Manipulating Data with “dplyr”

OVERVIEW

- Introduction to dplyr
- Built-in functions
  - filter/select
  - arrange, mutate/transmute
  - summarise
- Join data sets
- Groupwise operations
  - group_by & summarise

dplyr

- We have now covered the major data structures, built-in functions, and programming features of R. *In principle*, we can do anything. In practice, using R effectively involves learning a variety of packages to simplify your tasks.
- Today we will look at **dplyr**. It provides a set of functions, somewhat similar to database query-type operations, that help efficiently manipulate data frames.
  - Filtering & rearranging: Built-in functions to do basic transformations.
  - Joins: When the analysis requires information from multiple data frames.
  - Groupwise operations: When analysis requires aggregation.

Basic dplyr Functions

- dplyr is based on surprisingly few operations which we will study in detail:
  - `filter` - Take subsets of rows
  - `select` - Take subsets of columns
  - `arrange` - Reorder rows
  - `mutate/transmute` - Add or replace columns
  - `summarise` - Compute aggregate values
  - Joins - Various “join” methods to combine multiple data frames.

Baby Births Dataset

- We introduce the sample data sets we will use during class today. **births.csv** contains counts of boys and girls born in each year.

```
births <- read.csv("births.csv",
                   stringsAsFactors = FALSE)
births[c(1:2, 131:132),]

    year  sex births
1   1880  boy 118405
2   1881  boy 108290
131 1880 girl  97606
132 1881 girl  98860
```

Baby Names Dataset

- **`bnames.csv`** is a much larger file giving information on babies with different names born in each year. For each year and child, the prop column gives the percentage of boys or girls given that name in that year. The soundex column gives the soundex code, which descibes the pronunciation of that name (see en.wikipedia.org/wiki/Soundex).

```
bnames <- read.csv("bnames.csv",
                   stringsAsFactors = FALSE)
head(bnames, 5)

  year    name     prop sex soundex
1 1880    John 0.081541 boy    J500
2 1880 William 0.080511 boy    W450
3 1880   James 0.050057 boy    J520
4 1880 Charles 0.045167 boy    C642
5 1880  George 0.043292 boy    G620
```

Baby Names Dataset

- We might want to ask: How has the percentage of each name evolved since 1880? For example:

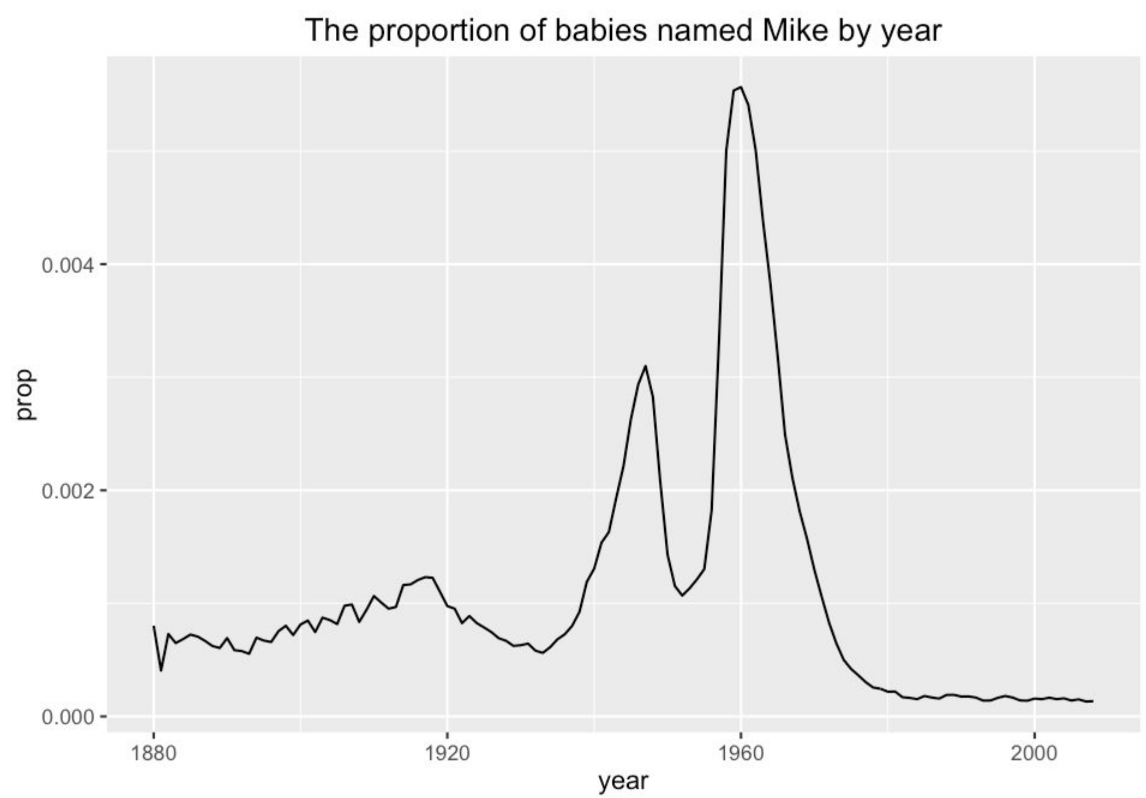
```
mike = bnames[bnames$name == "Mike", ]
head(mike, 3)

     year name     prop sex soundex
143  1880 Mike 0.000802 boy    M200
1231 1881 Mike 0.000406 boy    M200
2156 1882 Mike 0.000729 boy    M200
```

- The code above selects the rows with name “Mike”. We see that for each year the percentage of the name changes. This can be better seen with visualization.

