5.3 Aggregating transforms

This section covers transforms that combine multiple rows or multiple columns.

5.3.1 Combining many rows into summary rows

Here we address the situation where there are multiple observations or measurements of a single subject, in this case species of Iris, that we wish to aggregate into a single observation.

SCENARIO

We have been asked to make a report summarizing iris petals by species.

PROBLEM

Summarize measurements by category, a

```
library("datasets")
library("ggplot2")
head(iris)
```


```
library("datasets")
library("ggplot2")
head(iris)
```


A data.frame: 6 × 5

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
	<dbl>	<dbl>	<dbl>	<dbl>	<fct>
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

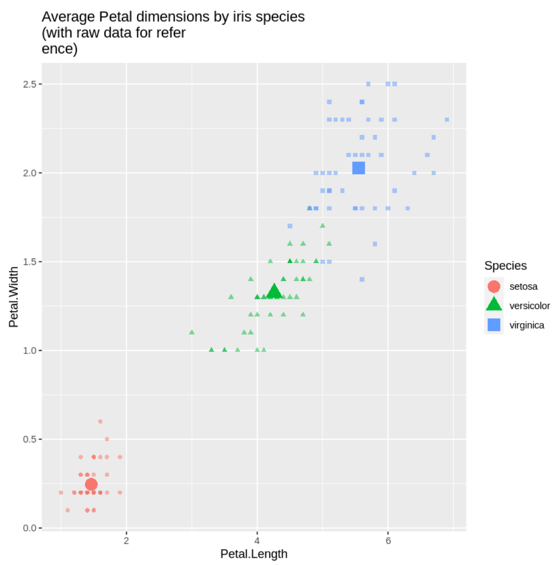
```
# Base R solution
iris_summary <- aggregate(
cbind(Petal.Length, Petal.Width) ~ Species,
data = iris,
FUN = mean)
print(iris_summary)
```


```
# Base R solution
iris_summary <- aggregate(
cbind(Petal.Length, Petal.Width) ~ Species,
data = iris,
FUN = mean)
print(iris_summary)
```


```
     Species Petal.Length Petal.Width
1     setosa        1.462       0.246
2 versicolor        4.260       1.326
3  virginica        5.552       2.026
```

```
library(ggplot2)
ggplot(mapping = aes(x = Petal.Length, y = Petal.Width,
shape = Species, color = Species)) +
geom_point(data = iris, # raw data
alpha = 0.5) +
geom_point(data = iris_summary, # per-group summaries
size = 5) +
ggtitle("Average Petal dimensions by iris species\n(with raw data for refer
ence)")
```


```
library(ggplot2)
ggplot(mapping = aes(x = Petal.Length, y = Petal.Width,
shape = Species, color = Species)) +
geom_point(data = iris, # raw data
alpha = 0.5) +
geom_point(data = iris_summary, # per-group summaries
size = 5) +
ggtitle("Average Petal dimensions by iris species\n(with raw data for refer
ence)")
```


```
# data.table solution
library("data.table")
iris_data.table <- as.data.table(iris)
iris_data.table <- iris_data.table[,
.(Petal.Length = mean(Petal.Length),
Petal.Width = mean(Petal.Width)),
by = .(Species)]
# print(iris_data.table)
```

```
# data.table solution
library("data.table")
iris_data.table <- as.data.table(iris)
iris_data.table <- iris_data.table[,
.(Petal.Length = mean(Petal.Length),
Petal.Width = mean(Petal.Width)),
by = .(Species)]
# print (iris_data.table)
print(iris_data.table)
```

```
      Species Petal.Length Petal.Width
1:     setosa        1.462       0.246
2: versicolor        4.260       1.326
3:  virginica        5.552       2.026
```

