %>% group_by(Species) %>% summarise(…)
Compute separate summary row for each group.

Make New Variables

dplyr::**mutate(iris, sepal = Sepal.Length + Sepal. Width)**
Compute and append one or more new columns.

dplyr::**mutate_each(iris, funs(min_rank))**
Apply window function to each column.

dplyr::**transmute(iris, sepal = Sepal.Length + Sepal. Width)**
Compute one or more new columns. Drop original columns.

Mutate uses **window functions**, functions that take a vector of values and return another vector of values, such as:

dplyr::**lead**
Copy with values shifted by 1.

dplyr::**lag**
Copy with values lagged by 1.

dplyr::**dense_rank**
Ranks with no gaps.

dplyr::**min_rank**
Ranks. Ties get min rank.

dplyr::**percent_rank**
Ranks rescaled to [0, 1].

dplyr::**row_number**
Ranks. Ties got to first value.

dplyr::**ntile**
Bin vector into n buckets.

dplyr::**between**
Are values between a and b?

dplyr::**cume_dist**
Cumulative distribution.

dplyr::**cumall**
Cumulative `all`

dplyr::**cumany**
Cumulative `any`

dplyr::**cummean**
Cumulative `mean`

cumsum
Cumulative `sum`

cummax
Cumulative `max`

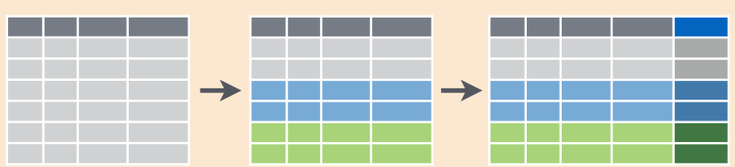
cummin
Cumulative `min`

cumprod
Cumulative `prod`

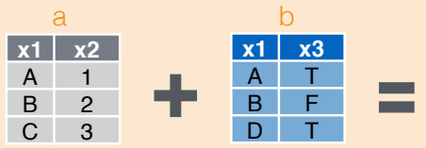
pmax
Element-wise `max`

pmin
Element-wise `min`

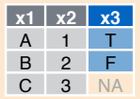
iris %>% group_by(Species) %>% mutate(…)
Compute new variables by group.



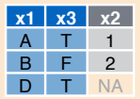
Combine Data Sets



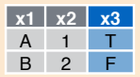
Mutating Joins



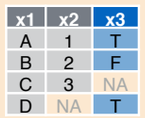
dplyr::**left_join(a, b, by = "x1")**
Join matching rows from b to a.



dplyr::**right_join(a, b, by = "x1")**
Join matching rows from a to b.

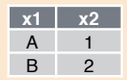


dplyr::**inner_join(a, b, by = "x1")**
Join data. Retain only rows in both sets.

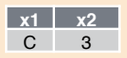


dplyr::**full_join(a, b, by = "x1")**
Join data. Retain all values, all rows.

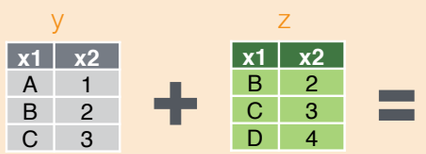
Filtering Joins



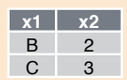
dplyr::**semi_join(a, b, by = "x1")**
All rows in a that have a match in b.



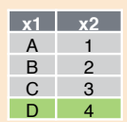
dplyr::**anti_join(a, b, by = "x1")**
All rows in a that do not have a match in b.



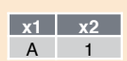
Set Operations



dplyr::**intersect(y, z)**
Rows that appear in both y and z.

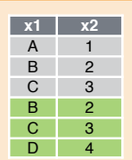


dplyr::**union(y, z)**
Rows that appear in either or both y and z.

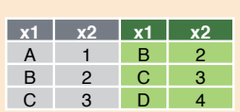


dplyr::**setdiff(y, z)**
Rows that appear in y but not z.

