

データハンドリング系

鈴木瑞人

東京大学大学院 新領域創成科学研究科

メディカル情報生命専攻

博士課程1年

今回よく出てくる人物紹介

Hadley Wickham氏

<http://hadley.nz/>



Who is Hadley Wickham?

- Chief Scientist at RStudio
- Adjunct Professor of Statistics at the University of Auckland, Stanford University, and Rice University.

TEACHING

If you'd like to learn more about what I do, and how to use R effectively, I'd recommend starting with one of my books:

- [R for Data Science](#), with Garrett Golemund, introduces the key tools for doing data science with R.
- [ggplot2: elegant graphics for data analysis](#) shows you how to use ggplot2 to create graphics that help you understand your data.
- [Advanced R](#) helps you master R as a programming language, teaching you what makes R tick.
- [R packages](#) teaches good software engineering practices for R, using packages for bundling, documenting, and testing your code.

I also teach in person workshops from time-to-time; see the [RStudio workshops page](#) for more details.

TEACHING

If you'd like to learn more about what I do, and how to use R effectively, I'd recommend starting with one of my books:

- [R for Data Science](#), with Garrett Golemund, introduces the key tools for doing data science with R.
- [ggplot2: elegant graphics for data analysis](#) shows you how to use ggplot2 to create graphics that help you understand your data.
- [Advanced R](#) helps you master R as a programming language, teaching you what makes R tick.
- [R packages](#) teaches good software engineering practices for R, using packages for bundling, documenting, and testing your code.

I also teach in person workshops from time-to-time; see the [RStudio workshops page](#) for more details.

R for Data Science

Welcome

1 Introduction

1.1 What you will learn

1.2 How this book is organised

1.3 What you won't learn

1.4 Prerequisites

1.5 Running R code

1.6 Getting help and learning more

1.7 Acknowledgements

1.8 Colophon

Explore

2 Introduction

3 Data visualisation

4 Workflow: basics

5 Data transformation


☰ 🔍 ⌨ ✍ R for Data Science

1 Introduction

Data science is an exciting discipline that allows you to turn raw data into understanding, insight, and knowledge. The goal of “R for Data Science” is to help you learn the most important tools in R that will allow you to do data science. After reading this book, you’ll have the tools to tackle a wide variety of data science challenges, using the best parts of R.

1.1 What you will learn

Data science is a huge field, and there’s no way you can master it by reading a single book. The goal of this book is to give you a solid foundation in the most important tools. Our model of the tools needed in a typical data science project looks something like this:



TEACHING

If you'd like to learn more about what I do, and how to use R effectively, I'd recommend starting with one of my books:

- [R for Data Science](#), with Garrett Grolemund, introduces the key tools for doing data science with R.
- [ggplot2: elegant graphics for data analysis](#) shows you how to use ggplot2 to create graphics that help you understand your data.
- [Advanced R](#) helps you master R as a programming language, teaching you what makes R tick.
- [R packages](#) teaches good software engineering practices for R, using packages for bundling, documenting, and testing your code.

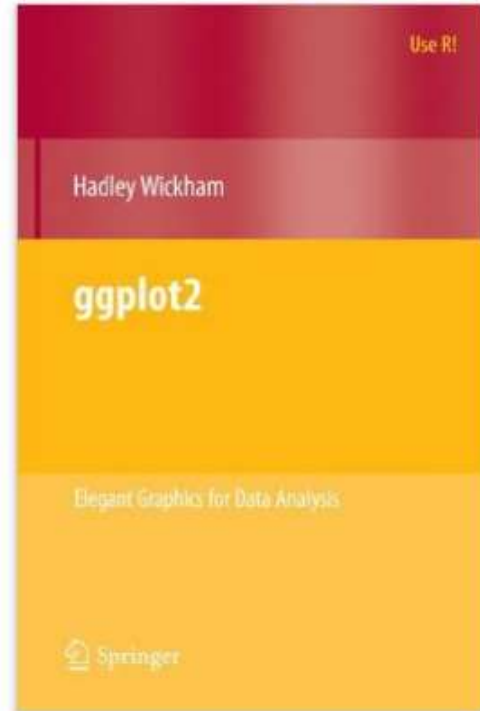
I also teach in person workshops from time-to-time; see the [RStudio workshops page](#) for more details.

ggplot2: Elegant Graphics for Data Analysis (Use R!) 1st ed. 2009. Corr. 3rd printing 2010 Edition

by [Hadley Wickham](#) (Author)

★★★★★ 57 customer reviews

[Look inside](#)



ISBN-13: 978-0387981406

ISBN-10: 0387981403

[Why is ISBN important?](#)

Paperback
from \$50.13

Other Sellers
from \$50.13

More Buying Choices

14 New from \$64.34 | 30 Used from \$50.13

44 used & new from \$50.13

[See All Buying Options](#)

There is a newer edition of this item:



ggplot2: Elegant Graphics for Data Analysis (Use R!)

\$56.99

★★★★★ (57)

In Stock

Primestudent

FREE Two-Day Shipping
For college students

[Learn more](#)

Provides both rich theory and powerful applications

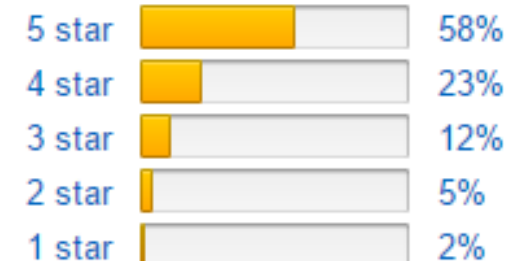
Figures are accompanied by code required to produce them

Full color figures

Customer Reviews

★★★★★ 57

4.3 out of 5 stars



https://www.amazon.com/dp/0387981403/ref=cm_sw_su_dp?tag=ggplot2-20

TEACHING

If you'd like to learn more about what I do, and how to use R effectively, I'd recommend starting with one of my books:

- [R for Data Science](#), with Garrett Golemund, introduces the key tools for doing data science with R.
- [ggplot2: elegant graphics for data analysis](#) shows you how to use ggplot2 to create graphics that help you understand your data.
- [Advanced R](#) helps you master R as a programming language, teaching you what makes R tick.
- [R packages](#) teaches good software engineering practices for R, using packages for bundling, documenting, and testing your code.

I also teach in person workshops from time-to-time; see the [RStudio workshops page](#) for more details.

Want to learn from me in person?
I'm next teaching in [DC, Sep 14-15](#).

Want a physical copy of this material? [Buy a book from amazon!](#).

Contents

[How to contribute](#)

[Edit this page](#)

This is the companion website for “**Advanced R**”, a book in Chapman & Hall's R Series. The book is designed primarily for R users who want to improve their programming skills and understanding of the language. It should also be useful for programmers coming to R from other languages, as it explains some of R's quirks and shows how some parts that seem horrible do have a positive side.

- [Introduction](#)

Foundations

- [Data structures](#)
- [Subsetting](#)
- [Vocabulary](#)
- [Style](#)
- [Functions](#)
- [OO field guide](#)
- [Environments](#)
- [Exceptions and debugging](#)

Functional programming

- [Functional programming](#)
- [Functionals](#)
- [Function operators](#)

Metaprogramming

- [Non-standard evaluation](#)
- [Expressions](#)
- [Domain specific languages](#)

Performant code

- [Performance](#)
- [Profiling](#)
- [Memory](#)
- [Rcpp](#)
- [R's C interface](#)

TEACHING

If you'd like to learn more about what I do, and how to use R effectively, I'd recommend starting with one of my books:

- [R for Data Science](#), with Garrett Golemund, introduces the key tools for doing data science with R.
- [ggplot2: elegant graphics for data analysis](#) shows you how to use ggplot2 to create graphics that help you understand your data.
- [Advanced R](#) helps you master R as a programming language, teaching you what makes R tick.
- [R packages](#) teaches good software engineering practices for R, using packages for bundling, documenting, and testing your code.

I also teach in person workshops from time-to-time; see the [RStudio workshops page](#) for more details.

Want to learn from me in person?
I'm next teaching in [DC](#), [Sep 14-15](#).

Want a physical copy of this
material? [Buy from amazon!](#).

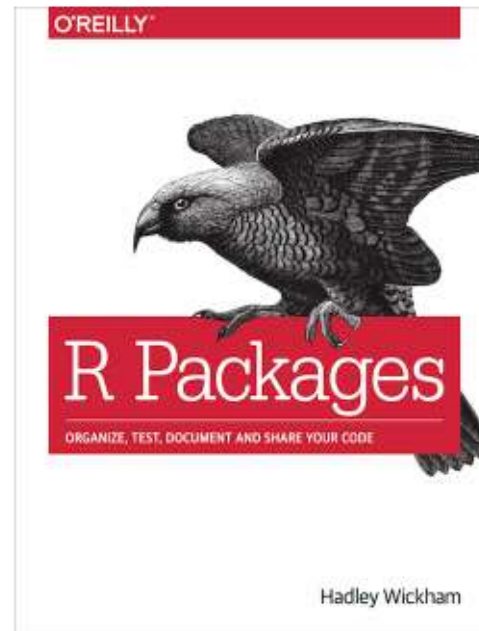
Contents

[How to contribute](#)

[Edit this page](#)

R packages

This is the book site for “**R packages**”. It was published with O'Reilly in April 2015. You can [order](#) a copy from Amazon.



Packages are the fundamental units of reproducible R code. They include reusable R functions, the documentation that describes how to use them, and sample data. In this section you'll learn how to turn your code into packages that others can easily download and use. Writing a package can seem overwhelming at first. So start with the basics and

CODE

Most of my work is in the form of open source R code, which you can find on [my github](#). You can roughly divide my work into three categories: tools for data science, tools for data import, and software engineering tools.

DATA SCIENCE

- [ggplot2](#) for visualising data.
- [dplyr](#) for manipulating data.
- [tidyr](#) for tidying data.
- [stringr](#) for working with strings.
- [lubridate](#) for working with date/times.