dplyr solution

- dplyr::group_by
- dplyr::summarize
- A one-argument aggregation function, for example sum or mean

```
library("dplyr")
iris_summary <- iris %>% group_by(., Species) %>%
summarize(.,
Petal.Length = mean(Petal.Length),
Petal.Width = mean(Petal.Width)) %>%
ungroup(.)
# print(iris_summary)
```

```
library("dplyr")
iris_summary <- iris %>% group_by(., Species) %>%
summarize(.,
Petal.Length = mean(Petal.Length),
Petal.Width = mean(Petal.Width)) %>%
ungroup(.)
# print(iris_summary)
print(iris_summary)
```

```
Attaching package: ‘dplyr’


The following objects are masked from ‘package:data.table’:

    between, first, last


The following objects are masked from ‘package:stats’:

    filter, lag


The following objects are masked from ‘package:base’:

    intersect, setdiff, setequal, union


# A tibble: 3 × 3
  Species    Petal.Length Petal.Width
  <fct>             <dbl>       <dbl>
1 setosa             1.46       0.246
2 versicolor         4.26       1.33
3 virginica          5.55       2.03
```

```
# In data.table, the task looks like the following:
library("data.table")
iris_data.table <- as.data.table(iris)
iris_data.table[ ,
`:=`(mean_Petal.Length = mean(Petal.Length),
mean_Petal.Width = mean(Petal.Width)),
by = "Species"]
print(iris_data.table)
```

```
# In data.table, the task looks like the following:
library("data.table")
iris_data.table <- as.data.table(iris)
iris_data.table[,
`:=`(mean_Petal.Length = mean(Petal.Length),
mean_Petal.Width = mean(Petal.Width)),
by = "Species"]
print(iris_data.table)
```

```
     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
 ---
```

```
146:          6.7         3.0          5.2         2.3 virginica
147:          6.3         2.5          5.0         1.9 virginica
148:          6.5         3.0          5.2         2.0 virginica
149:          6.2         3.4          5.4         2.3 virginica
150:          5.9         3.0          5.1         1.8 virginica
     mean_Petal.Length mean_Petal.Width
  1:             1.462            0.246
  2:             1.462            0.246
  3:             1.462            0.246
  4:             1.462            0.246
  5:             1.462            0.246
 ---
146:             5.552            2.026
147:             5.552            2.026
148:             5.552            2.026
149:             5.552            2.026
150:             5.552            2.026
```

dplyr has similar functionality:

```
library("dplyr")
iris_dplyr <- iris %>%
group_by(., Species) %>%
mutate(.,
mean_Petal.Length = mean(Petal.Length),
mean_Petal.Width = mean(Petal.Width)) %>%
ungroup(.)
head(iris_dplyr)
```

```
library("dplyr")
iris_dplyr <- iris %>%
group_by(., Species) %>%
mutate (.,
mean_Petal.Length = mean(Petal.Length),
mean_Petal.Width = mean(Petal.Width)) %>%
ungroup(.)
head(iris_dplyr)
```

A tibble: 6 × 7

Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species	mean_Petal.Length	mean_Petal.Width
<dbl>	<dbl>	<dbl>	<dbl>	<fct>	<dbl>	<dbl>
5.1	3.5	1.4	0.2	setosa	1.462	0.246
4.9	3.0	1.4	0.2	setosa	1.462	0.246
4.7	3.2	1.3	0.2	setosa	1.462	0.246
4.6	3.1	1.5	0.2	setosa	1.462	0.246
5.0	3.6	1.4	0.2	setosa	1.462	0.246
5.4	3.9	1.7	0.4	setosa	1.462	0.246

Again, it is critical to ungroup() when applying per-group transforms. Also, be aware that dplyr grouped operations (in particular, row selection through filter()) can be much slower than ungrouped operations, so you want to make your group()/ ungroup() intervals as short as possible. And dplyr grouped operations are usually much slower than data.table grouped operations in general.

5.4 Multitable data transforms

This section covers operations between multiple tables. This includes the tasks of splitting tables, concatenating tables, and joining tables.

5.4.1 Combining two or more ordered data frames quickly

Here we discuss combining two data frames, with the same number of rows or columns (and same order!).