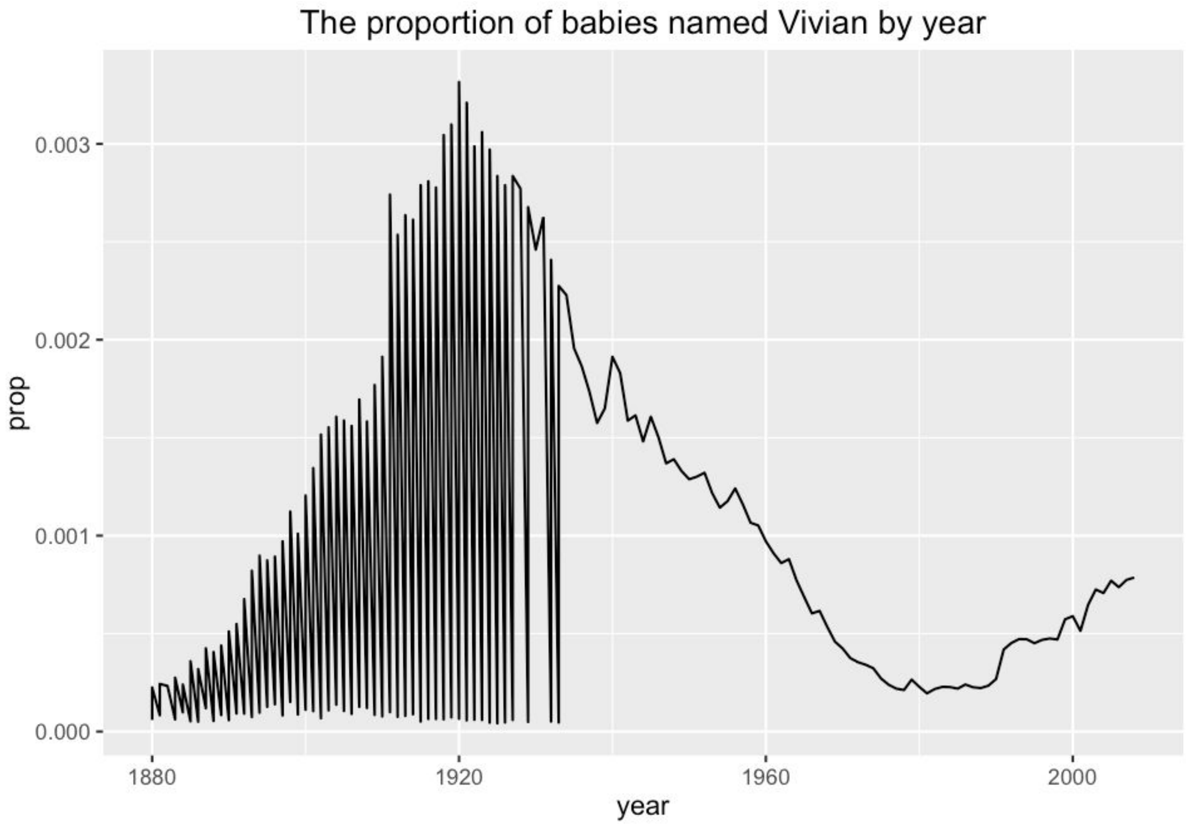
Baby Names Dataset

- The graph below is plotted with `ggplot2`, a package we will cover in a separate class. It plots how popular the name "Mike" was in each year. It reached its peak popularity in 1960.



