Practical R: Data Munging in the tidyverse

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Where we left off

We learned how to

1. `separate` columns into multiple columns based on patterns or index
2. `gather` many columns into 2 columns, with one column having the header information and the other having the values
3. `spread` two columns into many columns, with one column providing the new column headers and the other the values.

Tidying the weather data

```
library(tidyverse)
weather_data <- rio::import('data/weather.csv')
```

```
#>          id year month element d1   d2   d3 d4   d5
#>  1 MX17004 2010     1    tmax NA   NA   NA NA   NA
#>  2 MX17004 2010     1    tmin NA   NA   NA NA   NA
#>  3 MX17004 2010     2    tmax NA 27.3 24.1 NA   NA
#>  4 MX17004 2010     2    tmin NA 14.4 14.4 NA   NA
#>  5 MX17004 2010     3    tmax NA   NA   NA NA 32.1
#>  6 MX17004 2010     3    tmin NA   NA   NA NA 14.2
#>     d12 d13 d14 d15  d16 d17 d18 d19 d20 d21 d22  d
#>  1   NA  NA  NA  NA   NA  NA  NA  NA  NA  NA  NA
#>  2   NA  NA  NA  NA   NA  NA  NA  NA  NA  NA  NA
#>  3   NA  NA  NA  NA   NA  NA  NA  NA  NA  NA  NA 29
#>  4   NA  NA  NA  NA   NA  NA  NA  NA  NA  NA  NA 10
#>  5   NA  NA  NA  NA 31.1  NA  NA  NA  NA  NA  NA
#>  6   NA  NA  NA  NA 17.6  NA  NA  NA  NA  NA  NA
#>     d29  d30 d31
#>  1   NA 27.8  NA
#>  2   NA 14.5  NA
#>  3   NA   NA  NA
#>  4   NA   NA  NA
#>  5   NA   NA  NA
#>  6   NA   NA  NA
```

1. Days are in separate columns
2. Temperatures for each day is in two rows, max and min
3. Don't worry about missing values. Just work on getting the shape right

Tidying the weather data

```
weather1 <- tidyr::gather(weather_data, day, temp, -(
head(weather1,20)
```

```
#>          id year month element day temp
#>  1  MX17004 2010     1    tmax  d1   NA
#>  2  MX17004 2010     1    tmin  d1   NA
#>  3  MX17004 2010     2    tmax  d1   NA
#>  4  MX17004 2010     2    tmin  d1   NA
#>  5  MX17004 2010     3    tmax  d1   NA
#>  6  MX17004 2010     3    tmin  d1   NA
#>  7  MX17004 2010     4    tmax  d1   NA
#>  8  MX17004 2010     4    tmin  d1   NA
#>  9  MX17004 2010     5    tmax  d1   NA
#>  10 MX17004 2010     5    tmin  d1   NA
#>  11 MX17004 2010     6    tmax  d1   NA
#>  12 MX17004 2010     6    tmin  d1   NA
#>  13 MX17004 2010     7    tmax  d1   NA
#>  14 MX17004 2010     7    tmin  d1   NA
#>  15 MX17004 2010     8    tmax  d1   NA
#>  16 MX17004 2010     8    tmin  d1   NA
#>  17 MX17004 2010    10    tmax  d1   NA
#>  18 MX17004 2010    10    tmin  d1   NA
#>  19 MX17004 2010    11    tmax  d1   NA
#>  20 MX17004 2010    11    tmin  d1   NA
```

Tidying the weather data

```
weather1 <- tidyr::gather(weather_data, day, temp, -(
weather2 <- spread(weather1, element, temp)
head(weather2, 20)
```

```
#>          id year month day tmax tmin
#>  1  MX17004 2010     1  d1   NA   NA
#>  2  MX17004 2010     1 d10   NA   NA
#>  3  MX17004 2010     1 d11   NA   NA
#>  4  MX17004 2010     1 d12   NA   NA
#>  5  MX17004 2010     1 d13   NA   NA
#>  6  MX17004 2010     1 d14   NA   NA
#>  7  MX17004 2010     1 d15   NA   NA
#>  8  MX17004 2010     1 d16   NA   NA
#>  9  MX17004 2010     1 d17   NA   NA
#>  10 MX17004 2010     1 d18   NA   NA
#>  11 MX17004 2010     1 d19   NA   NA
#>  12 MX17004 2010     1  d2   NA   NA
#>  13 MX17004 2010     1 d20   NA   NA
#>  14 MX17004 2010     1 d21   NA   NA
#>  15 MX17004 2010     1 d22   NA   NA
#>  16 MX17004 2010     1 d23   NA   NA
#>  17 MX17004 2010     1 d24   NA   NA
#>  18 MX17004 2010     1 d25   NA   NA
#>  19 MX17004 2010     1 d26   NA   NA
#>  20 MX17004 2010     1 d27   NA   NA
```

Tidying the weather data

```
weather1 <- tidyr::gather(weather_data, day, temp, -(
weather2 <- spread(weather1, element, temp)
weather3 <- separate(weather2, col='day', into=c('sym
head(weather3)
```

This gets us into the right shape for the data.

