Introduction to dplyr

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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.

Data: nycflights13

To explore the basic data manipulation verbs of dplyr, we'll start with the built in `nycflights13` data frame. This dataset contains all 336776 flights that departed from New York City in 2013. The data comes from the US Bureau of Transportation Statistics, and is documented in `?nycflights13`

```
library(nycflights13)
dim(flights)
#> [1] 336776     19
head(flights)
#> # A tibble: 6 x 19
#>    year month   day dep_time sched_dep_time dep_delay arr_time
```

```
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>
#> 1  2013     1     1      517            515         2      830
#> 2  2013     1     1      533            529         4      850
#> 3  2013     1     1      542            540         2      923
#> 4  2013     1     1      544            545        -1     1004
#> ... with 2 more rows, and 12 more variables: sched_arr_time <int>,
#>   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#>   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>   minute <dbl>, time_hour <time>
```

dplyr can work with data frames as is, but if you're dealing with large data, it's worthwhile to convert them to a `tbl_df`: this is a wrapper around a data frame that won't accidentally print a lot of data to the screen.

Single table verbs

Dplyr aims to provide a function for each basic verb of data manipulation:

- `filter()` (and `slice()`)
- `arrange()`
- `select()` (and `rename()`)
- `distinct()`
- `mutate()` (and `transmute()`)
- `summarise()`
- `sample_n()` (and `sample_frac()`)

If you've used plyr before, many of these will be familar.

Filter rows with `filter()`

`filter()` allows you to select a subset of rows in a data frame. The first argument is the name of the data frame. The second and subsequent arguments are the expressions that filter the data frame:

For example, we can select all flights on January 1st with:

```
filter(flights, month == 1, day == 1)
#> # A tibble: 842 x 19
#>    year month   day dep_time sched_dep_time dep_delay arr_time
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>
#> 1  2013     1     1      517            515         2      830
#> 2  2013     1     1      533            529         4      850
#> 3  2013     1     1      542            540         2      923
#> 4  2013     1     1      544            545        -1     1004
#> ... with 838 more rows, and 12 more variables: sched_arr_time <int>,
```

```
#>   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#>   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>   minute <dbl>, time_hour <time>
```

This is equivalent to the more verbose code in base R:

```
flights[flights$month == 1 & flights$day == 1, ]
```

`filter()` works similarly to `subset()` except that you can give it any number of filtering conditions, which are joined together with `&` (not `&&` which is easy to do accidentally!). You can also use other boolean operators:

```
filter(flights, month == 1 | month == 2)
```

To select rows by position, use `slice()`:

```
slice(flights, 1:10)
#> # A tibble: 10 x 19
#>    year month   day dep_time sched_dep_time dep_delay arr_time
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>
#> 1  2013     1     1      517            515         2      830
#> 2  2013     1     1      533            529         4      850
#> 3  2013     1     1      542            540         2      923
#> 4  2013     1     1      544            545        -1     1004
#> ... with 6 more rows, and 12 more variables: sched_arr_time <int>,
#>   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#>   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>   minute <dbl>, time_hour <time>
```

Arrange rows with `arrange()`

`arrange()` works similarly to `filter()` except that instead of filtering or selecting rows, it reorders them. It takes a data frame, and a set of column names (or more complicated expressions) to order by. If you provide more than one column name, each additional column will be used to break ties in the values of preceding columns:

```
arrange(flights, year, month, day)
#> # A tibble: 336,776 x 19
#>    year month   day dep_time sched_dep_time dep_delay arr_time
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>
#> 1  2013     1     1      517            515         2      830
```

```
#> 2  2013     1     1      533            529         4      850
#> 3  2013     1     1      542            540         2      923
#> 4  2013     1     1      544            545        -1     1004
#> ... with 336,772 more rows, and 12 more variables: sched_arr_time <int>,
#>   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#>   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>   minute <dbl>, time_hour <time>
```