Binding



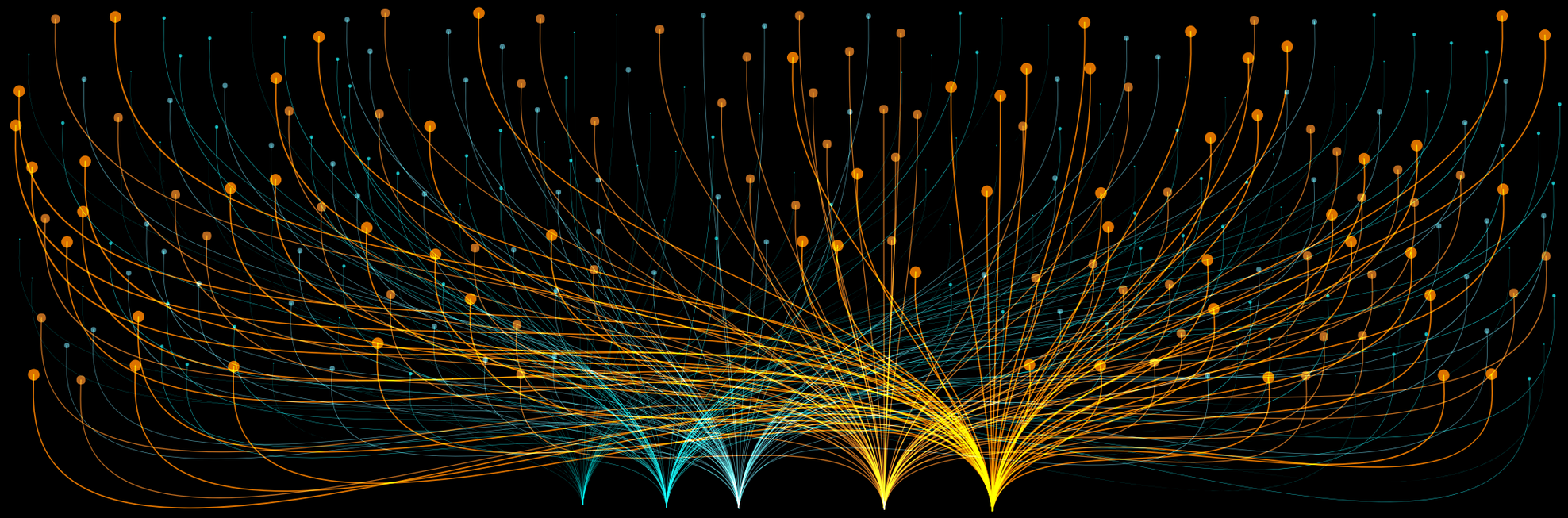
dplyr::**bind_rows(y, z)**
Append z to y as new rows.



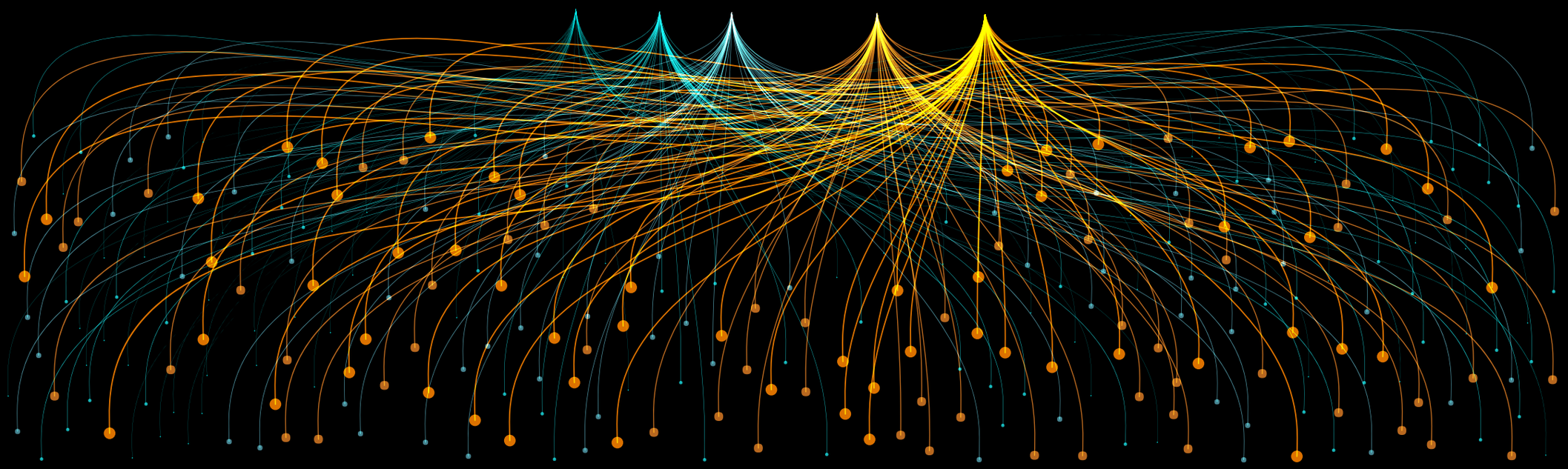
dplyr::**bind_cols(y, z)**
Append z to y as new columns.
Caution: matches rows by position.

devtools::install_github("rstudio/EDAWR") for data sets

Learn more with browseVignettes(package = c("dplyr", "tidyr")) • dplyr 0.4.0• tidyr 0.2.0 • Updated: 1/15