DATA IMPORT

- [readr](#) for reading .csv and fwf files.
- [readxl](#) for reading .xls and .xlsx files.
- [haven](#) for SAS, SPSS, and Stata files.
- [httr](#) for talking to web APIs.
- [rvest](#) for scraping websites.
- [xml2](#) for importing XML files.

SOFTWARE ENGINEERING

- [devtools](#) for general package development.
- [roxygen2](#) for in-line documentation.
- [testthat](#) for unit testing

彼の作品には、有名なパッケージが勢ぞろい。
Reshape2など、有名でも載せられていない彼の作品も多数。

<http://hadley.nz/>

本講義資料では、Hadley氏の作品が頻出します。彼に感謝しましょう。

- 彼のパッケージについて、詳しく知りたければ、彼のサイトに行って調べましょう。

データの出力①(復習)

#iris_table_out.csvファイルを出力

```
write.table(iris, "iris_table_out.csv", sep = ",")
```

#iris_table_out.csvファイルを読み込み

```
result1 <- read.table("iris_table_out.csv", sep = ",", header = TRUE)
```

#読み込んだ結果の表示

```
head(result1)
```

write.table関数または、read.table関数はセパレータの指定が必要。
この場合はコンマ。


```
> #iris_table_out.csvファイルを出力
> write.table(iris, "iris_table_out.csv", sep = ",")
> #iris_table_out.csvファイルを読み込み
> result1 <- read.table("iris_table_out.csv", sep = ",", header = TRUE)
> #読み込んだ結果の表示
> head(result1)
```

	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

```
, ,
```

データの入出力②(復習)

#iris_csv_out.csvファイルを出力

```
write.csv(iris, "iris_csv_out.csv")
```

#iris_csv_out.csvファイルを読み込み

```
result2 <- read.csv("iris_csv_out.csv", header = TRUE)
```

#読み込んだ結果の表示

```
head(result2)
```

write.csv関数または、read.csv関数はセパレータの指定が不要。

```
> #iris_csv_out.csvファイルを出力
> write.csv(iris, "iris_csv_out.csv")
> #iris_csv_out.csvファイルを読み込み
> result2 <- read.csv("iris_csv_out.csv", header = TRUE)
> #読み込んだ結果の表示
> head(result2)
```

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

行名を消去。

#iris_csv2_out.csvファイルを出力

```
write.csv(iris, "iris_csv2_out.csv", row.names=F)
```

#iris_csv2_out.csvファイルを読み込み

```
result3 <- read.csv("iris_csv2_out.csv", header = TRUE)
```

#読み込んだ結果の表示

```
head(result3)
```

```
> #iris_csv_out.csvファイルを出力
> write.csv(iris, "iris_csv2_out.csv", row.names=F)
> #iris_csv2_out.csvファイルを読み込み
> result3 <- read.csv("iris_csv2_out.csv", header = TRUE)
> #読み込んだ結果の表示
> head(result3)
```

	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

```
.
```

大きなデータを読み込む場合。

- 2008年の米国のフライトデータを読み込んでみる。
- データの大きさは、658MB。
- 航空機の発着に関する情報を収録した29列の表データ。
- データはデータExpo2009の[サイトからダウンロード](#)し、read.csv関数で読み込む。
- 解凍にはR.utilsパッケージのbunzip2関数を使用する。

パッケージのダウンロード

```
install.packages("R.utils", quiet = TRUE, dependencies=T)  
library(R.utils)
```

今回使用するデータは、bzip2形式で圧縮されているため、
R.utilsパッケージのbunzip2関数を使用して解凍する。

ディレクトリ作成とデータのダウンロード

#カレントディレクトリ確認

getwd()

ディレクトリ作成とデータのダウンロード(getwd()で確認したカレントディレクトリ下にdataというフォルダを作成)

dir.create("C:/Users/Administrator/Documents/data")

#dataというフォルダの下にDataExpo2009というフォルダを作成

dir.create("data/DataExpo2009")

#データのダウンロード

download.file("http://stat-computing.org/dataexpo/2009/2008.csv.bz2",
"data/DataExpo2009/2008.csv.bz2")

データの解凍と読み込み

bunzip2関数を用いたデータの解凍

```
bunzip2("data/DataExpo2009/2008.csv.bz2")
```

データの読み込みと速度計測

```
system.time(al.2008.df <- read.csv("data/DataExpo2009/2008.csv", as.is = TRUE))
```

csvファイルを読み込むときに、数値データの他に、何か文字等が混ざっていると自動的にfactor型として読み込まれるときがある。それを防ぐためには、as.is=TRUEを入れておくとよい。

```
> getwd()
[1] "C:/Users/Administrator/Documents"
> dir.create("C:/Users/Administrator/Documents/data")
> dir()
[1] "data"          "desktop.ini"  "My Music"     "My Pictures"  "My Videos"
> dir.create("data/DataExpo2009")
> download.file("http://stat-computing.org/dataexpo/2009/2008.csv.bz2",
+   "data/DataExpo2009/2008.csv.bz2")
trying URL 'http://stat-computing.org/dataexpo/2009/2008.csv.bz2'
Content type 'application/x-bzip2' length 113753229 bytes (108.5 MB)
downloaded 108.5 MB

> bunzip2("data/DataExpo2009/2008.csv.bz2")
> system.time(al.2008.df <- read.csv("data/DataExpo2009/2008.csv", as.is = TRUE))
   user  system elapsed 
71.77    3.08    74.94
```

データの読み込みに74.94秒かかっている。。もっと早く読み込めないか。。

read.csv関数より高速にデータを読み込む関数

- readrパッケージ(Hadley Wickham氏作)のread_csv関数

readrパッケージのダウンロード

```
install.packages("readr", quiet = TRUE, dependencies=T)  
library(readr)
```

データの読み込み

2008年のフライトデータの読み込み

```
system.time(al.2008.readr <- read_csv("data/DataExpo2009/2008.csv"))
```

```
user  system elapsed  
14.34    1.55    18.90
```

18.9秒！！

先ほどの、74.94秒より4倍高速！

読み込んだ中身を見てみる。

#先頭3行

```
head(al.2008.readr, 3)
```



```

> #先頭3行
> head(al.2008.readr, 3)
# A tibble: 3 × 29
   Year Month DayOfMonth DayOfWeek DepTime CRSDepTime ArrTime CRSArrTime
  <int> <int>      <int>      <int>   <int>      <int>    <int>      <int>
1  2008     1         3         4    2003      1955     2211      2225
2  2008     1         3         4     754       735     1002      1000
3  2008     1         3         4     628       620      804       750
# ... with 21 more variables: UniqueCarrier <chr>, FlightNum <int>, TailNum <chr>,
#   ActualElapsedTime <int>, CRSElapsedTime <int>, AirTime <int>, ArrDelay <int>,
#   DepDelay <int>, Origin <chr>, Dest <chr>, Distance <int>, TaxiIn <int>,
#   TaxiOut <int>, Cancelled <int>, CancellationCode <chr>, Diverted <int>,
#   CarrierDelay <int>, WeatherDelay <int>, NASDelay <int>, SecurityDelay <int>,
#   LateAircraftDelay <int>

```

読み込んだ中身を見てみる

#オブジェクトのクラスの確認

```
class(al.2008.readr)
```

```
> #オブジェクトのクラスの確認
> class(al.2008.readr)
[1] "tbl_df"      "tbl"          "data.frame"
```

data.frame以外は見慣れない。。しかし、tbl_dfやtbl型は今後使用するパッケージの関数で使用する型！

読み込んだ中身を見てみる

#各列のデータ型の確認

```
sapply(al.2008.readr, class)
```

> #各列のデータ型の確認

> sapply(al.2008.readr, class)

Year	Month	DayofMonth	DayOfWeek
"integer"	"integer"	"integer"	"integer"
DepTime	CRSDepTime	ArrTime	CRSArrTime
"integer"	"integer"	"integer"	"integer"
UniqueCarrier	FlightNum	TailNum	ActualElapsedTime
"character"	"integer"	"character"	"integer"
CRSElapsedTime	AirTime	ArrDelay	DepDelay
"integer"	"integer"	"integer"	"integer"
Origin	Dest	Distance	TaxiIn
"character"	"character"	"integer"	"integer"
TaxiOut	Cancelled	CancellationCode	Diverted
"integer"	"integer"	"character"	"integer"
CarrierDelay	WeatherDelay	NASDelay	SecurityDelay
"integer"	"integer"	"integer"	"integer"
LateAircraftDelay			
"integer"			

Numericや、Factor型として読み込まれていないので注意！

データを読み込むときのデータ型の指定

- col_types引数で指定する。
- 整数"i"
- 論理値"l"
- 倍精度浮動小数点"d"
- ユーロタイプの不動小数点"e"
- 日付(Y-m-d形式)"D"

もし1,2,3,4,5列目がそれぞれ、文字列、倍精度浮動小数点、整数、論理値、文字列の場合、col_types="cdilc" という指定になる。

すなわち先ほどの読み込みは、

```
al.2008.readr <- read_csv("data/DataExpo2009/2008.csv", col_types="cdilc"))
```









データフレームのハンドリング

データの加工・集計

- ここでは、Rのコアメンバーである、Hadley Wickham氏が作成した、dplyrパッケージを用いる。
- このパッケージは、特定の条件を満たす行や列の抽出グループごとの集計などの処理を高速に行うために開発されたもの。

dplyrパッケージ

Index of /web/packages/dplyr/vignettes

Name	Last modified	Size	Description
 Parent Directory		-	
 data_frames.html	29-Aug-2016 11:12	15K	
 databases.html	29-Aug-2016 11:12	46K	
 hybrid-evaluation.html	29-Aug-2016 11:12	24K	
 index.rds	29-Aug-2016 11:12	322	
 introduction.html	29-Aug-2016 11:12	137K	
 new-sql-backend.html	29-Aug-2016 11:12	16K	
 nse.html	29-Aug-2016 11:12	16K	
 two-table.html	29-Aug-2016 11:12	39K	
 window-functions.html	29-Aug-2016 11:12	75K	

Apache/2.2.22 (Ubuntu) Server at cran.rstudio.com Port 443

Data frame performance

Data frame performance

2016-06-23

One of the reasons that dplyr is fast is that it's very careful about when to make copies. This section describes how this works, and gives you some useful tools for understanding the memory usage of data frames in R.