Use `desc()` to order a column in descending order:

```
arrange(flights, desc(arr_delay))
#> # A tibble: 336,776 x 19
#>    year month   day dep_time sched_dep_time dep_delay arr_time
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>
#> 1  2013     1     9      641            900      1301     1242
#> 2  2013     6    15     1432           1935      1137     1607
#> 3  2013     1    10     1121           1635      1126     1239
#> 4  2013     9    20     1139           1845      1014     1457
#> ... with 336,772 more rows, and 12 more variables: sched_arr_time <int>,
#>   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#>   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>   minute <dbl>, time_hour <time>
```

`dplyr::arrange()` works the same way as `plyr::arrange()`. It's a straightforward wrapper around `order()` that requires less typing. The previous code is equivalent to:

```
flights[order(flights$year, flights$month, flights$day), ]
flights[order(flights$arr_delay, decreasing = TRUE), ] or flights[order(-flights$arr_delay), ]
```

Select columns with `select()`

Often you work with large datasets with many columns but only a few are actually of interest to you. `select()` allows you to rapidly zoom in on a useful subset using operations that usually only work on numeric variable positions:

```
# Select columns by name
select(flights, year, month, day)
#> # A tibble: 336,776 x 3
#>    year month   day
#>   <int> <int> <int>
#> 1  2013     1     1
```

```
#> 2  2013     1     1
#> 3  2013     1     1
#> 4  2013     1     1
#> ... with 336,772 more rows
# Select all columns between year and day (inclusive)
select(flights, year:day)
#> # A tibble: 336,776 x 3
#>    year month   day
#>   <int> <int> <int>
#> 1  2013     1     1
#> 2  2013     1     1
#> 3  2013     1     1
#> 4  2013     1     1
#> ... with 336,772 more rows
# Select all columns except those from year to day (inclusive)
select(flights, -(year:day))
#> # A tibble: 336,776 x 16
#>   dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay
#>      <int>          <int>     <dbl>    <int>          <int>     <dbl>
#> 1      517            515         2      830            819        11
#> 2      533            529         4      850            830        20
#> 3      542            540         2      923            850        33
#> 4      544            545        -1     1004           1022       -18
#> ... with 336,772 more rows, and 10 more variables: carrier <chr>,
#>   flight <int>, tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>,
#>   distance <dbl>, hour <dbl>, minute <dbl>, time_hour <time>
```

This function works similarly to the `select` argument in `base::subset()`. Because the dplyr philosophy is to have small functions that do one thing well, it's its own function in dplyr.

There are a number of helper functions you can use within `select()`, like `starts_with()`, `ends_with()`, `matches()` and `contains()`. These let you quickly match larger blocks of variables that meet some criterion. See `?select` for more details.

You can rename variables with `select()` by using named arguments:

```
select(flights, tail_num = tailnum)
#> # A tibble: 336,776 x 1
#>   tail_num
#>      <chr>
#> 1   N14228
#> 2   N24211
#> 3   N619AA
#> 4   N804JB
#> ... with 336,772 more rows
```

But because `select()` drops all the variables not explicitly mentioned, it's not that useful. Instead, use `rename()`:

```
rename(flights, tail_num = tailnum)
#> # A tibble: 336,776 x 19
#>    year month   day dep_time sched_dep_time dep_delay arr_time
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>
#> 1  2013     1     1      517            515         2      830
#> 2  2013     1     1      533            529         4      850
#> 3  2013     1     1      542            540         2      923
#> 4  2013     1     1      544            545        -1     1004
#> ... with 336,772 more rows, and 12 more variables: sched_arr_time <int>,
#>   arr_delay <dbl>, carrier <chr>, flight <int>, tail_num <chr>,
#>   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>   minute <dbl>, time_hour <time>
```

Extract distinct (unique) rows

Use `distinct()`to find unique values in a table:

```
distinct(flights, tailnum)
#> # A tibble: 4,044 x 1
#>   tailnum
#>     <chr>
#> 1  N14228
#> 2  N24211
#> 3  N619AA
#> 4  N804JB
#> ... with 4,040 more rows
distinct(flights, origin, dest)
#> # A tibble: 224 x 2
#>   origin  dest
#>    <chr> <chr>
#> 1    EWR   IAH
#> 2    LGA   IAH
#> 3    JFK   MIA
#> 4    JFK   BQN
#> ... with 220 more rows
```

(This is very similar to `base::unique()` but should be much faster.)