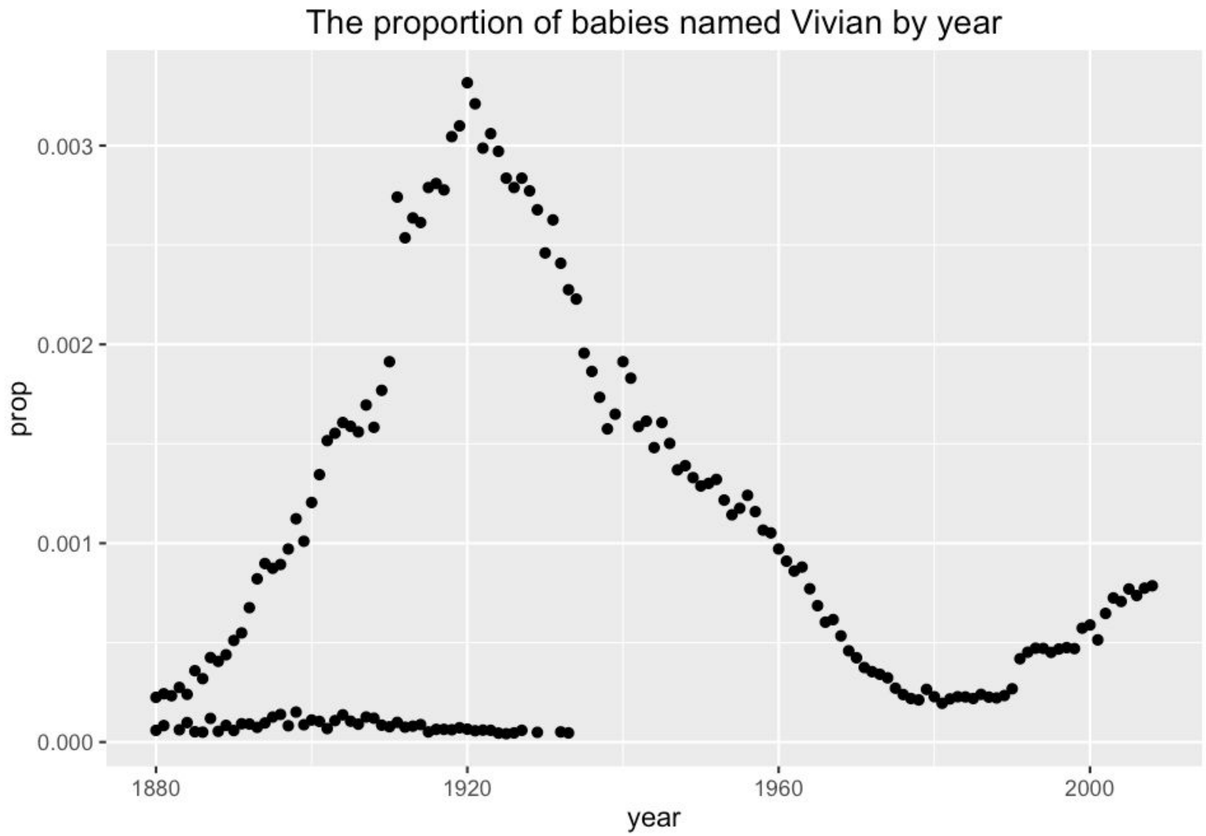
Baby Names Dataset

❖ We see a problem if we visualize the name Vivian. Why does the proportion seem to be oscillating so frequently?



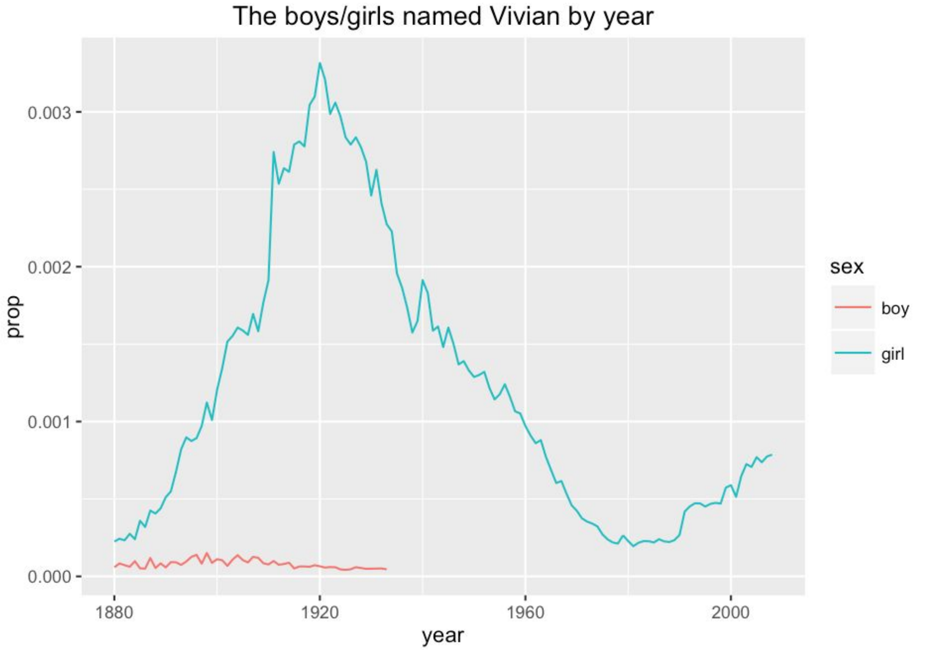
Baby Names Dataset

- Let's try sketching a scatterplot instead. What do you think causes the oscillation from the previous slide?



Baby Names Dataset

- From the scatter plot, it seems that there are actually *two* curves, instead of an oscillating one. With more careful investigation, we see that the two curves represent different genders. It turns out that Vivian was once a fairly common *boy*'s name. In the class today, we survey the tools that facilitate this kind of analysis in `dplyr`.