The first tool we'll use is `dplyr::location()`. It tells us the memory location of three components of a data frame object:

- the data frame itself
- each column
- each attribute

```
location(iris)
#> <0x7fdc68e309a8>
#> Variables:
#> * Sepal.Length: <0x7fdc68f06200>
#> * Sepal.Width: <0x7fdc68f25000>
#> * Petal.Length: <0x7fdc68f25600>
#> * Petal.Width: <0x7fdc68f25c00>
#> * Species: <0x7fdc6843e9e0>
#> Attributes:
#> * names: <0x7fdc68e30940>
#> * row.names: <0x7fdc6843fa00>
#> * class: <0x7fdc688bbb48>
```

It's useful to know the memory address, because if the address changes, then you'll know that R has made a copy. Copies are bad because they take time to create. This isn't usually a bottleneck if you have a few thousand values, but if you have millions or tens of millions of values it starts to take significant amounts of time. Unnecessary copies are also bad because they take up memory.

Databasesとの連携

Databases

2016-06-23

As well as working with local in-memory data like data frames and data tables, dplyr also works with remote on-disk data stored in databases. Generally, if your data fits in memory there is no advantage to putting it in a database: it will only be slower and more hassle. The reason you'd want to use dplyr with a database is because either your data is already in a database (and you don't want to work with static csv files that someone else has dumped out for you), or you have so much data that it does not fit in memory and you have to use a database. Currently dplyr supports the three most popular open source databases (sqlite, mysql and postgresql), and google's bigquery.

Since R almost exclusively works with in-memory data, if you do have a lot of data in a database, you can't just dump it into R. Instead, you'll have to work with subsets or aggregates. dplyr aims to make this task as easy as possible. If you're working with large data, it's also likely that you'll need support to get the data into the database and to ensure you have the right indices for good performance. While dplyr provides some simple tools to help with these tasks, they are no substitute for a local expert.

The motivation for supporting databases in dplyr is that you never pull down the right subset or aggregate from the database on your first try. Usually you have to iterate between R and SQL many times before you get the perfect dataset. But because switching between languages is cognitively challenging (especially because R and SQL are so perilously similar), dplyr helps you by allowing you to write R code that is automatically translated to SQL. The goal of dplyr is not to replace every SQL function with an R function; that would be difficult and error prone. Instead, dplyr only generates `SELECT` statements, the SQL you write most often as an analyst.

To get the most out of this chapter, you'll need to be familiar with querying SQL databases using the `SELECT` statement. If you have some familiarity with SQL and you'd like to learn more, I found [how indexes work in SQLite](#) and [10 easy steps to a complete understanding of SQL](#) to be particularly helpful.

Introduction

Introduction to dplyr

2016-06-23

When working with data you must:

- Figure out what you want to do.
- Describe those tasks in the form of a computer program.
- Execute the program.

The dplyr package makes these steps fast and easy:

- By constraining your options, it simplifies how you can think about common data manipulation tasks.
- It provides simple “verbs”, functions that correspond to the most common data manipulation tasks, to help you translate those thoughts into code.
- It uses efficient data storage backends, so you spend less time waiting for the computer.

This document introduces you to dplyr’s basic set of tools, and shows you how to apply them to data frames.

Other vignettes provide more details on specific topics:

- databases: Besides in-memory data frames, dplyr also connects to out-of-memory, remote databases. And by translating your R code into the appropriate SQL, it allows you to work with both types of data using the same set of tools.
- benchmark-baseball: see how dplyr compares to other tools for data manipulation on a realistic use case.
- window-functions: a window function is a variation on an aggregation function. Where an aggregate function uses n inputs to produce 1 output, a window function uses n inputs to produce n outputs.

<https://cran.rstudio.com/web/packages/dplyr/vignettes/introduction.html>

Window functions and grouped mutate/filter

Window functions and grouped mutate/filter

2016-06-23

A **window function** is a variation on an aggregation function. Where an aggregation function, like `sum()` and `mean()`, takes `n` inputs and return a single value, a window function returns `n` values. The output of a window function depends on all its input values, so window functions don't include functions that work element-wise, like `+` or `round()`. Window functions include variations on aggregate functions, like `cumsum()` and `cummean()`, functions for ranking and ordering, like `rank()`, and functions for taking offsets, like `lead()` and `lag()`.

Window functions are used in conjunction with `mutate` and `filter` to solve a wide range of problems, some of which are shown below:

```
library(Lahman)
batting <- select(tbl_df(Batting), playerID, yearID, teamID, G, AB:H)
batting <- arrange(batting, playerID, yearID, teamID)
players <- group_by(batting, playerID)

# For each player, find the two years with most hits
filter(players, min_rank(desc(H)) <= 2 & H > 0)
# Within each player, rank each year by the number of games played
mutate(players, G_rank = min_rank(G))

# For each player, find every year that was better than the previous year
filter(players, G > lag(G))
# For each player, compute avg change in games played per year
mutate(players, G_change = (G - lag(G)) / (yearID - lag(yearID)))
```

<https://cran.rstudio.com/web/packages/dplyr/vignettes/window-functions.html>

パッケージのロード

```
# dplyr, nycflights13のダウンロード・インストール
install.packages("dplyr", quiet = TRUE, dependencies=T)
#nycflight13パッケージのflightsデータセットを用いる
install.packages("nycflights13", quiet = TRUE, dependencies=T)
#パッケージのロード
library(dplyr)
library(nycflights13)
#nycflights13パッケージでは、データを呼び出すことなく使用可能
#つまりdata(nycflights13) のような宣言が必要ない
```

#クラスの確認
class(flights)


```
> library(nycflights13)
> #クラスの確認
> class(flights)
[1] "tbl_df"      "tbl"         "data.frame"
```

tbl_df型か、tbl型に属しているものは、データを表示させたときに、全体が表示されず、コンソール画面を埋め尽くさないので便利。

#データの先頭の確認
flights

> #データの先頭の確認

> flights

A tibble: 336,776 × 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

... with 336,766 more rows, and 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 <dtm>

data.frame形式から、tbl形式への変更

#tbl_df関数を用いる

```
y <- tbl_df(x)
```

xという、データフレームがあった場合です。
ここではxは具体的にないので、実行しないでください。

dplyrと標準Rの比較

	行の抽出	列の抽出	列の追加	行の並べ替え	データの集約	グループ化処理
dplyr	filter関数	select関数	mutate関数	arrange関数	summerize関数	group_by関数
標準のR	subset関数	subset関数	transform関数	order関数	aggregate関数	tapply関数 by関数

特定の列で条件を指定して抽出

#12月31日のレコードの抽出(AND条件で抽出)

```
filter(flights, month == 12, day == 31)
```

```
> #12月31日のレコードの抽出 (AND条件で抽出)
```

```
> filter(flights, month == 12, day == 31)
```

```
# A tibble: 776 × 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	31	13	2359	14	439	437
2	2013	12	31	18	2359	19	449	444
3	2013	12	31	26	2245	101	129	2353
4	2013	12	31	459	500	-1	655	651
5	2013	12	31	514	515	-1	814	812
6	2013	12	31	549	551	-2	925	900
7	2013	12	31	550	600	-10	725	745
8	2013	12	31	552	600	-8	811	826
9	2013	12	31	553	600	-7	741	754
10	2013	12	31	554	550	4	1024	1027

```
# ... with 766 more rows, and 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 <dtm>
```

特定の列で条件を指定して抽出

#1月または31日のレコードの抽出(OR条件で抽出)

```
filter(flights, month == 1 | day == 31)
```


> #1月または31日のレコードの抽出 (OR条件で抽出)

> filter(flights, month == 1 | day == 31)

A tibble: 32,266 × 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

... with 32,256 more rows, and 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 <dtm>

指定した列の抽出

#年、月、日の抽出

```
select(flights, year, month, day)
```

```
> #年、月、日の抽出
> select(flights, year, month, day)
# A tibble: 336,776 × 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
# ... with 336,766 more rows
```

連続する列の取り出し

```
select(flights, year:day)
```

```
> select(flights, year:day)
# A tibble: 336,776 × 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
# ... with 336,766 more rows
```

一演算子による、列の削除

#年、月、日以外の列の抽出

```
select(flights, -(year:day))
```

> #年、月、日以外の列の抽出

> select(flights, -(year:day))

A tibble: 336,776 × 16

	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier
	<int>	<int>	<dbl>	<int>	<int>	<dbl>	<chr>
1	517	515	2	830	819	11	UA
2	533	529	4	850	830	20	UA
3	542	540	2	923	850	33	AA
4	544	545	-1	1004	1022	-18	B6
5	554	600	-6	812	837	-25	DL
6	554	558	-4	740	728	12	UA
7	555	600	-5	913	854	19	B6
8	557	600	-3	709	723	-14	EV
9	557	600	-3	838	846	-8	B6
10	558	600	-2	753	745	8	AA

... with 336,766 more rows, and 9 more variables: flight <int>, tailnum <chr>,
origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
minute <dbl>, time_hour <dtm>

Warning message:
In as.POSIXlt.POSIXct(x, tz) : unable to identify current timezone 'C':
please set environment variable 'TZ'

mutate関数による列の追加

```
mutate(flights, gain = arr_delay - dep_delay, gain_per_hour =  
gain/(air_time/60))
```