Add new columns with `mutate()`

Besides selecting sets of existing columns, it's often useful to add new columns that are functions of existing columns. This is the job of `mutate()`:

```
mutate(flights,
  gain = arr_delay - dep_delay,
  speed = distance / air_time * 60)
#> # A tibble: 336,776 x 21
#>    year month   day dep_time sched_dep_time dep_delay arr_time
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>
#> 1  2013     1     1      517            515         2      830
#> 2  2013     1     1      533            529         4      850
#> 3  2013     1     1      542            540         2      923
#> 4  2013     1     1      544            545        -1     1004
#> ... with 336,772 more rows, and 14 more variables: sched_arr_time <int>,
#>   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#>   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>   minute <dbl>, time_hour <time>, gain <dbl>, speed <dbl>
```

`dplyr::mutate()` works the same way as `plyr::mutate()` and similarly to `base::transform()`. The key difference between `mutate()` and `transform()` is that mutate allows you to refer to columns that you've just created:

```
mutate(flights,
  gain = arr_delay - dep_delay,
  gain_per_hour = gain / (air_time / 60)
)
#> # A tibble: 336,776 x 21
#>    year month   day dep_time sched_dep_time dep_delay arr_time
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>
#> 1  2013     1     1      517            515         2      830
#> 2  2013     1     1      533            529         4      850
#> 3  2013     1     1      542            540         2      923
#> 4  2013     1     1      544            545        -1     1004
#> ... with 336,772 more rows, and 14 more variables: sched_arr_time <int>,
#>   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#>   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>   minute <dbl>, time_hour <time>, gain <dbl>, gain_per_hour <dbl>


transform(flights,
  gain = arr_delay - delay,
```

```
  gain_per_hour = gain / (air_time / 60)
)
#> Error: object 'gain' not found
```

If you only want to keep the new variables, use `transmute()`:

```
transmute(flights,
  gain = arr_delay - dep_delay,
  gain_per_hour = gain / (air_time / 60)
)
#> # A tibble: 336,776 x 2
#>    gain gain_per_hour
#>   <dbl>         <dbl>
#> 1     9      2.378855
#> 2    16      4.229075
#> 3    31     11.625000
#> 4   -17     -5.573770
#> ... with 336,772 more rows
```

Summarise values with `summarise()`

The last verb is `summarise()`. It collapses a data frame to a single row (this is exactly equivalent to `plyr::summarise()`):

```
summarise(flights,
  delay = mean(dep_delay, na.rm = TRUE))
#> # A tibble: 1 x 1
#>      delay
#>      <dbl>
#> 1 12.63907
```

Below, we'll see how this verb can be very useful.

Randomly sample rows with `sample_n()` and `sample_frac()`

You can use `sample_n()` and `sample_frac()` to take a random sample of rows: use `sample_n()` for a fixed number and `sample_frac()` for a fixed fraction.

```
sample_n(flights, 10)
#> # A tibble: 10 x 19
```

```
#>    year month   day dep_time sched_dep_time dep_delay arr_time
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>
#> 1  2013     7     8     2205           2019       106      103
#> 2  2013     9    12     1602           1545        17       NA
#> 3  2013    11     4     1459           1459         0     1642
#> 4  2013    10    25     1354           1350         4     1534
#> ... with 6 more rows, and 12 more variables: sched_arr_time <int>,
#>   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#>   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>   minute <dbl>, time_hour <time>
sample_frac(flights, 0.01)
#> # A tibble: 3,368 x 19
#>    year month   day dep_time sched_dep_time dep_delay arr_time
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>
#> 1  2013     5    14      850            850         0     1237
#> 2  2013    11     8      832            840        -8     1016
#> 3  2013    12     1     1155           1155         0     1309
#> 4  2013     1     1      929            925         4     1220
#> ... with 3,364 more rows, and 12 more variables: sched_arr_time <int>,
#>   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#>   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#>   minute <dbl>, time_hour <time>
```

Use `replace = TRUE` to perform a bootstrap sample. If needed, you can weight the sample with the `weight` argument.