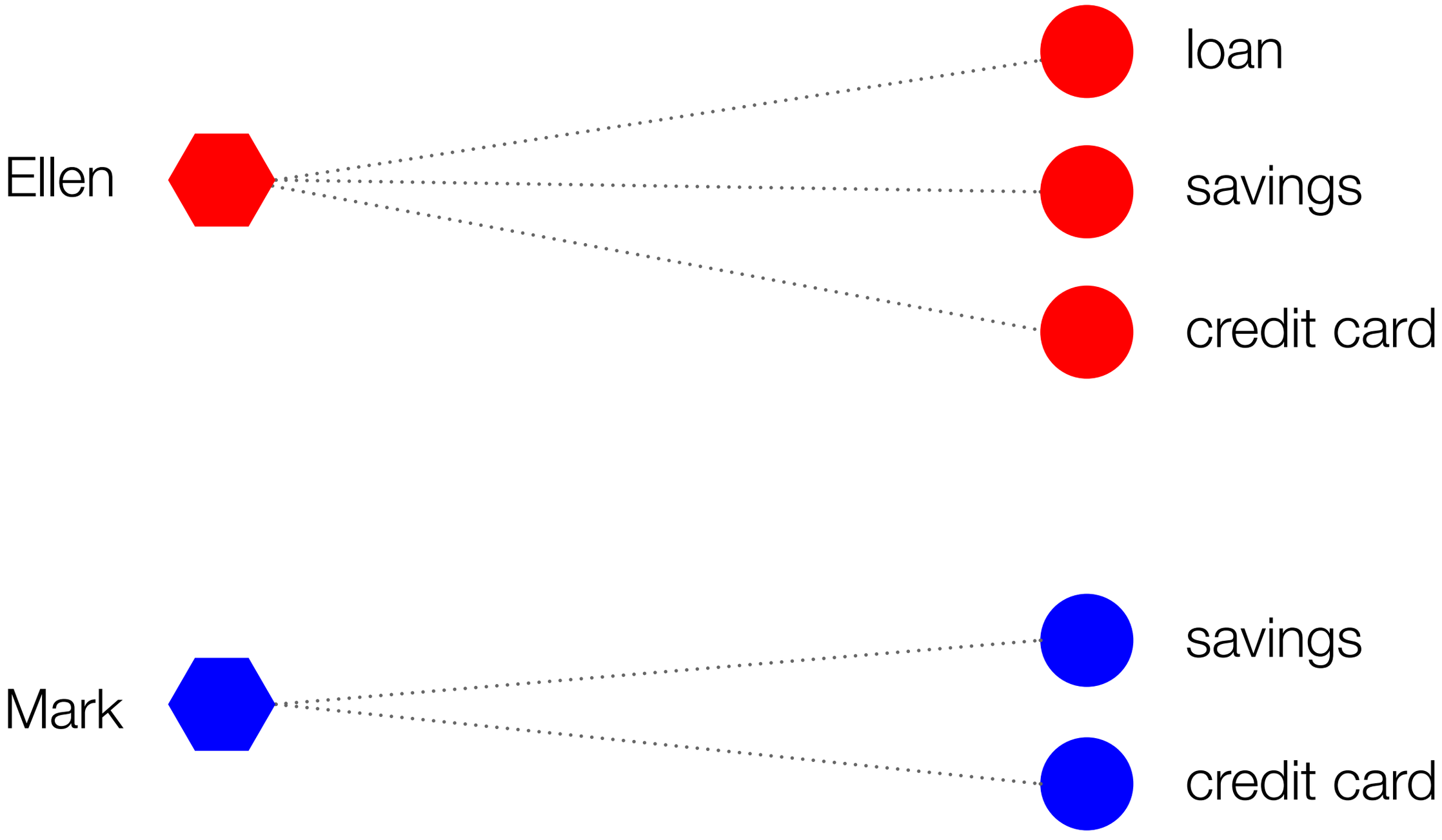


EXAMPLE DATA



ONE TO MANY

One customer to <u>many</u> accounts



CUSTOMER TABLE

cust_no (pk)	name	birthdate	gender	address
10	andrew	1980	m	north
15	andrew	1970	m	south
20	mark	1985	m	north
30	ellen	1990	f	south
40	cathy	1987	f	north
50	megan	1978	f	south
60	colin	1992	m	north
70	trung	1990	m	north

ACCOUNTS TABLE

acct_no (pk)	cust_num (fk)	type	balance	name	birthdate
A	30	loan	400	ellen	1990
B	40	savings	80	cathy	1987
C	30	savings	200	ellen	1990
D	50	savings	400	megan	1978
E	60	loan	90	colin	1992
F	10	loan	200	andrew	1980
G	60	credit_card	120	colin	1992
H	60	savings	40	colin	1992
I	20	credit_card	50	mark	1985
J	40	term_deposit	200	cathy	1987
K	50	loan	300	megan	1978
L	20	savings	300	mark	1985
M	30	credit_card	50	ellen	1990
N	15	savings	20	andrew	1970