```

> mutate(flights, gain = arr_delay - dep_delay, gain_per_hour = gain/(air_time/60))
# A tibble: 336,776 × 21
   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
# ... with 336,766 more rows, and 13 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 <dtm>, gain <dbl>,
#   gain_per_hour <dbl>

```

arrange関数による、行順番の並び替え

```
arrange(flights, month, arr_delay)
```

```

> arrange(flights, month, arr_delay)
# A tibble: 336,776 × 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     4    1026         1030          -4    1305         1415
2  2013     1     3     941          945          -4    1153         1258
3  2013     1    14    1840         1845          -5    2117         2221
4  2013     1     3    1153         1200          -7    1442         1545
5  2013     1     3    1228         1235          -7    1503         1606
6  2013     1    27    1845         1850          -5    2110         2212
7  2013     1     3    1605         1610          -5    1816         1917
8  2013     1     3    1857         1900          -3    2200         2301
9  2013     1     4    1219         1221          -2    1454         1555
10 2013     1     6     812          819          -7    1102         1203
# ... with 336,766 more rows, and 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 <dtm>

```

arrange関数による行の降順で並べ替え

#desc関数を用いることで、降順に
arrange(flights, desc(arr_delay))

```

> arrange(flights, desc(arr_delay))
# A tibble: 336,776 × 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     7    22    2257           759          898     121           1026
9  2013    12     5     756          1700          896    1058           2020
10 2013     5     3    1133          2055          878    1250           2215
# ... with 336,766 more rows, and 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 <dtm>

```

summarise関数による統計量算出

```
summarise(flights, DepDelay = mean(dep_delay, na.rm = TRUE),  
ArrDelay = mean(arr_delay, na.rm = TRUE))
```

```
# A tibble: 1 × 2  
  DepDelay ArrDelay  
    <dbl>    <dbl>  
1 12.63907  6.895377
```

group_by関数による、グループごとの処理

#機体番号ごとの平均距離・平均出発遅延時間・平均到着遅延時間の算出

```
planes <- group_by(flights, tailnum)
```

```
delay <- summarise(planes, Dist = mean(distance, na.rm = TRUE),
```

```
DepDelay = mean(dep_delay, na.rm = TRUE), ArrDelay = mean(arr_delay, na.rm  
= TRUE))
```

```
delay
```

```

> #機体番号ごとの平均距離・平均出発遅延時間・平均到着遅延時間の算出
> planes <- group_by(flights, tailnum)
> delay <- summarise(planes, Dist = mean(distance, na.rm = TRUE),
+ DepDelay = mean(dep_delay, na.rm = TRUE), ArrDelay = mean(arr_delay, na.rm = TRUE))
> delay
# A tibble: 4,044 × 4
   tailnum      Dist DepDelay ArrDelay
   <chr>      <dbl>    <dbl>    <dbl>
1  D942DN  854.5000  31.50000000  31.50000000
2  NOEGMQ  676.1887   8.4915254   9.9829545
3  N10156  757.9477  17.8150685  12.7172414
4  N102UW  535.8750   8.00000000   2.9375000
5  N103US  535.1957  -3.1956522  -6.9347826
6  N104UW  535.2553   9.9361702   1.8043478
7  N10575  519.7024  22.6507353  20.6914498
8  N105UW  524.8444   2.5777778  -0.2666667
9  N107US  528.7073  -0.4634146  -5.7317073
10 N108UW  534.5000   4.2166667  -1.2500000
# ... with 4,034 more rows

```


chain関数(%>%)によるパイプ処理

#年、月、日を集計軸に設定

```
a1 <- group_by(flights, year, month, day)
```

a1

#年から日まで、および到着の遅延時間、出発の遅延時間を抽出

```
a2 <- select(a1, year:day, arr_delay, dep_delay)
```

a2

#年ごと、日ごとに到着の遅延時間の平均と出発の遅延時間の平均を算出

```
a3 <- summarise(a2, arr = mean(arr_delay, na.rm = TRUE), dep = mean(dep_delay, na.rm = TRUE))
```

a3

#到着の遅延時間が50分以上かつ出発の遅延時間が50分以上の行の抽出

```
a4 <- filter(a3, arr >= 50 | dep >= 50)
```

a4

#年、月、日を集計軸に設定

```
a1 <- group_by(flights, year, month, day)
```

```
a1
```

```
> #年、月、日を集計軸に設定
```

```
> a1 <- group_by(flights, year, month, day)
```

```
> a1
```

```
Source: local data frame [336,776 x 19]
```

```
Groups: year, month, day [365]
```

	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight
	<int>	<int>	<int>	<int>	<int>	<dbl>	<int>	<int>	<dbl>	<chr>	<int>
1	2013	1	1	517	515	2	830	819	11	UA	1545
2	2013	1	1	533	529	4	850	830	20	UA	1714
3	2013	1	1	542	540	2	923	850	33	AA	1141
4	2013	1	1	544	545	-1	1004	1022	-18	B6	725
5	2013	1	1	554	600	-6	812	837	-25	DL	461
6	2013	1	1	554	558	-4	740	728	12	UA	1696
7	2013	1	1	555	600	-5	913	854	19	B6	507
8	2013	1	1	557	600	-3	709	723	-14	EV	5708
9	2013	1	1	557	600	-3	838	846	-8	B6	79
10	2013	1	1	558	600	-2	753	745	8	AA	301

```
# ... with 336,766 more rows, and 8 more variables: tailnum <chr>, origin <chr>, dest <chr>,  
#   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dtm>
```

#年から日まで、および到着の遅延時間、出発の遅延時間を抽出

```
a2 <- select(a1, year:day, arr_delay, dep_delay)
```

a2

```
> #年から日まで、および到着の遅延時間、出発の遅延時間を抽出
```

```
> a2 <- select(a1, year:day, arr_delay, dep_delay)
```

```
> a2
```

```
Source: local data frame [336,776 x 5]
```

```
Groups: year, month, day [365]
```

	year	month	day	arr_delay	dep_delay
	<int>	<int>	<int>	<dbl>	<dbl>
1	2013	1	1	11	2
2	2013	1	1	20	4
3	2013	1	1	33	2
4	2013	1	1	-18	-1
5	2013	1	1	-25	-6
6	2013	1	1	12	-4
7	2013	1	1	19	-5
8	2013	1	1	-14	-3
9	2013	1	1	-8	-3
10	2013	1	1	8	-2

```
# ... with 336,766 more rows
```

#年ごと、日ごとに到着の遅延時間の平均と出発の遅延時間の平均を算出

```
a3 <- summarise(a2, arr = mean(arr_delay, na.rm = TRUE), dep = mean(dep_delay, na.rm = TRUE))
```

a3

```
> #年ごと、日ごとに到着の遅延時間の平均と出発の遅延時間の平均を算出
```

```
> a3 <- summarise(a2, arr = mean(arr_delay, na.rm = TRUE), dep = mean(dep_delay, na.rm = TRUE))
```

```
> a3
```

```
Source: local data frame [365 x 5]
```

```
Groups: year, month [?]
```

	year	month	day	arr	dep
	<int>	<int>	<int>	<dbl>	<dbl>
1	2013	1	1	12.6510229	11.548926
2	2013	1	2	12.6928879	13.858824
3	2013	1	3	5.7333333	10.987832
4	2013	1	4	-1.9328194	8.951595
5	2013	1	5	-1.5258020	5.732218
6	2013	1	6	4.2364294	7.148014
7	2013	1	7	-4.9473118	5.417204
8	2013	1	8	-3.2275785	2.553073
9	2013	1	9	-0.2642777	2.276477
10	2013	1	10	-5.8988159	2.844995
#	... with 355 more rows				

#到着の遅延時間が50分以上かつ出発の遅延時間が50分以上の行の抽出

```
a4 <- filter(a3, arr >= 50 | dep >= 50)
```

a4

```
> #到着の遅延時間が50分以上かつ出発の遅延時間が50分以上の行の抽出
```

```
> a4 <- filter(a3, arr >= 50 | dep >= 50)
```

```
> a4
```

```
Source: local data frame [12 x 5]
```

```
Groups: year, month [7]
```

	year	month	day	arr	dep
	<int>	<int>	<int>	<dbl>	<dbl>
1	2013	3	8	85.86216	83.53692
2	2013	5	23	61.97090	51.14472
3	2013	6	13	63.75369	45.79083
4	2013	6	24	51.17681	47.15742
5	2013	7	1	58.28050	56.23383
6	2013	7	10	59.62648	52.86070
7	2013	7	22	62.76340	46.66705
8	2013	8	8	55.48116	43.34995
9	2013	9	2	45.51843	53.02955
10	2013	9	12	58.91242	49.95875
11	2013	12	5	51.66625	52.32799
12	2013	12	17	55.87186	40.70560

関数のネストとパイプ処理の比較

- ネスト処理
- パイプ処理(magiretteパッケージ)

ネスト処理

```
filter(summarise(select(group_by(flights, year, month, day), year:day,  
  arr_delay, dep_delay), arr = mean(arr_delay, na.rm = TRUE), dep =  
mean(dep_delay, na.rm = TRUE)), arr >= 50 | dep >= 50)
```

Source: local data frame [12 x 5]

Groups: year, month [7]

	year	month	day	arr	dep
	<int>	<int>	<int>	<dbl>	<dbl>
1	2013	3	8	85.86216	83.53692
2	2013	5	23	61.97090	51.14472
3	2013	6	13	63.75369	45.79083
4	2013	6	24	51.17681	47.15742
5	2013	7	1	58.28050	56.23383
6	2013	7	10	59.62648	52.86070
7	2013	7	22	62.76340	46.66705
8	2013	8	8	55.48116	43.34995
9	2013	9	2	45.51843	53.02955
10	2013	9	12	58.91242	49.95875
11	2013	12	5	51.66625	52.32799
12	2013	12	17	55.87186	40.70560

パイプ処理