SCENARIO

We have been asked to draw information about products from a sales database and produce a report. Typically, different facts (in this case, price and units sold) are stored in different tables, so to produce our report, we will have to combine data from more than one table

For example, suppose our example data was the following:productTable <-

```
productTable <-wrapr::build_frame(
"productID", "price" |
"p1" , 9.99 |
"p2" , 16.29 |
"p3" , 19.99 |
"p4" , 5.49 |
"p5" , 24.49 )
```

```
install.packages("wrapr")
library(wrapr)
productTable <- wrapr::build_frame(
"productID", "price" |
"p1" , 9.99 |
"p2" , 16.29 |
"p3" , 19.99 |
"p4" , 5.49 |
"p5" , 24.49 )
```

```
Installing package into '/usr/local/lib/R/site-library'
(as 'lib' is unspecified)


Attaching package: 'wrapr'


The following object is masked from 'package:dplyr':

    coalesce


The following object is masked from 'package:data.table':

    :=
```

```
salesTable <- wrapr::build_frame(
"productID", "sold_store", "sold_online" |
"p1" , 6 , 64 |
"p2" , 31 , 1 |
"p3" , 30 , 23 |
"p4" , 31 , 67 |
"p5" , 43 , 51 )
```

```
salesTable <- wrapr::build_frame(
"productID", "sold store", "sold_online" |
"p1" , 6, 64 |
"p2" , 31, 1 |
"P3" , 30, 23 |
"pa" , 31, 67 |
"p5" , 43, 51 )
```

```
productTable2 <- wrapr::build_frame(
"productID", "price" |
"n1" , 25.49 |
"n2" , 33.99 |
"n3" , 17.99 )
```


```
productTable2 <- wrapr::build_frame(
"productID", "price" |
"n1" , 25.49 |
"n2" , 33.99 |
"n3" , 17.99 )
```


```
productTable$productID <- factor(productTable$productID)
productTable2$productID <- factor(productTable2$productID)
```


```
productTable$productID <- factor(productTable$productID)
productTable2$productID <- factor(productTable2$productID)
```


PROBLEM 1: APPENDING ROWS

When two tables have the exact same column structure, we can concatenate them to get a larger table

```
# Base R solution
rbind_base = rbind(productTable,
productTable2)
rbind_base
```


```
# Base R solution
rbind_base = rbind(productTable,
productTable2)
rbind_base
```


A data.frame: 8 × 2

productID	price
<fct>	<dbl>
p1	9.99
p2	16.29
p3	19.99
p4	5.49
p5	24.49
n1	25.49
n2	33.99
n3	17.99

```
# Note that rbind creates a new factor variable when merging incompatible factor variables:
str(rbind_base)
```

```
'data.frame':	8 obs. of  2 variables:
 $ productID: Factor w/ 8 levels "p1","p2","p3",..: 1 2 3 4 5 6 7 8
 $ price    : num  9.99 16.29 19.99 5.49 24.49 ...
```

```
# data.table solution
library("data.table")
rbindlist(list(productTable,
productTable2))
```


```
# data.table solution
library("data.table")
```

```
rbindlist(list(productTable,
productTable2))
```

A data.table: 8 × 2

productID	price
<fct>	<dbl>
p1	9.99
p2	16.29
p3	19.99
p4	5.49
p5	24.49
n1	25.49
n2	33.99
n3	17.99

data.table also correctly merges factor types.

```
# dplyr solution
dplyr::bind_rows
library("dplyr")
bind_rows(list(productTable,
productTable2))
```


```
# dplyr solution
dplyr::bind_rows
library("dplyr")
bind_rows(list(productTable,
productTable2))
```

```
        dots <- list_flatten(dots, fn = is_flattenable)
        dots <- discard(dots, is.null)
        if (length(dots) == 0) {
            first <- NULL
        }
        else {
            first <- dots[[1L]]
        }
        if (is_named(dots) && !all(map_lgl(dots, dataframe_ish))) {
            return(as_tibble(dots))
        }
        for (i in seq_along(dots)) {
            .x <- dots[[i]]
            if (!dataframe_ish(.x)) {
                abort(glue("Argument {i} must be a data frame or a named atomic vector."))
            }
            if (obj_is_list(.x)) {
                dots[[i]] <- vctrs::data_frame(!!!.x, .name_repair = "minimal")
            }
        }
        if (!is_null(.id)) {
            check_string(.id)
            if (!is_named(dots)) {
                names(dots) <- seq_along(dots)
```