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Built-in Functions

- We start with some built-in function in dplyr. Most of what we're doing here can be done with basic programming methods as well; however, dplyr provides a friendlier syntax as well as a better data storage method that improves efficiency. We will take a look at the functions:
  - `filter`
  - `select`
  - `arrange`
  - `mutate/transmute`
  - `summarise`
- We will see that the functions listed above all take a data frame as their first argument and the "instructions" in their second argument. They all return a data frame.

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Built-in Functions

- We first construct a toy sample:

```
df = data.frame(
  color = c("blue","black", "blue", "blue","black"),
  value = 1:5)
df
  color value
1  blue     1
2 black     2
3  blue     3
4  blue     4
5 black     5
```

- We'll want to import the `dplyr` package as well:

```
library(dplyr)
```

filter

- We then use the function `filter` to select the rows whose color is blue:

```
filter(df, color == "blue")
  color value
1  blue     1
2  blue     3
3  blue     4
```

- As we've seen before, this can also be done by ordinary slicing:

```
df[df$color == "blue",]
```

The `filter` function has a simpler syntax; while the difference may be slight here, it will pay off as we do more complex things.

filter

- The first parameter of `filter()` is the data frame and the second is the filtering condition. (Note that we don't have to write "`df$`" when referring to a column of `df`.)

```
filter(df, value %in% c(3, 4, 5))
  color value
1  blue     3
2  blue     4
3 black     5
```

- Logical operators like and (&) can be used as well:

```
filter(df, value %in% c(3, 4, 5) & color=='blue')
  color value
1  blue     3
2  blue     4
```

filter

- Another example of logical operators using the or (|):

```
filter(df, value %in% c(1, 4) | color=="black")
  color value
1  blue     1
2 black     2
3  blue     4
4 black     5
```

- The second parameter is essentially broken down into a logical vector:

```
filter(df, c(T,F,F,F,T))
  color value
1  blue     1
2 black     5
```

select

- The `select()` function, like `filter()`, is used for slicing a data frame. `select` picks *columns* with column names (instead of picking *rows* with conditions).

```
select(df, color)
  color
1  blue
2 black
3  blue
4  blue
5 black
```

- You can select multiple columns:

```
select(df, color, value)
  color value
1  blue     1    #...some rows omitted...
```

select

- `select` can exclude columns by the “-” notation as well:

```
select(df, -color)
  value
1     1
2     2
3     3
4     4
5     5
```

- We can specify the columns by indexes instead of names:

```
select(df, 1)
  color
1  blue
2 black
3  blue    #...some rows omitted...
```

select

- When given integer arguments, `select` uses column numbers in the *original* data frame, not in any subsequential data frame. What do you think `select(df, -1, -1)` does?
- You might think this call first removes column 1 (`color`) and then removes the *new* column 1 (`value`), returning an empty data frame; this is not the case. The call `select(df, -1, -1)` is the same as the call `select(df, -1)`.
- To remove both columns, instead wen can use the call `select(df, -1, -2)` or `select(df, -2, -1)`:

```
select(df, -1, -2)
data frame with 0 columns and 5 rows
```

select

- It is possible to nest statements as well. What if we nested a selection statement with a negative index?

```
select(select(df, -1), -1)
data frame with 0 columns and 5 rows
```

- Why does this occur when it didn't work the same for the previous `select(df, -1, -1)` statement?

select

- It is important to note that selection is performed in a linear fashion, from left to right. Consider the statement below:

```
select(df, -1, 1)

  value color
1     1  blue
2     2 black
3     3  blue
4     4  blue
5     5 black
```

- First column 1 (`color`) is removed. At this point, there is only the column (`value`) left. Afterwards, column 1 from the original data frame is added back (`color`). Ultimately, we just ended up flipping the column order.

select

- What happens if we reverse the order of the indices?

```
select(df, 1, -1)
data frame with 0 columns and 5 rows
```

- This time, column 1 is selected first (`color`). At this point, column 2 (`value`) is removed and only the column 1 (`color`) is left in the data frame. Then, when we remove column 1, nothing is left. Thus, we ultimately ended up with an empty data frame.

select

- The function `select`, unlike `filter`, cannot take logical vectors; however, it provides some functions to select columns by certain conditions. These, and others, can be used as the second argument of `select`:
  - **`starts_with(x, ignore.case=T)`**: pick column names starting with x, case insensitive when ignore.case is (by default) set true.
  - **`ends_with(x, ignore.case=T)`**: pick column names ending with x.
  - **`contains(x, ignore.case=T)`**: pick column names containing x.
  - **`matches(x, ignore.case=T)`**: pick columns whose names match x, where x is a regular expression.
  - **`one_of(name_1, name_2, ..., name_n)`**: pick columns that have any of the names in the list. (The argument can also be a character vector.)