Commonalities

You may have noticed that the syntax and function of all these verbs are very similar:

- The first argument is a data frame.
- The subsequent arguments describe what to do with the data frame. Notice that you can refer to columns in the data frame directly without using `$`.
- The result is a new data frame

Together these properties make it easy to chain together multiple simple steps to achieve a complex result.

These five functions provide the basis of a language of data manipulation. At the most basic level, you can only alter a tidy data frame in five useful ways: you can reorder the rows (`arrange()`), pick observations and variables of interest (`filter()` and `select()`), add new variables that are functions of existing variables (`mutate()`), or collapse many values to a summary (`summarise()`). The remainder of the language comes from applying the five functions to different types of data. For example, I'll discuss how these functions work with grouped data.

Grouped operations

These verbs are useful on their own, but they become really powerful when you apply them to groups of observations within a dataset. In dplyr, you do this by with the `group_by()` function. It breaks down a dataset into specified groups of rows. When you then apply the verbs above on the resulting object they'll be automatically applied "by group". Most importantly, all this is achieved by using the same exact syntax you'd use with an ungrouped object.

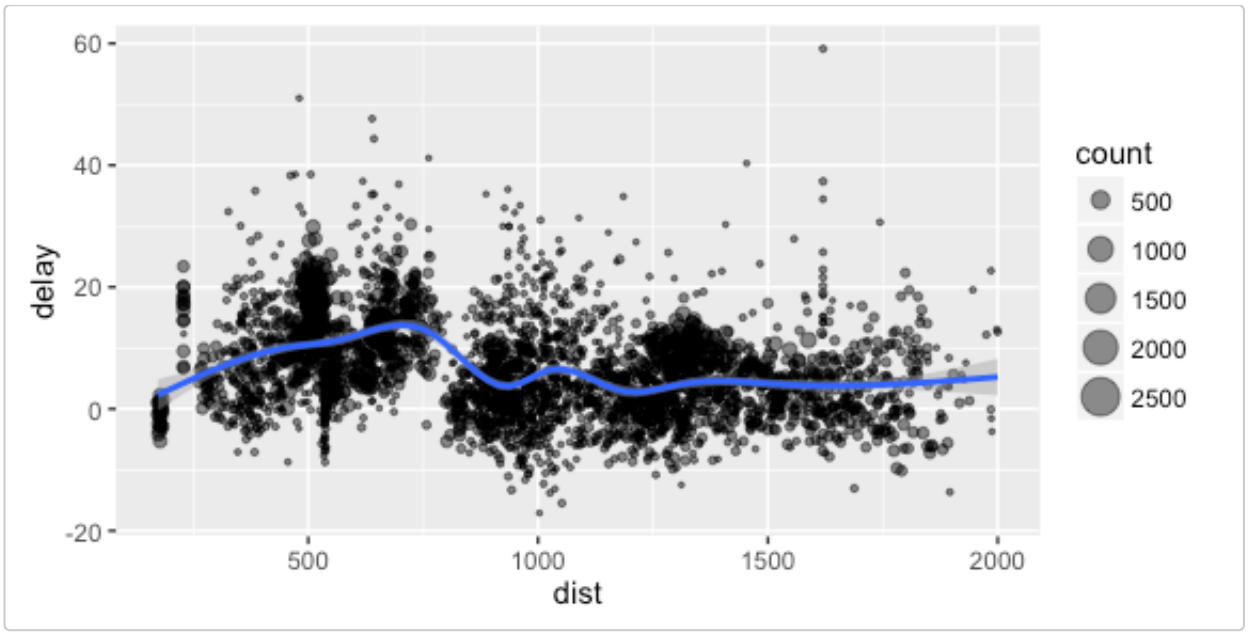
Grouping affects the verbs as follows:

- grouped `select()` is the same as ungrouped `select()`, except that grouping variables are always retained.
- grouped `arrange()` orders first by the grouping variables
- `mutate()` and `filter()` are most useful in conjunction with window functions (like `rank()`, or `min(x) == x`). They are described in detail in `vignette("window-functions")`.
- `sample_n()` and `sample_frac()` sample the specified number/fraction of rows in each group.
- `slice()` extracts rows within each group.
- `summarise()` is powerful and easy to understand, as described in more detail below.