Notice that bind_rows coerces incompatible factor variables to character.

```
        else {
```

```
# add an extra column telling us which table
# each row comes from
productTable_marked <- productTable
productTable_marked$table <- "productTable"
productTable2_marked <- productTable2
productTable2_marked$table <- "productTable2"
# combine the tables
rbind_base <- rbind(productTable_marked,
productTable2_marked)
rbind_base
```


```
# add an extra column telling us which table
# each row comes from
productTable_marked <- productTable
productTable_marked$table <- "productTable"
productTable2_marked <- productTable2
productTable2_marked$table <- "productTable2"
# combine the tables
rbind_base <- rbind(productTable_marked,
productTable2_marked)
rbind_base
```


A data.frame: 8 × 3

productID	price	table
<fct>	<dbl>	<chr>
p1	9.99	productTable
p2	16.29	productTable
p3	19.99	productTable
p4	5.49	productTable
p5	24.49	productTable
n1	25.49	productTable2
n2	33.99	productTable2
n3	17.99	productTable2

data.table solution

data.table combines the split, apply, and recombine steps into a single, very efficient operation. We will continue our example with the rbind_base object to show the effect. data.table is willing to call a user function or execute a user expression for each data group and supplies special variables to work per-group:

- .BY—A named list of the grouping variables and values per group. .BY is a list of scalars, as by definition grouping variables do not vary per group.
- .SD—A data.table representation of the set of rows for the given group with the grouping columns removed. For instance, to compute a max price per group, we can do the following:

```
library("data.table")
# convert to data.table
dt <- as.data.table(rbind_base)
# arbitrary user defined function
f <- function(.BY, .SD) {
max(.SD$price)
}
# apply the function to each group
# and collect results
dt[ , max_price := f(.BY, .SD), by = table]
print(dt)
```


```
library("data.table")
# convert to data.table
dt <- as.data.table(rbind_base)
# arbitrary user defined function
f <- function(.BY, .SD) {
max(.SD$price)
}
# apply the function to each group
# and collect results
dt[ , max_price := f(.BY, .SD), by = table]
print(dt)
```


```
   productID price         table max_price
1:        p1  9.99  productTable     24.49
2:        p2 16.29  productTable     24.49
3:        p3 19.99  productTable     24.49
4:        p4  5.49  productTable     24.49
5:        p5 24.49  productTable     24.49
6:        n1 25.49 productTable2     33.99
7:        n2 33.99 productTable2     33.99
8:        n3 17.99 productTable2     33.99
```

```
library("data.table")
dt <- as.data.table(rbind_base)
grouping_column <- "table"
dt[ , max_price := max(price), by = eval(grouping_column)]
print(dt)
```


```
library("data.table")
dt <- as.data.table(rbind_base)
grouping_column <- "table"
dt[ , max_price := max(price), by = eval(grouping_column)]
print(dt)
```


```
   productID price         table max_price
1:        p1  9.99  productTable     24.49
2:        p2 16.29  productTable     24.49
3:        p3 19.99  productTable     24.49
4:        p4  5.49  productTable     24.49
5:        p5 24.49  productTable     24.49
6:        n1 25.49 productTable2     33.99
7:        n2 33.99 productTable2     33.99
8:        n3 17.99 productTable2     33.99
```

PROBLEM 3: APPENDING COLUMNS

Append a data frame as columns to another data frame. The data frames must have the same number of rows and same row order (with respect to what we consider to be row-keys).

Create a table of product information (price and units sold), from productTable and salesTable. This assumes that the products are sorted in the same order in both tables. If they are not, then sort them, or use a join command to merge the tables together

```
# Base R solution
# cbind
cbind(productTable, salesTable[, -1])
```

A data.frame: 5 × 4

productID	price	sold store	sold_online
<fct>	<dbl>	<dbl>	<dbl>
p1	9.99	6	64
p2	16.29	31	1
p3	19.99	30	23
p4	5.49	31	67
p5	24.49	43	51

```
# data.table solution
# For binding columns, data.table methods require the data to already be of type
# data.table.
library("data.table")
cbind(as.data.table(productTable),
as.data.table(salesTable[, -1]))
```


```
# data. table solution
# For binding columns, data. table methods require the data to already be of type
# data.table.
library("data.table")
cbind(as.data.table(productTable),
as.data.table(salesTable[, -1]))
```