```
flights %>% group_by(year, month, day) %>% select(year:day, arr_delay,  
dep_delay) %>% summarise(arr = mean(arr_delay, na.rm = TRUE), dep =  
mean(dep_delay, na.rm = TRUE)) %>% filter(arr >= 50 | dep >= 50)
```

Source: local data frame [12 x 5]

Groups: year, month [7]

	year	month	day	arr	dep
	<int>	<int>	<int>	<dbl>	<dbl>
1	2013	3	8	85.86216	83.53692
2	2013	5	23	61.97090	51.14472
3	2013	6	13	63.75369	45.79083
4	2013	6	24	51.17681	47.15742
5	2013	7	1	58.28050	56.23383
6	2013	7	10	59.62648	52.86070
7	2013	7	22	62.76340	46.66705
8	2013	8	8	55.48116	43.34995
9	2013	9	2	45.51843	53.02955
10	2013	9	12	58.91242	49.95875
11	2013	12	5	51.66625	52.32799
12	2013	12	17	55.87186	40.70560

dplyrパッケージのその他の関数

```
library(dplyr)
```

```
data(flights)
```

dplyrパッケージのその他の関数

出発・到着の遅延時間の平均値・中央値・標準偏差を求める

```
summarise_each(select(flights, dep_delay, arr_delay), funs(mean = mean(.,  
na.rm = TRUE), median = median(., na.rm = TRUE), sd = sd(., na.rm = TRUE)))
```

summarise_each関数のmatchesを使用すれば、select関数は不要。

```
summarise_each(flights, funs(mean = mean(., na.rm = TRUE), median =  
median(., na.rm = TRUE), sd = sd(., na.rm = TRUE)), matches("_delay"))
```

#chain関数を用いたパイプ処理

```
flights %>% summarise_each(funs(mean = mean(., na.rm = TRUE), median =  
median(., na.rm = TRUE), sd = sd(., na.rm = TRUE)), matches("_delay"))
```

出発・到着の遅延時間の平均値・中央値・標準偏差を求める

```
summarise_each(select(flights, dep_delay, arr_delay), funs(mean = mean(., na.rm = TRUE), median =  
median(., na.rm = TRUE), sd = sd(., na.rm = TRUE)))
```

> # 出発・到着の遅延時間の平均値・中央値・標準偏差を求める

```
> summarise_each(select(flights, dep_delay, arr_delay), funs(mean = mean(., na.rm = TRUE), median = median(., na.rm = TRUE), sd = sd(., na.rm = TRUE)))
```

```
# A tibble: 1 × 6
```

	dep_delay_mean	arr_delay_mean	dep_delay_median	arr_delay_median	dep_delay_sd	arr_delay_sd
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	12.63907	6.895377	-2	-5	40.21006	44.63329

summarise_each関数のmatchesを使用すれば、select関数は不要。

```
summarise_each(flights, funs(mean = mean(., na.rm = TRUE), median = median(., na.rm = TRUE), sd = sd(., na.rm = TRUE)), matches("_delay"))
```

```
> # summarise_each関数のmatchesを使用すれば、select関数は不要。
```

```
> summarise_each(flights, funs(mean = mean(., na.rm = TRUE), median = median(., na.rm = TRUE), sd = sd(., na.rm = TRUE)), matches("_delay"))
```

```
# A tibble: 1 × 6
```

	dep_delay_mean	arr_delay_mean	dep_delay_median	arr_delay_median	dep_delay_sd	arr_delay_sd
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	12.63907	6.895377	-2	-5	40.21006	44.63329

#chain関数を用いたパイプ処理

```
flights %>% summarise_each(funs(mean = mean(., na.rm = TRUE), median = median(., na.rm = TRUE), sd = sd(., na.rm = TRUE)), matches("_delay"))
```

> #chain関数を用いたパイプ処理

```
> flights %>% summarise_each(funs(mean = mean(., na.rm = TRUE), median = median(., na.rm = TRUE)
```

```
# A tibble: 1 × 6
```

	dep_delay_mean	arr_delay_mean	dep_delay_median	arr_delay_median	dep_delay_sd	arr_delay_sd
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	12.63907	6.895377	-2	-5	40.21006	44.63329

dplyrパッケージのその他の関数

#出発・到着の遅延時間を正規化する

```
mutate_each(flights, funs(scale), matches("_delay"))
```

#chain関数を用いたパイプ処理の場合

```
flights %>% mutate_each(funs(scale), matches("_delay"))
```



```

> #出発・到着の遅延時間を正規化する
> mutate_each(flights, funs(scale), matches("_delay"))
# A tibble: 336,776 × 19
   year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay carrier flight
   <int> <int> <int>   <int>         <int>         <dbl>   <int>         <int>         <dbl>   <chr>   <int>
1  2013     1     1     517             515 -0.2645873     830             819  0.09196327    UA     1545
2  2013     1     1     533             529 -0.2148485     850             830  0.29360647    UA     1714
3  2013     1     1     542             540 -0.2645873     923             850  0.58486888    AA     1141
4  2013     1     1     544             545 -0.3391955    1004            1022 -0.55777595    B6       725
5  2013     1     1     554             600 -0.4635425     812             837 -0.71460956    DL       461
6  2013     1     1     554             558 -0.4138037     740             728  0.11436807    UA     1696
7  2013     1     1     555             600 -0.4386731     913             854  0.27120167    B6       507
8  2013     1     1     557             600 -0.3889343     709             723 -0.46815675    EV     5708
9  2013     1     1     557             600 -0.3889343     838             846 -0.33372795    B6        79
10 2013     1     1     558             600 -0.3640649     753             745  0.02474886    AA      301
# ... with 336,766 more rows, and 8 more variables: tailnum <chr>, origin <chr>, dest <chr>,
#   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dtm>

```

> #chain関数を用いたパイプ処理の場合

> flights %>% mutate_each(funs(scale), matches("_delay"))

A tibble: 336,776 × 19

	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight
	<int>	<int>	<int>	<int>	<int>	<dbl>	<int>	<int>	<dbl>	<chr>	<int>
1	2013	1	1	517	515	-0.2645873	830	819	0.09196327	UA	1545
2	2013	1	1	533	529	-0.2148485	850	830	0.29360647	UA	1714
3	2013	1	1	542	540	-0.2645873	923	850	0.58486888	AA	1141
4	2013	1	1	544	545	-0.3391955	1004	1022	-0.55777595	B6	725
5	2013	1	1	554	600	-0.4635425	812	837	-0.71460956	DL	461
6	2013	1	1	554	558	-0.4138037	740	728	0.11436807	UA	1696
7	2013	1	1	555	600	-0.4386731	913	854	0.27120167	B6	507
8	2013	1	1	557	600	-0.3889343	709	723	-0.46815675	EV	5708
9	2013	1	1	557	600	-0.3889343	838	846	-0.33372795	B6	79
10	2013	1	1	558	600	-0.3640649	753	745	0.02474886	AA	301

... with 336,766 more rows, and 8 more variables: tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>,
distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dtm>

テーブルの形式の変換

- data.frame形式はR特有の行列の形をしたデータ形式。
- data.frameで表現するデータの形式は大別すると
 - 1, wide形式(横持ち形式): データの項目が横に並んだ形式
 - 2, long形式(縦持ち形式): 項目名とその値が縦に並んだ形式があるが、これらはreshapeパッケージを用いると互いに変換できる。
reshapeは、reshape2パッケージにグレードアップして提供されている。

wide型とlong型について

wide型

```
> births.wide
```

	caseid	v012	b2_01	b2_02	b2_03	b4_01	b4_02	b4_03
1	1	30	2000	2005	NA	1	1	NA
2	2	29	2001	2010	NA	1	2	NA
3	3	32	1999	2002	2006	1	1	1
4	4	35	1999	2009	NA	2	1	NA
5	5	34	1998	NA	NA	2	NA	NA
6	6	23	NA	NA	NA	NA	NA	NA
7	7	25	2000	NA	NA	1	NA	NA

行が母親のid

long型

行が子供のid

```
> births.long1
```

	caseid	v012	time	b2	b4
1.1	1	30	1	2000	1
2.1	2	29	1	2001	1
3.1	3	32	1	1999	1
4.1	4	35	1	1999	2
5.1	5	34	1	1998	2
6.1	6	23	1	NA	NA
7.1	7	25	1	2000	1
1.2	1	30	2	2005	1
2.2	2	29	2	2010	2
3.2	3	32	2	2002	1
4.2	4	35	2	2009	1
5.2	5	34	2	NA	NA
6.2	6	23	2	NA	NA
7.2	7	25	2	NA	NA
1.3	1	30	3	NA	NA
2.3	2	29	3	NA	NA
3.3	3	32	3	2006	1
4.3	4	35	3	NA	NA
5.3	5	34	3	NA	NA
6.3	6	23	3	NA	NA
7.3	7	25	3	NA	NA

テーブルの形式の変換

```
# reshape2(Hadley氏作)パッケージのダウンロード  
install.packages("reshape2", quiet = TRUE, dependencies=T)
```

#パッケージのロード

library(reshape2)

#データのロード

data(smiths)

smiths

> #パッケージのロード

> library(reshape2)

> #データのロード

> data(smiths)

> smiths

	subject	time	age	weight	height
1	John Smith	1	33	90	1.87
2	Mary Smith	1	NA	NA	1.54

melt関数での、wideからlongへの変換

```
melt(smiths)
```

```
melt(smiths, id = c("subject", "time"), measured = c("age", "weight", "height"))
```

```
> melt(smiths)
```

Using subject as **id** variables

	subject	variable	value
1	John Smith	time	1.00
2	Mary Smith	time	1.00
3	John Smith	age	33.00
4	Mary Smith	age	NA
5	John Smith	weight	90.00
6	Mary Smith	weight	NA
7	John Smith	height	1.87
8	Mary Smith	height	1.54