In the following example, we split the complete dataset into individual planes and then summarise each plane by counting the number of flights (`count = n()`) and computing the average distance (`dist = mean(Distance, na.rm = TRUE)`) and arrival delay (`delay = mean(ArrDelay, na.rm = TRUE)`). We then use ggplot2 to display the output.

```
by_tailnum <- group_by(flights, tailnum)
delay <- summarise(by_tailnum,
  count = n(),
  dist = mean(distance, na.rm = TRUE),
  delay = mean(arr_delay, na.rm = TRUE))
delay <- filter(delay, count > 20, dist < 2000)

# Interestingly, the average delay is only slightly related to the
# average distance flown by a plane.
ggplot(delay, aes(dist, delay)) +
  geom_point(aes(size = count), alpha = 1/2) +
  geom_smooth() +
  scale_size_area()
```



You use `summarise()` with **aggregate functions**, which take a vector of values and return a single number. There are many useful examples of such functions in base R like `min()`, `max()`, `mean()`, `sum()`, `sd()`, `median()`, and `IQR()`. dplyr provides a handful of others:

- `n()`: the number of observations in the current group
- `n_distinct(x)`:the number of unique values in `x`.
- `first(x)`, `last(x)` and `nth(x, n)` - these work similarly to `x[1]`, `x[length(x)]`, and `x[n]` but give you more control over the result if the value is missing.

For example, we could use these to find the number of planes and the number of flights that go to each possible destination:

```
destinations <- group_by(flights, dest)
summarise(destinations,
  planes = n_distinct(tailnum),
  flights = n()
)
#> # A tibble: 105 x 3
#>    dest planes flights
#>   <chr>  <int>   <int>
#> 1   ABQ    108     254
#> 2   ACK     58     265
#> 3   ALB    172     439
#> 4   ANC      6       8
#> ... with 101 more rows
```

You can also use any function that you write yourself. For performance, dplyr provides optimised C++ versions of many of these functions. If you want to provide your own C++ function, see the hybrid-

evaluation vignette for more details.

When you group by multiple variables, each summary peels off one level of the grouping. That makes it easy to progressively roll-up a dataset:

```
daily <- group_by(flights, year, month, day)
(per_day   <- summarise(daily, flights = n()))
#> Source: local data frame [365 x 4]
#> Groups: year, month [?]
#>
#> # A tibble: 365 x 4
#>    year month   day flights
#>   <int> <int> <int>   <int>
#> 1  2013     1     1     842
#> 2  2013     1     2     943
#> 3  2013     1     3     914
#> 4  2013     1     4     915
#> ... with 361 more rows
(per_month <- summarise(per_day, flights = sum(flights)))
#> Source: local data frame [12 x 3]
#> Groups: year [?]
#>
#> # A tibble: 12 x 3
#>    year month flights
#>   <int> <int>   <int>
#> 1  2013     1   27004
#> 2  2013     2   24951
#> 3  2013     3   28834
#> 4  2013     4   28330
#> ... with 8 more rows
(per_year  <- summarise(per_month, flights = sum(flights)))
#> # A tibble: 1 x 2
#>    year flights
#>   <int>   <int>
#> 1  2013  336776
```

However you need to be careful when progressively rolling up summaries like this: it's ok for sums and counts, but you need to think about weighting for means and variances (it's not possible to do this exactly for medians).