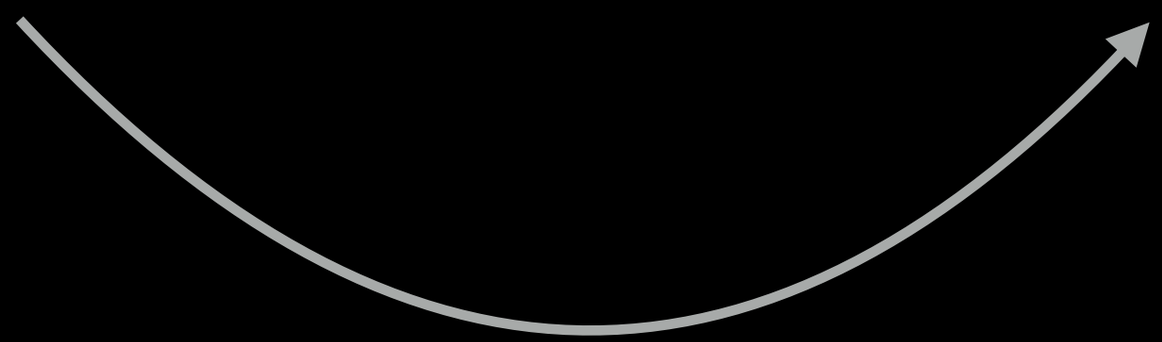
CODE EXAMPLES

MAGRITTR REVISION [a]

replace letters “a” with “” — demonstrates “.” operator*

```r
# syntax without magrittr
gsub("a", "*", df_customer$name)
```

```r
# syntax with magrittr
# using the "." if not the first argument
df_customer$name %>% gsub("a", "*", .)
```



MAGRITTR REVISION [b]

add “_suffix” to each customer name

```r
# following statements are equivalent
paste(df_customer$name, "_suffix")
```

```r
# syntax with magrittr – first argument inserted automatically
df_customer$name %>% paste(“_suffix")
```

DPLYR VERB STRUCTURE

*dplyr verbs have the table name as **first** argument*

```r
# following statements are equivalent
dplyr::select(df_customer, name, birthdate)
```

```r
# equivalent with magrittr
df_customer %>% dplyr::select(name, birthdate)
```

RESULTS

birthdate	name
1980	andrew
1970	andrew
1985	mark
1990	ellen
1987	cathy
1978	megan
1992	colin
1990	trung

COMPARISON TO SQL

```
# SQL Syntax


SELECT name, birthdate
FROM df_customer
ORDER BY birthdate
```

DPLYR EQUIVALENT

```r
# Equivalent using dplyr


df_customer %>%
  select(name, birthdate) %>%
  arrange(birthdate)
```

FLEXIBLE OPERATION ORDER

```r
# equivalent operation - flip verb order

df_customer %>%
  arrange(birthdate) %>%
  select(name, birthdate)
```

RESULTS

name	birthdate
andrew	1970
megan	1978
andrew	1980
mark	1985
cathy	1987
ellen	1990
trung	1990
colin	1992

ADD A CALCULATED COLUMN

Using mutate()

```
# add a calculated ‘age’ column and then sort by
# descending order
df_customer %>%
  mutate(age = 2018 - birthdate) %>%
  arrange(desc(age))
```

RESULTS

cust_no	name	birthdate	gender	address	age
15	andrew	1970	m	south	48
50	megan	1978	f	south	40
10	andrew	1980	m	north	38
20	mark	1985	m	north	33
40	cathy	1987	f	north	31
30	ellen	1990	f	south	28
70	trung	1990	m	north	28
60	colin	1992	m	north	26

AGGREGATION - NO GROUPS

```r
# calculate average birthdate for all rows
```

```r
df_customer %>%

  summarise(av_birth_date = mean(birthdate))
```

RESULTS

av_birth_date

1984

AGGREGATION WITH GROUPS

```r
# calculate mean age by gender

df_customer %>%
  mutate(age = 2018 - birthdate) %>%
  group_by(gender) %>%
  summarise(av_age = mean(age))
```

RESULTS

gender	av_age
f	33.0
m	34.6

COERCION TO TIBBLE

```
# Some dplyr verbs implicitly coerce to a Tibble.  Tibble is a
type of data.frame that has some better print functions
especially for large data.frames. The following explicitly
converts to Tibble and then back to data.frame
```

```
df_customer %>%
  tibble::as_tibble() %>%
  base::as_as.data.frame()
```

TWO TABLE VERBS — INNER JOIN

```r
# Use one primary key and foreign key to join the two
# tables: df_customer and df_account
df_customer %>%
  inner_join(df_account,
             by = c("cust_no" = "cust_num"))
```

RESULTS

cust_no	name.x	birthdate.x	gender	address	account_no	type	balance	name.y	birthdate.y
10	andrew	1980	m	north	F	loan	200	andrew	1980
15	andrew	1970	m	south	N	savings	20	andrew	1970
20	mark	1985	m	north	I	credit_card	50	mark	1985
20	mark	1985	m	north	L	savings	300	mark	1985
30	ellen	1990	f	south	A	loan	400	ellen	1990
30	ellen	1990	f	south	C	savings	200	ellen	1990
30	ellen	1990	f	south	M	credit_card	50	ellen	1990
40	cathy	1987	f	north	B	savings	80	cathy	1987
40	cathy	1987	f	north	J	term_deposit	200	cathy	1987
50	megan	1978	f	south	D	savings	400	megan	1978
50	megan	1978	f	south	K	loan	300	megan	1978
60	colin	1992	m	north	E	loan	90	colin	1992
60	colin	1992	m	north	G	credit_card	120	colin	1992
60	colin	1992	m	north	H	savings	40	colin	1992