A data.table: 5 × 4

productID	price	sold store	sold_online
<fct>	<dbl>	<dbl>	<dbl>
p1	9.99	6	64
p2	16.29	31	1
p3	19.99	30	23
p4	5.49	31	67
p5	24.49	43	51

```
# dplyr solution
# dplyr::bind_cols
library("dplyr")
# list of data frames calling convention
dplyr::bind_cols(list(productTable, salesTable[, -1]))
```


```
# dplyr solution
# dplyr::bind_cols
library("dplyr")
# list of data frames calling convention
dplyr::bind_cols(list(productTable, salesTable[, -1]))
```

A data.frame: 5 × 4

productID	price	sold store	sold_online

5.4.2 Principal methods to combine data from multiple tables

Join is the relational name for the process of combining two tables to create a third. The join results in a table that possibly has a new row for every pair of rows from the original two tables (plus possibly rows from each table that did not have matches from the other table). Rows are matched on key-values, matching from one table to another. The simplest case is when each table has a set of columns that uniquely determine each row (a unique key), and this is the case we will discuss here.

SCENARIO

Our example data is information about products in a sales database. Various facts (in this case, price and units sold) are stored in different tables. Missing values are allowed. We are tasked with combining these tables to produce a report.

```
install.packages("wrapr")
library(wrapr)
productTable <- wrapr::build_frame(
"productID", "price" |
"p1" , 9.99 |
"p3" , 19.99 |
"p4" , 5.49 |
"p5" , 24.49 )
```

```
install.packages("wrapr")
library(wrapr)
productTable <- wrapr::build_frame (
"productID", "price" |
"p1" , 9.99 |
"p3" , 19.99 |
"p4" , 5.49 |
"p5", 24.49 )
```

```
Installing package into '/usr/local/lib/R/site-library'
(as 'lib' is unspecified)
```

```
salesTable <- wrapr::build_frame(
"productID", "unitsSold" |
"p1" , 10 |
"p2" , 43 |
"p3" , 55 |
"p4" , 8 )
```

```
salesTable <- wrapr::build_frame (
"productID", "unitsSold" |
"p1" , 10 |
"p2" , 43 |
"p3" , 55 |
"p4" , 8 )
```

LEFT JOIN

The most important join for the data scientist is likely the left join. This join keeps every row from the left table and adds columns coming from matching rows in the right table. When there are no matching rows, NA values are substituted in. Usually, you design the right table (the second argument to your join command) to have unique keys; otherwise, the number of rows may grow (there is no need for the left table to have unique keys).

```
# Base R solution
# merge with argument all=TRUE
# note that merge orders the result by key column by default
# use sort=FALSE to skip the sorting
merge(productTable, salesTable, by = "productID", all=TRUE)
```

```
# Base R solution
# merge with argument all=TRUE
```

```
# note that merge orders the result by key column by default
# use sort=FALSE to skip the sorting
merge(productTable, salesTable, by = "productID", all=TRUE)
```

A data.frame: 5 × 3

productID	price	unitsSold
<chr>	<dbl>	<dbl>
p1	9.99	10
p2	NA	43
p3	19.99	55
p4	5.49	8
p5	24.49	NA

```
# data.table also overrides merge()
merge(productTable, salesTable, by = "productID", all.x = TRUE)
```


```
# data.table also overrides merge)
merge(productTable, salesTable, by = "productID", all.x = TRUE)
```


A data.frame: 4 × 3

productID	price	unitsSold
<chr>	<dbl>	<dbl>
p1	9.99	10
p3	19.99	55
p4	5.49	8
p5	24.49	NA

Base R indexing solution

The data.table index notation is another very good Base R way to use one table to add a single column to another: vectorized lookup through the match() and [] methods

```
library("data.table")
joined_table <- productTable
joined_table$unitsSold <- salesTable$unitsSold[match(joined_table$productID,
salesTable$productID)]
print(joined_table)
```


```
library("data.table")
joined_table <- productTable
joined_table$unitsSold <- salesTable$unitsSold[match(joined_table$productID,
salesTable$productID)]
print(joined_table)
```


```
  productID price unitsSold
1        p1  9.99        10
2        p3 19.99        55
3        p4  5.49         8
4        p5 24.49        NA
```

match() found the matching indices, and [] used the indices to retrieve the data. Please see help(match) for more details.

```
# dplyr solution
library("dplyr")
left_join(productTable, salesTable, by = "productID")
```