Chaining

The dplyr API is functional in the sense that function calls don't have side-effects. You must always save their results. This doesn't lead to particularly elegant code, especially if you want to do many

operations at once. You either have to do it step-by-step:

```
a1 <- group_by(flights, year, month, day)
a2 <- select(a1, arr_delay, dep_delay)
a3 <- summarise(a2,
  arr = mean(arr_delay, na.rm = TRUE),
  dep = mean(dep_delay, na.rm = TRUE))
a4 <- filter(a3, arr > 30 | dep > 30)
```

Or if you don't want to save the intermediate results, you need to wrap the function calls inside each other:

```
filter(
  summarise(
    select(
      group_by(flights, year, month, day),
      arr_delay, dep_delay
    ),
    arr = mean(arr_delay, na.rm = TRUE),
    dep = mean(dep_delay, na.rm = TRUE)
  ),
  arr > 30 | dep > 30
)
#> Adding missing grouping variables: `year`, `month`, `day`
#> Source: local data frame [49 x 5]
#> Groups: year, month [11]
#>
#> # A tibble: 49 x 5
#>    year month   day      arr      dep
#>   <int> <int> <int>    <dbl>    <dbl>
#> 1  2013     1    16 34.24736 24.61287
#> 2  2013     1    31 32.60285 28.65836
#> 3  2013     2    11 36.29009 39.07360
#> 4  2013     2    27 31.25249 37.76327
#> ... with 45 more rows
```

This is difficult to read because the order of the operations is from inside to out. Thus, the arguments are a long way away from the function. To get around this problem, dplyr provides the `%>%` operator. `x %>% f(y)` turns into `f(x, y)` so you can use it to rewrite multiple operations that you can read left-to-right, top-to-bottom:

```
flights %>%
  group_by(year, month, day) %>%
  select(arr_delay, dep_delay) %>%
```

```
  summarise(
    arr = mean(arr_delay, na.rm = TRUE),
    dep = mean(dep_delay, na.rm = TRUE)
  ) %>%
  filter(arr > 30 | dep > 30)
```

Other data sources

As well as data frames, dplyr works with data that is stored in other ways, like data tables, databases and multidimensional arrays.

Data table

dplyr also provides data table methods for all verbs through dtplyr. If you're using data.tables already this lets you to use dplyr syntax for data manipulation, and data.table for everything else.

For multiple operations, data.table can be faster because you usually use it with multiple verbs simultaneously. For example, with data table you can do a mutate and a select in a single step. It's smart enough to know that there's no point in computing the new variable for rows you're about to throw away.

The advantages of using dplyr with data tables are:

- For common data manipulation tasks, it insulates you from the reference semantics of data.tables, and protects you from accidentally modifying your data.
- Instead of one complex method built on the subscripting operator (`[`), it provides many simple methods.

Databases

dplyr also allows you to use the same verbs with a remote database. It takes care of generating the SQL for you so that you can avoid the cognitive challenge of constantly switching between languages. See the databases vignette for more details.

Compared to DBI and the database connection algorithms:

- it hides, as much as possible, the fact that you're working with a remote database
- you don't need to know any SQL (although it helps!)
- it abstracts over the many differences between the different DBI implementations

Multidimensional arrays / cubes

`tbl_cube()` provides an experimental interface to multidimensional arrays or data cubes. If you're using this form of data in R, please get in touch so I can better understand your needs.

Comparisons

Compared to all existing options, dplyr:

- abstracts away how your data is stored, so that you can work with data frames, data tables and remote databases using the same set of functions. This lets you focus on what you want to achieve, not on the logistics of data storage.
- provides a thoughtful default `print()` method that doesn't automatically print pages of data to the screen (this was inspired by data table's output).

Compared to base functions:

- dplyr is much more consistent; functions have the same interface. So once you've mastered one, you can easily pick up the others
- base functions tend to be based around vectors; dplyr is based around data frames

Compared to plyr, dplyr:

- is much much faster
- provides a better thought out set of joins
- only provides tools for working with data frames (e.g. most of dplyr is equivalent to `ddply()` + various functions, `do()` is equivalent to `dlply()`)

Compared to virtual data frame approaches:

- it doesn't pretend that you have a data frame: if you want to run lm etc, you'll still need to manually pull down the data
- it doesn't provide methods for R summary functions (e.g. `mean()`, or `sum()`)