select

- We demonstrate the usage of the functions from the previous slide:

```
select(df, starts_with('c'))
  color
1  blue
2 black
3  blue
4  blue
5 black
select(df, contains('e'), starts_with('c'))
  value color
1     1  blue
2     2 black
3     3  blue
4     4  blue
5     5 black
```

select

- Another benefit of `select` is that it can be used to rename a column. While selecting, if we specify *new-column-name* = *original-column-name* in the second parameter of `select`, we will rename the selected column in the resulting data frame:

```
select(df, COLOR=color)
  COLOR
1  blue
2 black
3  blue
4  blue
5 black
```

select and rename

- If we desire to just rename columns without selecting a subset of columns, we could simply use the `rename()` function. The syntax is similar, but the function just renames and returns the whole (new) data frame:

```
rename(df, COLOR = color, Something.New = value)

  COLOR Something.New
1  blue             1
2 black             2
3  blue             3
4  blue             4
5 black             5
```

select and rename

- We remark here that `select()` and `rename()` are both non-mutating functions. Remember, they do not change the original data frame, but instead produce a *new* data frame. Even after doing all of the previous operations, we can see that the original data frame is unchanged:

```
df
  color value
1  blue     1
2 black     2
3  blue     3
4  blue     4
5 black     5
```

- If we would like to change `df`, we would have to use assignment:

```
df = rename(df, COLOR = colors)
```

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arrange

- The function `arrange()` positions the rows of the data frame in ascending order according to the values in the specified column:

```
arrange(df, value)
  color value
1  blue     1
2 black     2
3  blue     3
4  blue     4
5 black     5
```

arrange

- If we would like the column sorted in descending order, we can apply the function `desc()` to the column name:

```
arrange(df, desc(value))
  color value
1 black     5
2  blue     4
3  blue     3
4 black     2
5  blue     1
```

arrange

- arrange can also be used to order strings alphabetically as well:

```
arrange(df, color)
  color value
1 black     2
2 black     5
3  blue     1
4  blue     3
5  blue     4
```

mutate

- The function `mutate()` can be used to create a new column by deriving its value from an old column. For example, the code below doubles the numbers in `value` and also creates a new column called `double`.

```
mutate(df, double = value*2)
  color value double
1  blue     1      2
2 black     2      4
3  blue     3      6
4  blue     4      8
5 black     5     10
```

mutate

- `mutate` can create multiple columns all at once:

```
mutate(df, double = 2 * value, quadruple = 4 * value)

  color value double quadruple
1  blue     1      2         4
2 black     2      4         8
3  blue     3      6        12
4  blue     4      8        16
5 black     5     10        20
```

transmute

- It is possible to only include newly created columns and omit the old ones in the resulting data frame. To do so, use the same syntax as `mutate()`, but instead call the `transmute()` function:

```
transmute(df, double = 2 * value, quadruple = 4 * value)

  double quadruple
1      2         4
2      4         8
3      6        12
4      8        16
5     10        20
```

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Summarise

- We often need to extract summary information about a column. For example, we might want to know the mean and the standard deviation of a feature.
- The function `summarise()` returns a new data frame whose columns are aggregated from a column in the original data frame. The first argument is the data frame; the second is the new column name and the aggregation expression that defines its creation:

```
summarise(df, total = sum(value))
  total
1    15
```

Summarise

- `summarise()` can also create more than one column at a time:

```
summarise(df, total = sum(value),
              avg = mean(value))
  total avg
1    15   3
```

- We can perform computations within the `summarise()` function as well:

```
summarise(df, new_col=mean(value)/sd(value))
   new_col
1 1.897367
```

Summarise

- Below are some of the aggregating functions that can be used in `summarise()`:
  - Built-in aggregating functions which take a vector and return a scalar value: `min()`, `max()`, `mean()`, `sum()`, `sd()` and `median()`.
  - `n()`: returns the number of observations.
  - `n_distinct(x)`: returns the number of unique values in the column x.
  - `first(x)` or `last(x)`: returns the first or last observations in the column x.
  - nth(x, n): returns the nth observation in column x.

Summarise

- Examples:
  - `n_distinct()`: In our data frame `df`, there are two different colors.

```
summarise(df, n_distinct(color))
  n_distinct(color)
1                 2
```

  - `nth()`: The fourth element in the `value` column is 4:

```
summarise(df, nth(value, 4))
  nth(value, 4)
1             4
```

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Join Data Sets

- For better allocation of resources, related data is often stored in separate locations. Let's examine the baby datasets once again:
  - Recall that the `births` dataset contains the variables of `year`, `sex`, and `births`.
  - On the other hand, the `bnames` dataset contains the variables of `year`, `name`, `prop`, `sex`, and `soundex`.
- In an analysis, we might need the information from both data frames at once. We can combine these data frames with a **join**.
  - If you know SQL, you are familiar with the notion of joining two tables. As in SQL, dplyr has several kinds of joins: *inner join*, *outer join*, *left outer join*, and *right outer join*; dplyr also has *semi-join* and *anti-join*.

Joins

- The basic idea of a join: We have two data frames *df1* and *df2* with one or more columns in common; these columns contain the same type of data, and may even have the same name. Call these columns the *join columns*.
  - For `births` and `bnames`, the join columns are `year` and `sex`.
- Take any row from *df1* and any row from *df2*. If they have the same values in the join column(s), then combine those two rows into one and put the result into a new data frame.
  - Repeat this process for every pair of rows from *df1* and *df2*.
- The different types of joins mostly differ on how they deal with the situation where a row in one data frame has *no* matching row in the other.