DESELECTING COLUMNS

```
# We want to exclude two columns from df_customer

df_customer %>%
select(-c(name, birthdate)) %>%
inner_join(df_account,
           by = "cust_no" = “cust_num")
```

RESULTS

cust_no	gender	address	account_no	type	balance	name	birthdate
10	m	north	F	loan	200	andrew	1980
15	m	south	N	savings	20	andrew	1970
20	m	north	I	credit_card	50	mark	1985
20	m	north	L	savings	300	mark	1985
30	f	south	A	loan	400	ellen	1990
30	f	south	C	savings	200	ellen	1990
30	f	south	M	credit_card	50	ellen	1990
40	f	north	B	savings	80	cathy	1987
40	f	north	J	term_deposit	200	cathy	1987
50	f	south	D	savings	400	megan	1978
50	f	south	K	loan	300	megan	1978
60	m	north	E	loan	90	colin	1992
60	m	north	G	credit_card	120	colin	1992
60	m	north	H	savings	40	colin	1992

ANTI-JOIN

```r
# What customers do not have accounts.

# Joining using multiple columns
```

```r
df_customer %>%
  anti_join(df_account,
            by = c("name" = "name",
                   "birthdate = "birthdate"))
```

RESULTS

cust_no	name	birthdate	gender	address
70	trung	1990	m	north

SELECTING DISTINCT ROWS

```r
# The following two statements are equivalent

df_account %>% distinct(name, birthdate)
```

```r
df_account %>% select(name, birthdate) %>%
               distinct()
```

RESULTS

name	birthdate
ellen	1990
cathy	1987
megan	1978
colin	1992
andrew	1980
mark	1985
andrew	1970

FILTERING USING EXPRESSIONS

```r
# northern men
df_customer %>%

 filter(address == "north" &  gender == "m")
```

```r
# this is the same as the above
 df_customer %>%

  filter(address == ) %>%

  filter(gender == "m")
```

FILTERING USING VECTORS

```
# What is the total account balance for
Cathy, Mark & Megan

df_account %>%
  filter(name %in% c("cathy", "mark", “megan")) %>%
  summarise(total_balance = sum(balance))
```

RESULTS

total_balance
1330

VECTOR NEGATION

```r
# What is the total account balance for the rest

df_account %>%
filter(!name %in% c("cathy", "mark", “megan")) %>%
summarise(total_balance = sum(balance))
```

RESULTS

total_balance
1120

SLICING GROUPS

```
# For each customer what is the account with
# the highest value
# n() counts the number of rows in each group

df_account %>%
  group_by(cust_num) %>%
  arrange(balance) %>%
  slice(n())
```

RESULTS

account_no	cust_num	type	balance	name	birthdate
F	10	loan	200	andrew	1980
N	15	savings	20	andrew	1970
L	20	savings	300	mark	1985
A	30	loan	400	ellen	1990
J	40	term_deposit	200	cathy	1987
D	50	savings	400	megan	1978
G	60	credit_card	120	colin	1992

RENAMING COLUMNS

```r
# Select two columns

# and rename them.

df_customer %>%

  select(name, birthdate) %>%

  rename(new_name = name, new_birthdate = birthdate))
```

ADVANCED FUNCTIONS

ADVANCED SLICING

```r
# For customers with 3 or more accounts
# list the smallest and largest accounts

df_account %>%
  group_by(cust_num) %>%
  filter(n() >= 3) %>%
  arrange(balance) %>%
  slice(c(1, n()))
```

RESULTS

account_no	cust_num	type	balance	name	birthdate
M	30	credit_card	50	ellen	1990
A	30	loan	400	ellen	1990
H	60	savings	40	colin	1992
G	60	credit_card	120	colin	1992