```
> melt(smiths, id = c("subject", "time"), measured = c("age", "weight", "height"))
```

	subject	time	variable	value
1	John Smith	1	age	33.00
2	Mary Smith	1	age	NA
3	John Smith	1	weight	90.00
4	Mary Smith	1	weight	NA
5	John Smith	1	height	1.87
6	Mary Smith	1	height	1.54

#na.rm=TRUEにすることで、欠損値を含む行を除去する。

```
melt(smiths, na.rm = TRUE)
```

> #na.rm=TRUEにすることで、欠損値を含む行を除去する。

> melt(smiths, na.rm = TRUE)

Using subject as id variables

	subject	variable	value
1	John Smith	time	1.00
2	Mary Smith	time	1.00
3	John Smith	age	33.00
5	John Smith	weight	90.00
7	John Smith	height	1.87
8	Mary Smith	height	1.54

dcast関数での、longからwideへの変換

```
smithsm <- melt(smiths)
```

```
smithsm
```

```
dcast(smithsm, ... ~ variable)
```

```
dcast(smithsm, ... ~ subject)
```

```

> smithsm <- melt(smiths)
Using subject as id variables
> smithsm
  subject variable value
1 John Smith    time  1.00
2 Mary Smith    time  1.00
3 John Smith    age  33.00
4 Mary Smith    age   NA
5 John Smith   weight 90.00
6 Mary Smith   weight  NA
7 John Smith   height 1.87
8 Mary Smith   height 1.54
> dcast(smithsm, ... ~ variable)
  subject time age weight height
1 John Smith    1  33     90   1.87
2 Mary Smith    1  NA     NA   1.54
> dcast(smithsm, ... ~ subject)
  variable John Smith Mary Smith
1      time      1.00      1.00
2       age     33.00      NA
3    weight     90.00      NA
4    height      1.87      1.54

```

tidyrパッケージ

- Hadley Wickham氏によって開発された、tidyrパッケージは、より効率的に、wide形式とlong形式のデータフレームを変換する。
- tidyrパッケージは、tidy dataというコンセプトのもとに開発されている。



Journal of Statistical Software

August 2014, Volume 59, Issue 10.

<http://www.jstatsoft.org/>

Tidy Data

Hadley Wickham
RStudio

Abstract

A huge amount of effort is spent cleaning data to get it ready for analysis, but there has been little research on how to make data cleaning as easy and effective as possible. This paper tackles a small, but important, component of data cleaning: data tidying. Tidy datasets are easy to manipulate, model and visualize, and have a specific structure: each variable is a column, each observation is a row, and each type of observational unit is a table. This framework makes it easy to tidy messy datasets because only a small set of tools are needed to deal with a wide range of un-tidy datasets. This structure also makes it easier to develop tidy tools for data analysis, tools that both input and output tidy datasets. The advantages of a consistent data structure and matching tools are demonstrated with a case study free from mundane data manipulation chores.

パッケージのダウンロード・インストール

```
install.packages("tidyr", quiet = TRUE, dependencies=T)  
library(tidyr)
```

gather関数による、wide形式からlong形式への変換

- tidyrパッケージのgather関数は、reshape2パッケージのmelt関数に相当。
- 数列にまたがっていた値をカテゴリ変数と値の列に変換することで、wide形式のデータフレームをlong形式のデータフレームに変換する。

```
iris.l <- gather(iris, variable, value, -Species)
```

```
head(iris.l, 3)
```

```
> iris.l <- gather(iris, variable, value, -Species)
> head(iris.l, 3)
```

	Species	variable	value
1	setosa	Sepal.Length	5.1
2	setosa	Sepal.Length	4.9
3	setosa	Sepal.Length	4.7

spread関数によるlong形式からwide形式への変換

tidyrパッケージのspread関数は、reshape2パッケージのdcast関数に相当し、long形式のデータフレームを、wide形式に変換する。

```
library(dplyr)
```

```
iris.mean <- iris.l %>% group_by(Species, variable) %>%  
summarise(mean = mean(value))
```

```
iris.w <- spread(iris.mean, variable, mean)
```

```
iris.w
```



```
> library(dplyr)
> iris.mean <- iris.l %>% group_by(Species, variable) %>% summarise(mea$
> iris.w <- spread(iris.mean, variable, mean)
> iris.w
```

Source: local data frame [3 x 5]

Groups: Species [3]

	Species	Petal.Length	Petal.Width	Sepal.Length	Sepal.Width
*	<fctr>	<dbl>	<dbl>	<dbl>	<dbl>
1	setosa	1.462	0.246	5.006	3.428
2	versicolor	4.260	1.326	5.936	2.770
3	virginica	5.552	2.026	6.588	2.974

separate関数によるlongからwide形式への変換

tidyrパッケージのseparate関数は、reshape2パッケージのcolsplit関数に相当し、キーとなる列を複数の列に分割する。

```
iris.l <- gather(iris, variable, value, -Species)
iris.l.sep <- separate(iris.l, variable, c("part", "variable"))
head(iris.l.sep, 3)
```

```
> iris.l <- gather(iris, variable, value, -Species)
> iris.l.sep <- separate(iris.l, variable, c("part", "variable"))
> head(iris.l.sep, 3)
```

	Species	part	variable	value
1	setosa	Sepal	Length	5.1
2	setosa	Sepal	Length	4.9
3	setosa	Sepal	Length	4.7

unite関数による複数列の結合

unite関数は、separate関数の逆で、複数列の値を、一列に結合する。

```
iris.l.sep %>% unite("var", c(part, variable), sep = ".") %>% head(3)
```

```
> iris.l.sep %>% unite("var", c(part, variable), sep = ".") %>% head(3)
  Species      var value
1  setosa Sepal.Length  5.1
2  setosa Sepal.Length  4.9
3  setosa Sepal.Length  4.7
```

data.tableのハンドリング

- data.tableパッケージを使用する。

data.tableパッケージ

- data.frameを継承したdata.tableの型とそれに関する処理方法を提供する。
- キーの設定、バイナリサーチを用いた高速な検索、グループごとの処理などを提供。
- data.frameに対する処理より、data.tableに対する処理のほうが高速。

パッケージのダウンロード・インストール

```
install.packages("data.table", quiet = TRUE, dependencies=T)
```

#パッケージのメモリへのロード

```
library(data.table)
```

#fread関数を用いたデータの読み込み

```
system.time(al.2008.dt <- fread("data/DataExpo2009/2008.csv"))
```



```
> #fread関数を用いたデータの読み込み
> system.time(al.2008.dt <- fread("data/DataExpo2009/2008.csv"))
Read 7009728 rows and 29 (of 29) columns from 0.642 GB file in 00:00:12
   user  system elapsed 
 10.39    0.59   11.90 
Warning message:
In fread("data/DataExpo2009/2008.csv") :
  Bumped column 23 to type character on data row 179, field contains 'A'. Coercing pre$
```

#データ型の確認

```
class(al.2008.dt)
```

#データサイズの確認

```
dim(al.2008.dt)
```

```
> #データ型の確認
```

```
> class(al.2008.dt)
```

```
[1] "data.table" "data.frame"
```

```
> #データサイズの確認
```

```
> dim(al.2008.dt)
```

```
[1] 7009728      29
```

メモリ上に生成されたデータテーブルのリストの確認

- ・メモリ上に生成されたデータテーブルのリストは以下のように、tables関数を用いて確認できる。
- ・NAMEはオブジェクト名、NROWは行数、NCOLは列数、MBはデータサイズ、COLSは列名、KEYはキー。

tables()

```
> tables()
      NAME              NROW NCOL  MB
[1,] a1.2008.dt 7,009,728    29 910
      COLS
[1,] Year,Month,DayofMonth,DayOfWeek,DepTime,CRSDepTime,ArrTime,CRSArrTime,UniqueCarr
      KEY
[1,]
Total: 910MB
```

行の抽出

#data.frameと同じように行を指定する。

```
al.2008.dt[1:2, ]
```

```
> #data.frameと同じように行を指定する。
```

```
> al.2008.dt[1:2, ]
```

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime	UniqueCarrier
1:	2008	1	3	4	2003	1955	2211	2225	WN
2:	2008	1	3	4	754	735	1002	1000	WN

	FlightNum	TailNum	ActualElapsedTime	CRSElapsedTime	AirTime	ArrDelay	DepDelay	Origin
1:	335	N712SW	128	150	116	-14	8	IAD
2:	3231	N772SW	128	145	113	2	19	IAD

	Dest	Distance	TaxiIn	TaxiOut	Cancelled	CancellationCode	Diverted	CarrierDelay
1:	TPA	810	4	8	0		0	NA
2:	TPA	810	5	10	0		0	NA

	WeatherDelay	NASDelay	SecurityDelay	LateAircraftDelay
1:	NA	NA	NA	NA
2:	NA	NA	NA	NA

列の抽出

抽出する列名をlistの要素にして、指定したり、with=FALSEのオプションをつけて、列番号や列名を指定。