A data.frame: 4 × 3

productID	price	unitsSold
<chr>	<dbl>	<dbl>
p1	9.99	10
p3	19.99	55

Double-click (or enter) to edit

```
# dplyr solution
library("dplyr")
left_join(productTable, salesTable, by = "productID")
```



```
# dplyr solution
library("dplyr")
left_join(productTable, salesTable, by = "productID")
```


A data.frame: 4 × 3

productID	price	unitsSold
<chr>	<dbl>	<dbl>
p1	9.99	10
p3	19.99	55
p4	5.49	8
p5	24.49	NA

Right join

There is also a join called right join that is just the left join with the arguments reversed. As the right join is so similar to the left, we will forgo any right join examples.

INNER JOIN

In an inner join, you merge two tables into a single table, keeping only the rows where the key exists in both tables. This produces an intersection of the two tables,

```
# Base R solution
# merge
merge(productTable, salesTable, by = "productID")
```



```
# Base R solution
# merge
merge(productTable, salesTable, by = "productID")
```


A data.frame: 3 × 3

productID	price	unitsSold
<chr>	<dbl>	<dbl>
p1	9.99	10
p3	19.99	55
p4	5.49	8

```
# data.table solution
library("data.table")
productTable_data.table <- as.data.table(productTable)
salesTable_data.table <- as.data.table(salesTable)
merge(productTable, salesTable, by = "productID")
```

```
# data. table solution
library("data.table")
```

```
productTable_data.table <- as.data.table(productTable)
salesTable_data.table <- as.data.table(salesTable)
merge(productTable, salesTable, by="productID")
```

A data.frame: 3 × 3

productID	price	unitsSold
<chr>	<dbl>	<dbl>
p1	9.99	10
p3	19.99	55
p4	5.49	8

```
# dplyr solution
inner_join
library("dplyr")
inner_join(productTable, salesTable, by = "productID")
```


```
# dplyr solution
inner_join
library("dplyr")
inner_join(productTable, salesTable, by = "productID")
```


```
function (x, y, by = NULL, copy = FALSE, suffix = c(".x", ".y"),
    ..., keep = NULL)
{
    UseMethod("inner_join")
}
```

A data.frame: 3 × 3

productID	price	unitsSold
<chr>	<dbl>	<dbl>
p1	9.99	10
p3	19.99	55
p4	5.49	8

FULL JOIN

In a full join, you merge two tables into a single table, keeping rows for all key values. Notice that the two tables have equal importance here.

```
# Base R solution
# merge with argument all=TRUE
# note that merge orders the result by key column by default
# use sort=FALSE to skip the sorting
merge(productTable, salesTable, by = "productID", all=TRUE)
```


```
# Base R solution
# merge with argument all=TRUE
# note that merge orders the result by key column by default
# use sort=FALSE to skip the sorting
merge(productTable, salesTable, by = "productID", all=TRUE)
```


A data.frame: 5 × 3

productID	price	unitsSold
<chr>	<dbl>	<dbl>
p1	9.99	10
p2	NA	43
p3	19.99	55
p4	5.49	8
p5	24.49	NA

```
# data.table solution
library("data.table")
productTable_data.table <- as.data.table(productTable)
salesTable_data.table <- as.data.table(salesTable)
merge(productTable_data.table, salesTable_data.table,
by = "productID", all = TRUE)
```


```
# data.table solution
library("data.table")
productTable_data.table <- as.data.table(productTable)
salesTable_data.table <- as.data.table(salesTable)
merge(productTable_data.table, salesTable_data.table,
by = "productID", all = TRUE)
```


A data.table: 5 × 3

productID	price	unitsSold
<chr>	<dbl>	<dbl>
p1	9.99	10
p2	NA	43
p3	19.99	55
p4	5.49	8
p5	24.49	NA

```
# dplyr solution
dplyr::full_join
library("dplyr")
full_join(productTable, salesTable, by = "productID")
```


```
# dplyr solution
dplyr::full_join
library("dplyr")
full_join(productTable, salesTable, by = "productID")
```


```
function (x, y, by = NULL, copy = FALSE, suffix = c(".x", ".y"),
    ..., keep = NULL)
{
    UseMethod("full_join")
}
```