ADVANCED GROUP OPERATIONS

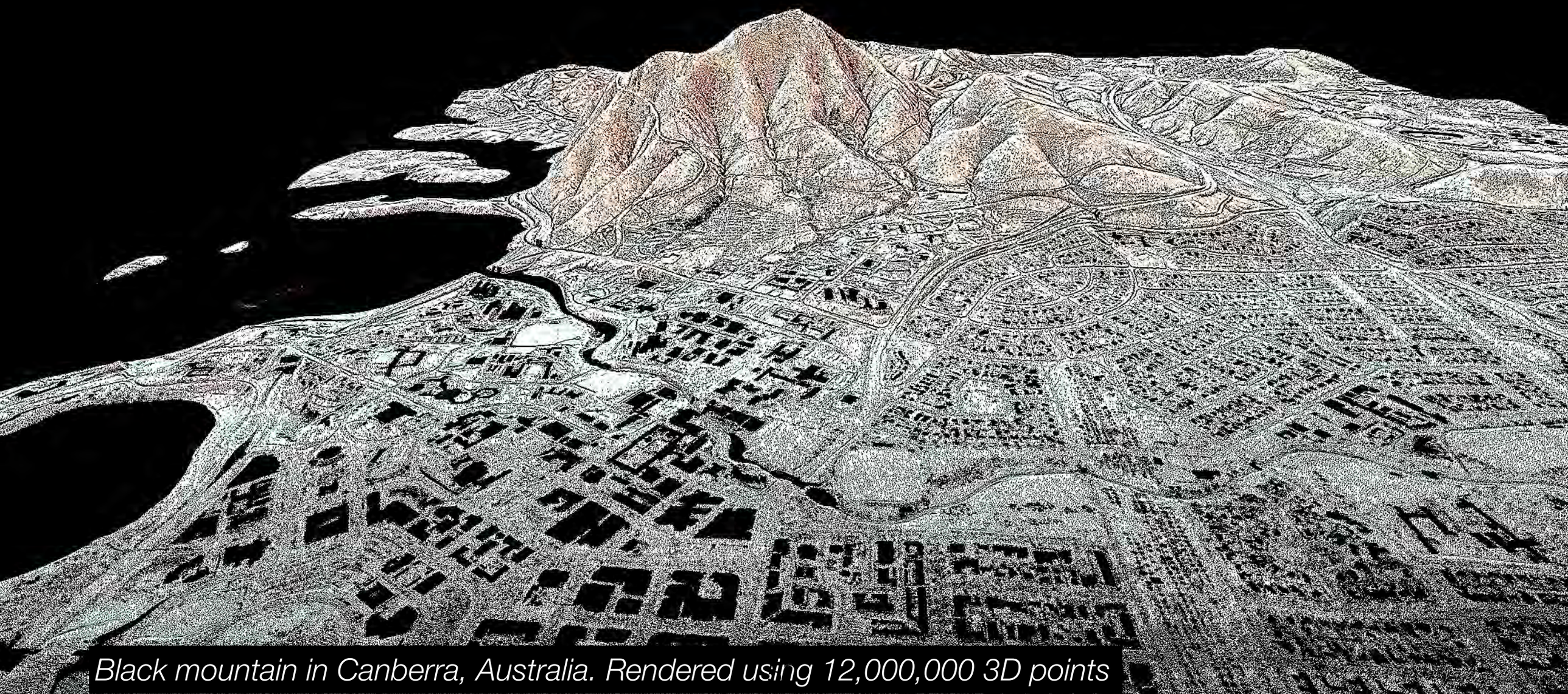
```r
# Get all accounts associated with a customer who has
# a loan account

df_account %>%
  group_by(cust_num) %>%
  filter(any(type == "loan")) %>%
  arrange(cust_num)
```

RESULTS

account_no	cust_num	type	balance	name	birthdate
F	10	loan	200	andrew	1980
A	30	loan	400	ellen	1990
C	30	savings	200	ellen	1990
M	30	credit_card	50	ellen	1990
D	50	savings	400	megan	1978
K	50	loan	300	megan	1978
E	60	loan	90	colin	1992
G	60	credit_card	120	colin	1992
H	60	savings	40	colin	1992

WIDE AND LONG FORMATS

Yes! you can even process process LIDAR data using dplyr



Black mountain in Canberra, Australia. Rendered using 12,000,000 3D points

LONG TO WIDE

And back again using tidyr::spread() and tidyr::gather()

```
# lets use account type as column headings
library(tidyr)

df_account_wide <-
 df_account %>%
  mutate(uniq_name = paste0(name,"_", birthdate)) %>%
  select(uniq_name, type, balance) %>%
  tidyr::spread(key = type, value = balance, fill = 0)
```

RESULTS

uniq_name	credit_card	loan	savings	term_deposit
andrew_1970	0	0	20	0
andrew_1980	0	200	0	0
cathy_1987	0	0	80	200
colin_1992	120	90	40	0
ellen_1990	50	400	200	0
mark_1985	50	0	300	0
megan_1978	0	300	400	0

WIDE TO LONG

Using tidyr::gather()

```
# go from wide format to long; sample 10 rows


 set.seed(123)
df_account_wide %>%
  tidyr::gather(key = type,
                value = value,
                -unique_name) %>%
  sample_n(10)
```

RESULTS

uniq_name	type	value
andrew_1980	loan	200
andrew_1970	term_deposit	0
colin_1992	loan	90
andrew_1980	term_deposit	0
colin_1992	term_deposit	0
andrew_1980	credit_card	0
ellen_1990	loan	400
ellen_1990	savings	200
mark_1985	term_deposit	0
megan_1978	term_deposit	0

NON STANDARD EVALUATION

NON STANDARD EVALUATION

Saves typing do not have to use quotes

```
# Non standard evaluation - no quotes
 df_customer %>%
   select(name, birthdate)
```

```
# Standard evaluation - uses quotes (note the underscore)
   df_customer %>%
    select_("name", "birthdate")
```

NON STANDARD Vs STANDARD EVALUATION

Non standard evaluation is useful for interactive programming as it saves time.