Joins

- Let's see what happens with an *inner join*. We have a table that matches buildings with cities, and another that matches cities with countries. We want to match buildings with countries:

Building	City
Empire State	New York
Eiffel Tower	Paris
Notre Dame	Paris

City	Country
New York	USA
Paris	France

- The join compares each pair of rows to find where the values in the City column match. The result is as follows:

Building	City	Country
Empire State	New York	USA
Eiffel Tower	Paris	France
Notre Dame	Paris	France

Join Data Sets

- Let's construct a couple sample data sets to illustrate different joining methods:

```
x = data.frame( name = c("John", "Paul", "George",
                         "Ringo", "Stuart", "Pete"),
                instrument = c("guitar", "bass", "guitar",
                               "drums", "bass", "drums"),
                stringsAsFactors = FALSE)
x
    name instrument
1   John     guitar
2   Paul       bass
3 George     guitar
4  Ringo      drums
5 Stuart       bass
6   Pete      drums
```

Join Data Sets

- Here's another data frame y:

```
y <- data.frame( name = c("John", "Paul", "George",
                          "Ringo", "Brian"),
                 band = c(TRUE, TRUE, TRUE,
                          TRUE, FALSE),
                 stringsAsFactors = FALSE)
y
    name  band
1   John  TRUE
2   Paul  TRUE
3 George  TRUE
4  Ringo  TRUE
5  Brian FALSE
```

- Note that x and y both have a column called name.

Inner Join

- The function `inner_join()` is the basic and original join. As described previously, it takes every pair of rows from the left and right data frames; if the values in the join column are the same, the combined row is kept in the resulting data frame:

```
inner_join(x, y, by = "name")
    name instrument band
1   John     guitar TRUE
2   Paul       bass TRUE
3 George     guitar TRUE
4  Ringo      drums TRUE
```

- Since the rows in x with names Stuart and Pete don't match any rows in y, they do not show up in the result.

Left Join

- The function `left_join()` differs from the inner join in that every row from the left data frame is included in the result, regardless of whether there is a match in the right data frame. How?
- If a row in the left data frame is not matched by any row in the right, it is still put into the result; however, the corresponding columns from the right data frame appear to have NAs instead of actual values:

```
left_join(x, y, by = "name")
    name instrument band
1   John     guitar TRUE
2   Paul       bass TRUE
3 George     guitar TRUE
4  Ringo      drums TRUE
5 Stuart       bass   NA
6   Pete      drums   NA
```

Left Join

- Let’s see how this works:

```
    name instrument
1   John     guitar
2   Paul       bass
3 George     guitar
4  Ringo      drums
5 Stuart       bass
6   Pete      drums
```

```
    name  band
1   John  TRUE
2   Paul  TRUE
3 George  TRUE
4  Ringo  TRUE
5  Brian FALSE
```

- Since Stuart and Pete don’t match anything, they are included in the result with NA.

- Note that Brian isn’t included in the final result. This is because we are performing a *left* join.

Right Join

- The function `right_join()` works in much the same way. The only difference is that rows in the right data frame are all kept, regardless of matches in the left data frame. NA values are placed accordingly:

```
right_join(x, y, by = "name")
    name instrument  band
1   John     guitar  TRUE
2   Paul       bass  TRUE
3 George     guitar  TRUE
4  Ringo      drums  TRUE
5  Brian       <NA> FALSE
```

Full Join

- The *full join* (aka *outer join* or *full outer join*) combines the processes of both the left and right joins into one process. Thus, all unmatched records are retained from both data frames. The function is called `full_join()`:

```
full_join(x, y, by = "name")
    name instrument  band
1   John     guitar  TRUE
2   Paul       bass  TRUE
3 George     guitar  TRUE
4  Ringo      drums  TRUE
5 Stuart       bass    NA
6   Pete      drums    NA
7  Brian       <NA> FALSE
```

Semi Join

- The function `semi_join()` is most similar to an `inner_join()` in that it keeps only the rows showing up in both of the data frames. The difference is that it retains only the columns in the left data frame:

```
semi_join(x, y, by = "name")
    name instrument
1   John     guitar
2   Paul       bass
3 George     guitar
4  Ringo      drums
```

- We could have used `filter()` if we referenced the name columns from both data frames as follows:

```
filter(x, name %in% y$name)
```

Anti Join

- The function `anti_join()` is similar to the `semi_join()` in that it keeps only the columns of the left data frame; however, it retains only the rows that do *not* have a match in the right data frame:

```
anti_join(x, y, by = "name")
    name instrument
1   Pete      drums
2 Stuart       bass
```

Join & Mutate Example Application

- We want to calculate the number of children with a particular name born in each year. First we create a data frame bnames2. Notice that the by parameter specifies a vector; in this example, rows are identified if both year and sex are the same when we set the by parameter to a vector:

```
bnames2 = inner_join(bnames, births,
                     by = c("year","sex"))
```