A data.frame: 5 × 3

productID	price	unitsSold
<chr>	<dbl>	<dbl>
p1	9.99	10
p3	19.99	55
p4	5.49	8
p5	24.49	NA
p2	NA	43

A HARDER JOIN PROBLEM

The examples we have given up to now do not use row order. Some problems can be solved much more efficiently with methods that do use row order, such as data.table's powerful rolling join operation

Scenario

You are given historic stock trade and quote (bid/ask) data. You are asked to perform the following analyses on the stock data: find what the bid and ask price were current when each trade was performed. This involves using row order to indicate time, and sharing information between rows.

Example data

In stock markets, the bid is the highest price somebody has declared they are willing to pay for a stock, and the ask is the lowest price that somebody has declared they are willing to sell a stock for. Bid and ask data are called quotes, and they usually are in an irregular time series (as new quotes can be formed at arbitrary times, not just at regular intervals), such as the following example:

```
library("data.table")
quotes <- data.table(
bid = c(5, 5, 7, 8),
ask = c(6, 6, 8, 10),
bid_quantity = c(100, 100, 100, 100),
ask_quantity = c(100, 100, 100, 100),
when = as.POSIXct(strptime(
c("2018-10-18 1:03:17",
"2018-10-18 2:12:23",
"2018-10-18 2:15:00",
"2018-10-18 2:17:51"),
"%Y-%m-%d %H:%M:%S")))
print(quotes)
```


```
library("data.table")
quotes <- data.table(
bid = c(5, 5, 7, 8),
ask = c(6, 6, 8, 10),
bid_quantity = c(100, 100, 100, 100),
ask_quantity = c(100, 100, 100, 100),
when = as.POSIXct(strptime(
c("2018-10-18 1:03:17",
"2018-10-18 2:12:23",
"2018-10-18 2:15:00",
"2018-10-18 2:17:51"),
"%Y-%m-%d %H:%M:%S")))
print(quotes)
```


```
   bid ask bid_quantity ask_quantity                when
1:   5   6          100          100 2018-10-18 01:03:17
2:   5   6          100          100 2018-10-18 02:12:23
3:   7   8          100          100 2018-10-18 02:15:00
4:   8  10          100          100 2018-10-18 02:17:51
```

Another irregular time series is trades. These are after-the-fact reports about exchanges of quantities of stock at a given price at a given time.

```
trades <- data.table(
trade_id = c(32525, 32526),
price = c(5.5, 9),
quantity = c(100, 200),
when = as.POSIXct(strptime(
c("2018-10-18 2:13:42",
"2018-10-18 2:19:20"),
"%Y-%m-%d %H:%M:%S")))
print(trades)
```


```
trades <- data.table(
trade_id = c(32525, 32526),
price = c(5.5, 9),
quantity = c(100, 200),
when = as.POSIXct(strptime(
c("2018-10-18 2:13:42",
"2018-10-18 2:19:20"),
"%Y-%m-%d %H:%M:%S")))
print(trades)
```


```
   trade_id price quantity                when
1:    32525   5.5      100 2018-10-18 02:13:42
2:    32526   9.0      200 2018-10-18 02:19:20
```

Rolling joins

The data.table rolling join is perfect for finding what was the most recent quote information for each trade. A rolling join is a type of join on an ordered column that gives us the most recent data available at the lookup time.

```
quotes[, quote_time := when]
trades[ , trade_time := when ]
quotes[ trades, on = "when", roll = TRUE ][
, .(quote_time, bid, price, ask, trade_id, trade_time) ]
```

```
quotes[, quote_time := when]
trades[, trade_time := when]
quotes[ trades, on = "when", roll = TRUE ][
,.(quote_time, bid, price, ask, trade_id, trade_time) ]
```

A data.table: 2 × 6

quote_time	bid	price	ask	trade_id	trade_time
<dttm>	<dbl>	<dbl>	<dbl>	<dbl>	<dttm>
2018-10-18 02:12:23	5	5.5	6	32525	2018-10-18 02:13:42
2018-10-18 02:17:51	8	9.0	10	32526	2018-10-18 02:19:20

✓ 0s completed at 12:26 AM