But what about programmatically specifying dplyr's arguments….

STANDARD EVALUATION

A simple example

```
# Create a simple list of column names
lst_names <- c("name", "birthdate") %>% lapply(as.name)

# Set the .dots argument equal to the list
df_customer %>% select_(.dots = lst_names)
```

RESULT

name	birthdate
andrew	1980
andrew	1970
mark	1985
ellen	1990
cathy	1987
megan	1978
colin	1992
trung	1990

A MORE USEFUL EXAMPLE [1]

Firstly *create a more useful data set by joining the two tables*

```
df_data <- df_customer %>%
  select(-c(name, birthdate)) %>%
  inner_join(df_account,
             by = c("cust_no" = "cust_num"))
```

RESULT

cust_no	gender	address	account_no	type	balance	name	birthdate
10	m	north	F	loan	200	andrew	1980
15	m	south	N	savings	20	andrew	1970
20	m	north	I	credit_card	50	mark	1985
20	m	north	L	savings	300	mark	1985
30	f	south	A	loan	400	ellen	1990
30	f	south	C	savings	200	ellen	1990
30	f	south	M	credit_card	50	ellen	1990
40	f	north	B	savings	80	cathy	1987
40	f	north	J	term_deposit	200	cathy	1987
50	f	south	D	savings	400	megan	1978
50	f	south	K	loan	300	megan	1978
60	m	north	E	loan	90	colin	1992
60	m	north	G	credit_card	120	colin	1992
60	m	north	H	savings	40	colin	1992

A MORE USEFUL EXAMPLE [2]

Secondly *create a standard evaluation function*

```
fn_demo_dots <- function(. . .) {
    lst_group_by <- list(. . .) %>% lapply(as.name)

    df_data %>%
      group_by_(.dots = list_group_by) %>%
      summarise(total = sum(balance))
}
```

A MORE USEFUL EXAMPLE [3]

Finally *apply the function*

```
# group_by address and gender
```

```
fn_demo_dots("address","gender")
```

RESULT

address	gender	total
north	f	280
north	m	800
south	f	1350
south	m	20

A MORE USEFUL EXAMPLE [4]

Apply the function again

```
# group_by type
fn_demo_dots("type")
```

For more complex usage of using standard evaluation with dplyr see the lazyeval or the rlang libraries

RESULT

type	total
credit_card	220
loan	990
savings	1040
term_deposit	200

LAZYEVAL EXAMPLE [1]

```r
# filter table where (loan) type == str_type

library(lazyeval)

fn_filter_account <- function(df, str_type) {
  filter_condition <- lazyeval::interp(~x == y, x =
   as.name("type"), y = str_type)
  df_rtn <- df %>% filter_(filter_condition)
  return(df_rtn)
}
```

LAZYEVAL EXAMPLE [2]