- Next, we add a new column n to bnames2 whose value is the desired number. The function round() makes sure we have an integer. (It doesn't really make sense to have 1.5 babies.):

```
bnames2 = mutate(bnames2, n = round(prop * births))
```

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Groupwise Operations

- Analysis often reveals different insights when applied to different a subsets of data. For example, in the baby names dataset, the total number of “Vivians” differs from the total number of “Vivians” within each year.
- In the last application, we created a column representing the total number of children with a particular name born in each year. If we sum the “Vivians,” we see that there were 183,011 total born from 1880 to 2008 (the whole dataset):

```
vivian = filter(bnames2,
                name == "Vivian")
sum(vivian$n)

[1] 183011
```

Groupwise Operations

- This is likely to be different from the total number of "Vivians" in 2008 only:

```
vivian2 = filter(bnames2, name == "Vivian",
                          year == 2008)
sum(vivian$n)

[1]  1629
```

- If we want to find the number in each year, must we type and run the same code for each year? What if we want to do the same for every name too? That will take us forever!
- Groupwise operations help in such a scenario by creating groups and aggregating values over each group.

Groupwise Operations

- Recall our sample data frame `df`, which we will use to illustrate the groupwise operations:

```
df
  color value
1  blue     1
2 black     2
3  blue     3
4  blue     4
5 black     5
```

group_by

- We see two different groups in the `color` column: `blue` and `black`. Let's use the `group_by()` function to create a "grouped data frame".
  - `group_by()` takes two or more arguments: (1) the data frame, and (2) the column(s) whose values will be used for grouping.
  - Its output has several types: in addition to `"data.frame"`, it has types `"tbl"`, `"tbl_df"` and `"grouped_df"`. The important one here is `"grouped_df,"` which contains the grouping information:

```
by_color = group_by(df, color)
class(by_color)
[1] "grouped_df" "tbl_df"    "tbl"      "data.frame"
```

group_by

- When a "grouped_df" object is printed, R shows the source data frame and any grouping factors:

```
by_color = group_by(df, color)
by_color

Source: local data frame [5 x 2]
Groups: color

  color value
1  blue     1
2 black     2
3  blue     3
4  blue     4
5 black     5
```

Summarise

- We can aggregate the values of the "`grouped_df`" object within each group by applying the `summarise()` function and the aggregating functions we introduced before:

```
summarise(by_color, total = sum(value))

Source: local data frame [2 x 2]

  color total
1 black     7
2  blue     8
```

group_by and summarise

- Now we are ready to answer our earlier question: How many babies with a particular name were born in each year? Let's group the data by both name and year:

```
group_by(bnames2, name, year)

Source: local data frame [258,000 x 7]
Groups: name, year

   year    name     prop sex soundex births    n
1  1880    John 0.081541 boy    J500 118405 9655
2  1880 William 0.080511 boy    W450 118405 9533
3  1880   James 0.050057 boy    J520 118405 5927
4  1880 Charles 0.045167 boy    C642 118405 5348
5  1880  George 0.043292 boy    G620 118405 5126
..  ...     ...      ... ...     ...    ...  ...
```

group_by and summarise

- Summarising the grouped data frame, we compare "Vivian 1895" in the summary and in the original data frame. We see that multiple rows in the original data frame were aggregated (summed) in the summary:

```
summary = summarise(group_by(bnames2, name, year), total=sum(n))
filter(summary, name=='Vivian', year==1895)
    name year total
1 Vivian 1895   232

filter(bnames2, name=='Vivian', year==1895)
  year   name     prop  sex soundex births   n
1 1895 Vivian 0.000126  boy    V150 126650  16
2 1895 Vivian 0.000874 girl    V150 247112 216
```

group_by and summarise

- Printing out the summary object, we see:

```
summary

Source: local data frame [244,078 x 3]
Groups: name

      name year total
1    Aaden 2008   959
2  Aaliyah 1994  1449
3  Aaliyah 1995  1254
4  Aaliyah 1996   831
5  Aaliyah 1997  1738
6  Aaliyah 1998  1398
..     ...  ...   ...
```

The %>% Operator

- The previous call was a bit complicated; the code is written "inside-out". We first called the `group_by()` function and then the `summarise()` function; however, when typing the code we need to type `summarise()` first and then `group_by()`. This can get confusing!
- `dplyr` provides a handy operator that allows us to type in an intuitive way. Note that the following three lines are equivalent:

```
group_by(bnames2, name, year)
```

```
bnames2 %>% group_by(., name, year)
```

```
bnames2 %>% group_by(name, year)
```

- The `%>%` ("chaining") operator passes the object into a function's data frame argument, which is indicated by ".". The period can be omitted if the data frame is the first argument of the function.