```
al.2008.dt[1:2, list(Year, Month, DayofMonth)]
```

```
al.2008.dt[1:2, 1:3, with = FALSE]
```

```
> al.2008.dt[1:2, list(Year, Month, DayofMonth)]
```

```
  Year Month DayofMonth
```

```
1: 2008      1         3
```

```
2: 2008      1         3
```

```
> al.2008.dt[1:2, 1:3, with = FALSE]
```

```
  Year Month DayofMonth
```

```
1: 2008      1         3
```

```
2: 2008      1         3
```

キーの設定

#月(Month)と曜日(DayOfWeek)の二つをキーに設定

```
setkey(al.2008.dt, Month, DayOfWeek)
```

#キーが設定されていることを確認

```
tables()
```

```
> #月(Month)と曜日(DayOfWeek)の二つをキーに設定
```

```
> setkey(al.2008.dt, Month, DayOfWeek)
```

```
> #キーが設定されていることを確認
```

```
> tables()
```

	NAME	NROW	NCOL	MB
[1,]	al.2008.dt	7,009,728	29	910

	COLS
[1,]	Year, Month, DayofMonth, DayOfWeek, DepTime, CRSDepTime, ArrTime, CRSArrTime, UniqueCarr

	KEY
[1,]	Month, DayOfWeek

Total: 910MB

バイナリサーチによるデータの高速抽出

キーを設定することで、バイナリサーチによりデータを高速に抽出することができる。

#4月 月曜日のフライトデータの抽出

al.2008.dt[J(4, 1)]

> #4月月曜日のフライトデータの抽出

> al.2008.dt[J(4, 1)]

	Year	Month	DayofMonth	DayOfWeek	DepTime	CRSDepTime	ArrTime	CRSArrTime
1:	2008	4	7	1	1950	1955	2153	2150
2:	2008	4	7	1	858	900	1423	1435
3:	2008	4	7	1	909	910	1138	1145
4:	2008	4	7	1	649	655	920	930
5:	2008	4	7	1	1312	1315	1541	1550

82459:	2008	4	14	1	1830	1829	1945	1951
82460:	2008	4	14	1	NA	1930	NA	2046
82461:	2008	4	14	1	1929	1930	2038	2049
82462:	2008	4	14	1	2030	2030	2146	2147
82463:	2008	4	14	1	2042	2030	2202	2149

	UniqueCarrier	FlightNum	TailNum	ActualElapsedTime	CRSElapsedTime	AirTime	ArrDelay
1:	WN	609	N623SW	63	55	43	3
2:	WN	3257	N795SW	205	215	194	-12
3:	WN	77	N694SW	89	95	78	-7
4:	WN	87	N342SW	91	95	78	-10
5:	WN	214	N770SA	89	95	78	-9

82459:	DL	1965	N914DE	75	82	46	-6
82460:	DL	1966	N908DE	NA	76	NA	NA
82461:	DL	1967	N909DE	69	79	38	-11
82462:	DL	1968	N914DE	76	77	50	-1
82463:	DL	1969	N908DE	80	79	43	13

	DepDelay	Origin	Dest	Distance	TaxiIn	TaxiOut	Cancelled	CancellationCode	Diverted
1:	-5	ABQ	AMA	277	6	14	0		0
2:	-2	ABQ	BWI	1670	4	7	0		0
3:	-1	ABQ	DAL	580	4	7	0		0
4:	-6	ABQ	DAL	580	3	10	0		0
5:	-3	ABQ	DAL	580	3	8	0		0

82459:	1	LGA	DCA	214	3	26	0		0
82460:	NA	DCA	LGA	214	NA	NA	1	A	0
82461:	-1	LGA	DCA	214	4	27	0		0
82462:	0	DCA	LGA	214	3	23	0		0
82463:	12	LGA	DCA	214	4	33	0		0

高速なテーブル結合

data.tableパッケージを用いると、テーブルの結合も高速化できる。以下の例は、データセットをデータテーブルに変換し、キー設定した後に、flightsデータセットとairportsデータセットを、内部結合および外部結合している。

```
library(data.table)
```

```
library(nycflights13)
```

```
flights
```

```
airports
```

```

> library(data.table)
> library(nycflights13)
> flights
# A tibble: 336,776 × 19
   year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay carrier flight tailnum origin dest
   <int> <int> <int>   <int>         <int>         <dbl>   <int>         <int>         <dbl>   <chr>   <int>   <chr>   <chr> <chr>
1  2013     1     1     517             515           2       830             819           11     UA     1545   N14228   EWR   IAH
2  2013     1     1     533             529           4       850             830           20     UA     1714   N24211   LGA   IAH
3  2013     1     1     542             540           2       923             850           33     AA     1141   N619AA   JFK   MIA
4  2013     1     1     544             545          -1      1004            1022          -18     B6       725   N804JB   JFK   BQN
5  2013     1     1     554             600          -6       812             837          -25     DL       461   N668DN   LGA   ATL
6  2013     1     1     554             558          -4       740             728           12     UA     1696   N39463   EWR   ORD
7  2013     1     1     555             600          -5       913             854           19     B6       507   N516JB   EWR   FLL
8  2013     1     1     557             600          -3       709             723          -14     EV     5708   N829AS   LGA   IAD
9  2013     1     1     557             600          -3       838             846           -8     B6        79   N593JB   JFK   MCO
10 2013     1     1     558             600          -2       753             745           8     AA       301   N3ALAA   LGA   ORD
# ... with 336,766 more rows, and 5 more variables: air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dtm>

```

```

> airports
# A tibble: 1,396 × 7
   faa      name      lat      lon    alt    tz    dst
  <chr>    <chr>    <dbl>    <dbl> <int> <dbl> <chr>
1  04G    Lansdowne Airport 41.13047 -80.61958 1044    -5    A
2  06A    Moton Field Municipal Airport 32.46057 -85.68003 264    -5    A
3  06C    Schaumburg Regional 41.98934 -88.10124 801    -6    A
4  06N    Randall Airport 41.43191 -74.39156 523    -5    A
5  09J    Jekyll Island Airport 31.07447 -81.42778 11    -4    A
6  0A9    Elizabethton Municipal Airport 36.37122 -82.17342 1593   -4    A
7  0G6    Williams County Airport 41.46731 -84.50678 730    -5    A
8  0G7    Finger Lakes Regional Airport 42.88356 -76.78123 492    -5    A
9  0P2    Shoestring Aviation Airfield 39.79482 -76.64719 1000   -5    U
10 0S9    Jefferson County Intl 48.05381 -122.81064 108    -8    A
# ... with 1,386 more rows

```

高速なテーブル結合

data.tableパッケージを用いると、テーブルの結合も高速化できる。以下の例は、データセットをデータテーブルに変換し、キー設定した後に、flightsデータセットとairportsデータセットを、内部結合および外部結合している。

データテーブルへの変換

```
flights.dt <- data.table(flights)
```

```
flights.dt
```

```
airports.dt <- data.table(airports)
```

```
airports.dt
```

```

> flights.dt <- data.table(flights)
> flights.dt
   year month day dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay carrier flight tailnum origin dest
1: 2013     1   1     517         515           2      830         819           11        UA    1545   N14228    EWR   IAH
2: 2013     1   1     533         529           4      850         830           20        UA    1714   N24211    LGA   IAH
3: 2013     1   1     542         540           2      923         850           33        AA    1141   N619AA    JFK   MIA
4: 2013     1   1     544         545          -1     1004        1022          -18        B6     725   N804JB    JFK   BQN
5: 2013     1   1     554         600          -6      812         837          -25        DL     461   N668DN    LGA   ATL
---
336772: 2013     9  30         NA         1455         NA         NA         1634         NA        9E    3393        NA    JFK   DCA
336773: 2013     9  30         NA         2200         NA         NA         2312         NA        9E    3525        NA    LGA   SYR
336774: 2013     9  30         NA         1210         NA         NA         1330         NA        MQ    3461   N535MQ    LGA   BNA
336775: 2013     9  30         NA         1159         NA         NA         1344         NA        MQ    3572   N511MQ    LGA   CLE
336776: 2013     9  30         NA         840          NA         NA         1020         NA        MQ    3531   N839MQ    LGA   RDU
   air_time distance hour minute      time_hour
1:      227      1400    5     15 2013-01-01 05:00:00
2:      227      1416    5     29 2013-01-01 05:00:00
3:      160      1089    5     40 2013-01-01 05:00:00
4:      183      1576    5     45 2013-01-01 05:00:00
5:      116       762    6      0 2013-01-01 06:00:00
---
336772:      NA      213    14     55 2013-09-30 14:00:00
336773:      NA      198    22      0 2013-09-30 22:00:00
336774:      NA      764    12     10 2013-09-30 12:00:00
336775:      NA      419    11     59 2013-09-30 11:00:00
336776:      NA      431     8     40 2013-09-30 08:00:00

```

```
> airports.dt <- data.table(airports)
> airports.dt
```

	faa	name	lat	lon	alt	tz	dst
1:	04G	Lansdowne Airport	41.13047	-80.61958	1044	-5	A
2:	06A	Moton Field Municipal Airport	32.46057	-85.68003	264	-5	A
3:	06C	Schaumburg Regional	41.98934	-88.10124	801	-6	A
4:	06N	Randall Airport	41.43191	-74.39156	523	-5	A
5:	09J	Jekyll Island Airport	31.07447	-81.42778	11	-4	A

1392:	ZUN	Black Rock	35.08323	-108.79178	6454	-7	A
1393:	ZVE	New Haven Rail Station	41.29867	-72.92599	7	-5	A
1394:	ZWI	Wilmington Amtrak Station	39.73667	-75.55167	0	-5	A
1395:	ZWU	Washington Union Station	38.89746	-77.00643	76	-5	A
1396:	ZYP	Penn Station	40.75050	-73.99350	35	-5	A

高速なテーブル結合

data.tableパッケージを用いると、テーブルの結合も高速化できる。以下の例は、データセットをデータテーブルに変換し、キー設定した後に、flightsデータセットとairportsデータセットを、内部結合および外部結合している。

キーの設定

```
setkey(flights.dt, origin)
```

```
setkey(airports.dt, faa)
```

内部結合

```
flights.dt[airports.dt, nomatch = 0]
```

外部結合(airports.dtをflights.dtに右結合)