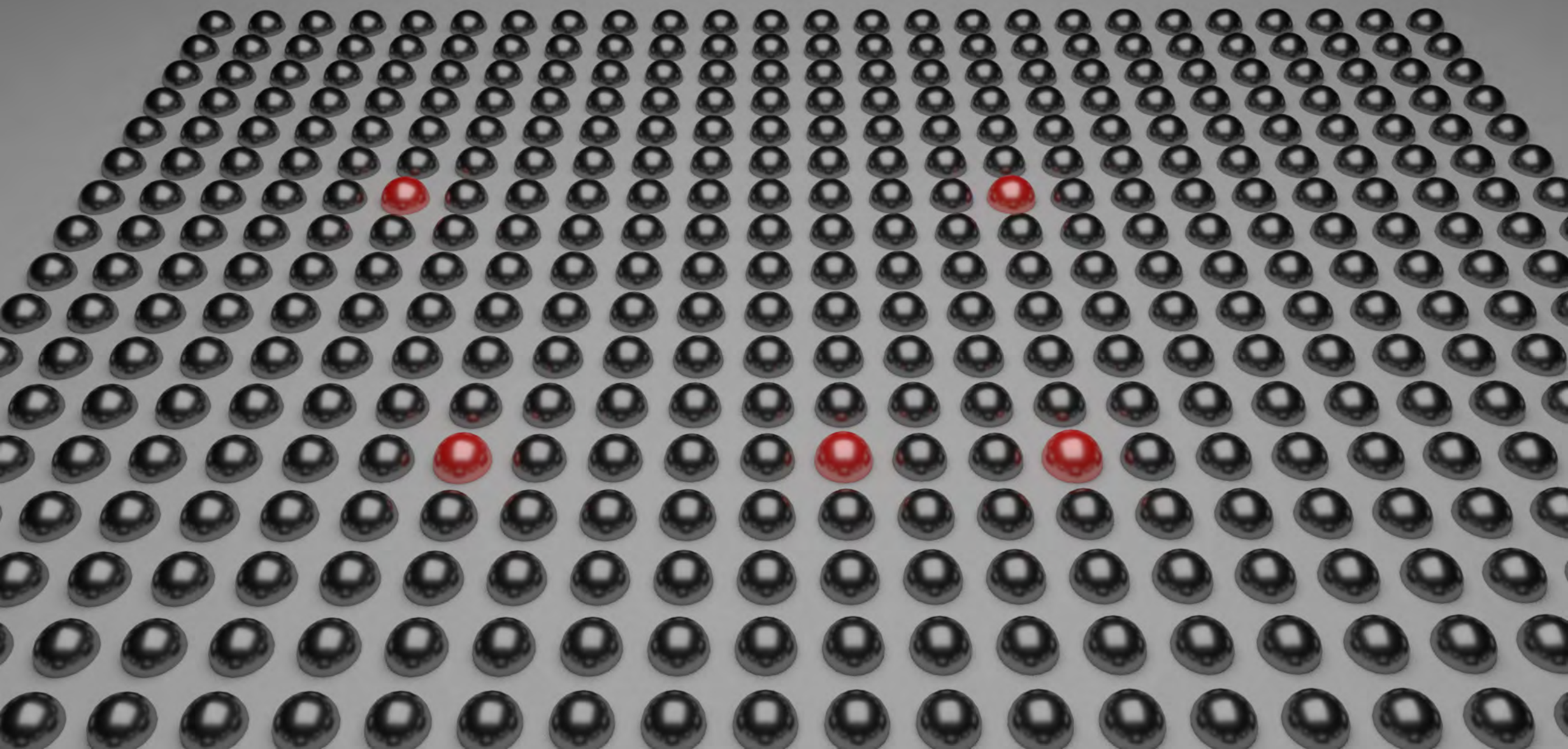
```
# filter the accounts table by: type == loan

# call the function we created previously
```

```
fn_filter_account(df_account, "loan")
```

RESULT

account_no	cust_num	type	balance	name	birthdate
A	30	loan	400	ellen	1990
E	60	loan	90	colin	1992
F	10	loan	200	andrew	1980
K	50	loan	300	megan	1978

MULTIPLE ROWS FROM GROUPS



MULTIPLE ROWS FROM A GROUP

Using do()

```
# previously we only obtain 1 row per group.

# Now, we get multiple rows from each group
```

```
df_data %>%
  group_by(type) %>%
  do(head(., 2))
```

RESULT

cust_no	gender	address	account_no	type	balance	name	birthdate
20	m	north	I	credit_card	50	mark	1985
30	f	south	M	credit_card	50	ellen	1990
10	m	north	F	loan	200	andrew	1980
30	f	south	A	loan	400	ellen	1990
15	m	south	N	savings	20	andrew	1970
20	m	north	L	savings	300	mark	1985
40	f	north	J	term_deposit	200	cathy	1987

MORE COMPLEX EXAMPLE

Fit a linear model to each group using do()

```
# regress balance against birthdate

df_models <- df_data %>%
   group_by(type) %>%
   do(mod = lm(balance ~ birthdate, data = .))


# problem is how to extract results

df_models
```

RESULT

Each row contains an S3 model

type	mod
credit_card	<S3: lm>
loan	<S3: lm>
savings	<S3: lm>
term_deposit	<S3: lm>

EXTRACTING LIST INFORMATION [1]

broom: "tidying statistical models into data.frames"

```
# broom::glance() returns one row per data.frame
df_models %>%
  broom::glance(mod)
```

RESULT

Selection of columns - output of broom::glance()

type	r.squared	sigma	statistic	p.value	AIC	BIC	df.residual
credit_card	0.51	39.62	1.08	0.48	33.29	30.59	1
loan	0.02	160.59	0.05	0.83	55.21	53.36	2
savings	0.001	171.69	0.01	0.93	82.34	81.71	4
term_deposit	0	NA	NA	NA	NA	NA	0

EXTRACTING LIST INFORMATION [2]

broom: "tidying statistical models into data.frames"

```
# broom::tidy() returns multiple rows per data.frame

df_models %>%

  broom::tidy(mod)
```

RESULT

Output of broom::tidy()

type	term	estimate	std.error	statistic	p.value
credit_card	(Intercept)	-15991.66	15458.57	-1.03	0.48
credit_card	birthdate	8.07	7.77	1.039	0.48
loan	(Intercept)	6551.21	26204.00	0.25	0.82
loan	birthdate	-3.17	13.20	-0.240	0.83
savings	(Intercept)	1761.81	18434.69	0.095	0.92
savings	birthdate	-0.80	9.29	-0.086	0.93
term_deposit	(Intercept)	200	NA	NA	NA

END