The %>% Operator

- We can use the chaining operator to apply the `dplyr` functions in a more intuitive order:

```
bnames2 %>% group_by(name, year)
        %>% summarise(total=sum(n))

Source: local data frame [244,078 x 3]
Groups: name

      name year total
1    Aaden 2008   959
2  Aaliyah 1994  1449
3  Aaliyah 1995  1254
4  Aaliyah 1996   831
5  Aaliyah 1997  1738
..     ...  ...   ...
```

Grouping Stepwise

- Instead of grouping multiple columns at once, we may do so in severals steps. For example, we may group bnames by name and then by year as follows. This results in the same grouping as before:

```
bnames2 %>% group_by(name) %>% group_by(year)

Source: local data frame [258,000 x 7]
Groups: year

   year    name     prop sex soundex births    n
1  1880    John 0.081541 boy    J500 118405 9655
2  1880 William 0.080511 boy    W450 118405 9533
3  1880   James 0.050057 boy    J520 118405 5927
4  1880 Charles 0.045167 boy    C642 118405 5348
..  ...     ...      ... ...     ...    ...  ...
```

Appendix

- Appendix of Exercises & Solutions

Exercise 1: filter

- Find all of the names that are in the same soundex as your name (or your favorite name, in case you don't have a common English name).
- Select the rows of all girls born in 1900 or 2000.
- How many times did a name reach a proportion greater than 0.01 after the year 2000?

Solution 1: filter

```
vivian <- filter(bnames, name == "Vivian")
vivian$soundex[1]
[1] V150    # Find the soundex of your name first

filter(bnames, soundex=="V150")
```

```
filter(bnames, sex=="girl"&(year==1900|year==2000))
```

```
nrow(filter(bnames, year > 2000 & prop > 0.01))
```

Exercise 2: select

- From `bnames`, select the columns whose names start with, ‘y’, ‘s’ or ‘p’.
  - *Note*: Because `bnames` is very large, be sure to assign the result of this (and subsequent) exercises to a variable. Then you can look at it using head or `str`.
- Create a data frame that is the same as `bnames` without the column “year”.
- Select the columns “year” and “name” from bnames. Use only one condition to achieve this.

Solution 2: select

- ```
  select(bnames, starts_with('y'), starts_with('s'),
  starts_with('p'))
  ```

- ```
  select(bnames, -starts_with('y'))  # either can be used
  select(bnames, -year)              # in this case
  ```

- ```
  select(bnames, contains('a'))
  ```
  ```

Exercise 3: arrange

- Reorder the dataset bnames by prop in descending order.
- In what year was your name the most popular?

Solution 3: arrange

- ```
  arrange(bnames, desc(prop))
  ```

- ```
  filter(arrange(bnames, desc(prop)),
         name=='Vivian')[1,]

    year   name     prop  sex soundex
  1 1920 Vivian 0.003316 girl    V150
  ```

Exercise 4: mutate

- For the data frame bnames, create a column “percentage”, which derives from “prop” by changing the proportion to a percentage.

Solution 4: mutate

- ```
  mutate(bnames, percentage=100*prop)
  ```

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  ```

Exercise 5: summarise

- Create a summary that displays the min, mean, and max prop for your name, from the data frame bnames.

Solution 5: summarise

- ```
  summarise(filter(bnames, name=='Vivian'), min(prop),
  mean(prop), max(prop))
  ```
  ```

Exercise 6: Join the Data Sets

- We want to calculate the number of children with a particular name born in each year.
  - Create a data frame bnames2 with the code below, replacing "*your_join*" by the join function you decide to use. Notice that the by parameter specifies a vector; how do you think it works?

```
bnames2 = your_join(bnames, births, by=c("year","sex"))
```

  - Add a new column to `bnames2` whose value is the desired number. Name the column "n".

Solution 6: Join the Data Sets

- We give the solution here because we will need to use `bnames2`.
  - Rows are identified if both year and sex are the same when we set the by parameter to a vector.

```
bnames2 = inner_join(bnames, births,
                     by = c("year","sex"))
```

  - The function `round()` makes sure we have an integer. It doesn’t really make sense to have 1.5 babies.

```
bnames2 = mutate(bnames2, n = round(prop * births))
```

Exercise 7: group_by and summarise

- We used a join function to construct `bnames2`.
  - Recover the `births` data frame from `bnames2` with `group_by()` and `summarise()`. Call it `births2`. Hint: Look at the `births` data frame; what information does it provide and how we can obtain this information from `bnames2`?
  - If the result you obtain is not exactly the same as the original `births` data frame, what do you think caused the difference?

Solution 7: group_by and summarise

- We used a join function to construct bnames2.
  - ```
    summarise(group_by(bnames2, year, sex),
                       births=first(births))
    # Since within a year, the number of boys/girls
    # born is independent of their name. We can just
    # pick the first one.
    ```
  - Because there is no data about 2009 in bnames, so the rows in 2009 from births are discarded by inner_join.
    ```

Exercise 8: %>% operator

- Recall our sample data set, df

```
df
  color value
1  blue     1
2 black     2
3  blue     3
4  blue     4
5 black     5
```

- Reproduce the result of sum of values for each color. Use the %>% operator this time.

Solution 8: %>% operator

- Recall our sample data set, df

```
df
  color value
1  blue     1
2 black     2
3  blue     3
4  blue     4
5 black     5
```

```
Df %>% group_by(color) %>% summarise(total=sum(value))
```