```
flights.dt[airports.dt, nomatch = NA, allow.cartesian = TRUE]
```

```
> # キーの設定
```

```
> setkey(flights.dt, origin)
```

```
> setkey(airports.dt, faa)
```

```
> flights.dt
```

	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight	tailnum	origin	dest
1:	2013	1	1	517	515	2	830	819	11	UA	1545	N14228	EWR	IAH
2:	2013	1	1	554	558	-4	740	728	12	UA	1696	N39463	EWR	ORD
3:	2013	1	1	555	600	-5	913	854	19	B6	507	N516JB	EWR	FLL
4:	2013	1	1	558	600	-2	923	937	-14	UA	1124	N53441	EWR	SFO
5:	2013	1	1	559	600	-1	854	902	-8	UA	1187	N76515	EWR	LAS

336772:	2013	9	30	NA	1842	NA	NA	2019	NA	EV	5274	N740EV	LGA	BNA
336773:	2013	9	30	NA	2200	NA	NA	2312	NA	9E	3525	NA	LGA	SYR
336774:	2013	9	30	NA	1210	NA	NA	1330	NA	MQ	3461	N535MQ	LGA	BNA
336775:	2013	9	30	NA	1159	NA	NA	1344	NA	MQ	3572	N511MQ	LGA	CLE
336776:	2013	9	30	NA	840	NA	NA	1020	NA	MQ	3531	N839MQ	LGA	RDU
	air_time	distance	hour	minute	time_hour									
1:	227	1400	5	15	2013-01-01 05:00:00									
2:	150	719	5	58	2013-01-01 05:00:00									
3:	158	1065	6	0	2013-01-01 06:00:00									
4:	361	2565	6	0	2013-01-01 06:00:00									
5:	337	2227	6	0	2013-01-01 06:00:00									

336772:	NA	764	18	42	2013-09-30 18:00:00									
336773:	NA	198	22	0	2013-09-30 22:00:00									
336774:	NA	764	12	10	2013-09-30 12:00:00									
336775:	NA	419	11	59	2013-09-30 11:00:00									
336776:	NA	431	8	40	2013-09-30 08:00:00									


```
> airports.dt
```

	faa	name	lat	lon	alt	tz	dst
1:	04G	Lansdowne Airport	41.13047	-80.61958	1044	-5	A
2:	06A	Moton Field Municipal Airport	32.46057	-85.68003	264	-5	A
3:	06C	Schaumburg Regional	41.98934	-88.10124	801	-6	A
4:	06N	Randall Airport	41.43191	-74.39156	523	-5	A
5:	09J	Jekyll Island Airport	31.07447	-81.42778	11	-4	A

1392:	ZUN	Black Rock	35.08323	-108.79178	6454	-7	A
1393:	ZVE	New Haven Rail Station	41.29867	-72.92599	7	-5	A
1394:	ZWI	Wilmington Amtrak Station	39.73667	-75.55167	0	-5	A
1395:	ZWU	Washington Union Station	38.89746	-77.00643	76	-5	A
1396:	ZYP	Penn Station	40.75050	-73.99350	35	-5	A

> # 内部結合

> flights.dt[airports.dt, nomatch = 0]

	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight	tailnum	origin	dest
1:	2013	1	1	517	515	2	830	819	11	UA	1545	N14228	EWR	IAH
2:	2013	1	1	554	558	-4	740	728	12	UA	1696	N39463	EWR	ORD
3:	2013	1	1	555	600	-5	913	854	19	B6	507	N516JB	EWR	FLL
4:	2013	1	1	558	600	-2	923	937	-14	UA	1124	N53441	EWR	SFO
5:	2013	1	1	559	600	-1	854	902	-8	UA	1187	N76515	EWR	LAS

336772:	2013	9	30	NA	1842	NA	NA	2019	NA	EV	5274	N740EV	LGA	BNA
336773:	2013	9	30	NA	2200	NA	NA	2312	NA	9E	3525	NA	LGA	SYR
336774:	2013	9	30	NA	1210	NA	NA	1330	NA	MQ	3461	N535MQ	LGA	BNA
336775:	2013	9	30	NA	1159	NA	NA	1344	NA	MQ	3572	N511MQ	LGA	CLE
336776:	2013	9	30	NA	840	NA	NA	1020	NA	MQ	3531	N839MQ	LGA	RDU
	air_time	distance	hour	minute	time_hour		name		lat	lon	alt	tz	dst	
1:	227	1400	5	15	2013-01-01	05:00:00	Newark	Liberty Intl	40.69250	-74.16867	18	-5	A	
2:	150	719	5	58	2013-01-01	05:00:00	Newark	Liberty Intl	40.69250	-74.16867	18	-5	A	
3:	158	1065	6	0	2013-01-01	06:00:00	Newark	Liberty Intl	40.69250	-74.16867	18	-5	A	
4:	361	2565	6	0	2013-01-01	06:00:00	Newark	Liberty Intl	40.69250	-74.16867	18	-5	A	
5:	337	2227	6	0	2013-01-01	06:00:00	Newark	Liberty Intl	40.69250	-74.16867	18	-5	A	

336772:	NA	764	18	42	2013-09-30	18:00:00	La Guardia		40.77725	-73.87261	22	-5	A	
336773:	NA	198	22	0	2013-09-30	22:00:00	La Guardia		40.77725	-73.87261	22	-5	A	
336774:	NA	764	12	10	2013-09-30	12:00:00	La Guardia		40.77725	-73.87261	22	-5	A	
336775:	NA	419	11	59	2013-09-30	11:00:00	La Guardia		40.77725	-73.87261	22	-5	A	
336776:	NA	431	8	40	2013-09-30	08:00:00	La Guardia		40.77725	-73.87261	22	-5	A	

```
> # 外部結合 (airports.dtをflights.dtに右結合)
```

```
> flights.dt[airports.dt, nomatch = NA, allow.cartesian = TRUE]
```

	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight	tailnum	origin	dest
1:	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	04G	NA
2:	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	06A	NA
3:	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	06C	NA
4:	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	06N	NA
5:	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	09J	NA

338165:	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	ZUN	NA
338166:	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	ZVE	NA
338167:	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	ZWI	NA
338168:	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	ZWU	NA
338169:	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	ZYP	NA
	air_time	distance	hour	minute	time_hour		name	lat	lon	alt	tz	dst		
1:	NA	NA	NA	NA	<NA>		Lansdowne Airport	41.13047	-80.61958	1044	-5	A		
2:	NA	NA	NA	NA	<NA>	Moton	Field Municipal Airport	32.46057	-85.68003	264	-5	A		
3:	NA	NA	NA	NA	<NA>		Schaumburg Regional	41.98934	-88.10124	801	-6	A		
4:	NA	NA	NA	NA	<NA>		Randall Airport	41.43191	-74.39156	523	-5	A		
5:	NA	NA	NA	NA	<NA>		Jekyll Island Airport	31.07447	-81.42778	11	-4	A		

338165:	NA	NA	NA	NA	<NA>		Black Rock	35.08323	-108.79178	6454	-7	A		
338166:	NA	NA	NA	NA	<NA>		New Haven Rail Station	41.29867	-72.92599	7	-5	A		
338167:	NA	NA	NA	NA	<NA>	Wilmington	Amtrak Station	39.73667	-75.55167	0	-5	A		
338168:	NA	NA	NA	NA	<NA>	Washington	Union Station	38.89746	-77.00643	76	-5	A		
338169:	NA	NA	NA	NA	<NA>		Penn Station	40.75050	-73.99350	35	-5	A		

#外部結合(airports.dtをflights.dtに右結合)
airports.dt[flights.dt, nomatch=NA]

```
> airports.dt[flights.dt, nomatch=NA]
```

	faa	name	lat	lon	alt	tz	dst	year	month	day	dep_time	sched_dep_time	dep_delay	arr_time
1:	EWR	Newark Liberty Intl	40.69250	-74.16867	18	-5	A	2013	1	1	517	515	2	830
2:	EWR	Newark Liberty Intl	40.69250	-74.16867	18	-5	A	2013	1	1	554	558	-4	740
3:	EWR	Newark Liberty Intl	40.69250	-74.16867	18	-5	A	2013	1	1	555	600	-5	913
4:	EWR	Newark Liberty Intl	40.69250	-74.16867	18	-5	A	2013	1	1	558	600	-2	923
5:	EWR	Newark Liberty Intl	40.69250	-74.16867	18	-5	A	2013	1	1	559	600	-1	854

336772:	LGA	La Guardia	40.77725	-73.87261	22	-5	A	2013	9	30	NA	1842	NA	NA
336773:	LGA	La Guardia	40.77725	-73.87261	22	-5	A	2013	9	30	NA	2200	NA	NA
336774:	LGA	La Guardia	40.77725	-73.87261	22	-5	A	2013	9	30	NA	1210	NA	NA
336775:	LGA	La Guardia	40.77725	-73.87261	22	-5	A	2013	9	30	NA	1159	NA	NA
336776:	LGA	La Guardia	40.77725	-73.87261	22	-5	A	2013	9	30	NA	840	NA	NA
	sched_arr_time	arr_delay	carrier	flight	tailnum	dest	air_time	distance	hour	minute	time_hour			
1:	819	11	UA	1545	N14228	IAH	227	1400	5	15	2013-01-01	05:00:00		
2:	728	12	UA	1696	N39463	ORD	150	719	5	58	2013-01-01	05:00:00		
3:	854	19	B6	507	N516JB	FLL	158	1065	6	0	2013-01-01	06:00:00		
4:	937	-14	UA	1124	N53441	SFO	361	2565	6	0	2013-01-01	06:00:00		
5:	902	-8	UA	1187	N76515	LAS	337	2227	6	0	2013-01-01	06:00:00		

336772:	2019	NA	EV	5274	N740EV	BNA	NA	764	18	42	2013-09-30	18:00:00		
336773:	2312	NA	9E	3525	NA	SYR	NA	198	22	0	2013-09-30	22:00:00		
336774:	1330	NA	MQ	3461	N535MQ	BNA	NA	764	12	10	2013-09-30	12:00:00		
336775:	1344	NA	MQ	3572	N511MQ	CLE	NA	419	11	59	2013-09-30	11:00:00		
336776:	1020	NA	MQ	3531	N839MQ	RDU	NA	431	8	40	2013-09-30	08:00:00		