There still is some work to do, but the format is tidy

```
#>         id year month symbol day tmax tmin
#>  1 MX17004 2010     1      d   1   NA   NA
#>  2 MX17004 2010     1      d  10   NA   NA
#>  3 MX17004 2010     1      d  11   NA   NA
#>  4 MX17004 2010     1      d  12   NA   NA
#>  5 MX17004 2010     1      d  13   NA   NA
#>  6 MX17004 2010     1      d  14   NA   NA
```

Data transformation (dplyr)

The `dplyr` package gives us a few verbs for data manipulation

Function	Purpose
select	Select columns based on name or position
mutate	Create or change a column
filter	Extract rows based on some criteria
arrange	Re-order rows based on values of variable(s)
group_by	Split a dataset by unique values of a variable
summarize	Create summary statistics based on columns

`select`

You can select columns by name or position, of course.

You can select consecutive columns using `:` notation, e.g. `select(weather, d1:d31)`

You can also select columns based on some criteria, which are encapsulated in functions.

- `starts_with("___")`, `ends_with("___")`, `contains("____")`
- `one_of("____","_____","______")`

There are others; see `help(starts_with)`.

These selection methods work in all tidyverse functions

> Note that for these functions, the names of the columns don't need to be quoted. This is called *non-standard evaluation* and is a convenience

select

```
weather1 <- tidyr::gather(weather_data, day, temp, d1
head(weather1, 20)
```

```
#>          id year month element day temp
#>  1  MX17004 2010     1    tmax  d1   NA
#>  2  MX17004 2010     1    tmin  d1   NA
#>  3  MX17004 2010     2    tmax  d1   NA
#>  4  MX17004 2010     2    tmin  d1   NA
#>  5  MX17004 2010     3    tmax  d1   NA
#>  6  MX17004 2010     3    tmin  d1   NA
#>  7  MX17004 2010     4    tmax  d1   NA
#>  8  MX17004 2010     4    tmin  d1   NA
#>  9  MX17004 2010     5    tmax  d1   NA
#>  10 MX17004 2010     5    tmin  d1   NA
#>  11 MX17004 2010     6    tmax  d1   NA
#>  12 MX17004 2010     6    tmin  d1   NA
#>  13 MX17004 2010     7    tmax  d1   NA
#>  14 MX17004 2010     7    tmin  d1   NA
#>  15 MX17004 2010     8    tmax  d1   NA
#>  16 MX17004 2010     8    tmin  d1   NA
#>  17 MX17004 2010    10    tmax  d1   NA
#>  18 MX17004 2010    10    tmin  d1   NA
#>  19 MX17004 2010    11    tmax  d1   NA
#>  20 MX17004 2010    11    tmin  d1   NA
```

select

```
weather1 <- tidyr::gather(weather_data, key='day', va
                  starts_with('d'))
head(weather1, 20)
```

```
#>          id year month element day temp
#>  1  MX17004 2010     1    tmax  d1   NA
#>  2  MX17004 2010     1    tmin  d1   NA
#>  3  MX17004 2010     2    tmax  d1   NA
#>  4  MX17004 2010     2    tmin  d1   NA
#>  5  MX17004 2010     3    tmax  d1   NA
#>  6  MX17004 2010     3    tmin  d1   NA
#>  7  MX17004 2010     4    tmax  d1   NA
#>  8  MX17004 2010     4    tmin  d1   NA
#>  9  MX17004 2010     5    tmax  d1   NA
#>  10 MX17004 2010     5    tmin  d1   NA
#>  11 MX17004 2010     6    tmax  d1   NA
#>  12 MX17004 2010     6    tmin  d1   NA
#>  13 MX17004 2010     7    tmax  d1   NA
#>  14 MX17004 2010     7    tmin  d1   NA
#>  15 MX17004 2010     8    tmax  d1   NA
#>  16 MX17004 2010     8    tmin  d1   NA
#>  17 MX17004 2010    10    tmax  d1   NA
#>  18 MX17004 2010    10    tmin  d1   NA
#>  19 MX17004 2010    11    tmax  d1   NA
#>  20 MX17004 2010    11    tmin  d1   NA
```

mutate

```
weather4 <- mutate(weather3,
                   num_day = as.numeric(day))
as_tibble(weather4)
```

```
#>  # A tibble: 341 x 8
#>     id       year month symbol day    tmax  tmin n
#>     <chr>   <int> <int> <chr>  <chr> <dbl> <dbl>
#>   1 MX17004  2010     1 d      1        NA    NA
#>   2 MX17004  2010     1 d      10       NA    NA
#>   3 MX17004  2010     1 d      11       NA    NA
#>   4 MX17004  2010     1 d      12       NA    NA
#>   5 MX17004  2010     1 d      13       NA    NA
#>   6 MX17004  2010     1 d      14       NA    NA
#>   7 MX17004  2010     1 d      15       NA    NA
#>   8 MX17004  2010     1 d      16       NA    NA
#>   9 MX17004  2010     1 d      17       NA    NA
#>  10 MX17004  2010     1 d      18       NA    NA
#>  # … with 331 more rows
```

mutate

`mutate` can either transform a column in place or create a new column in a dataset

```
weather4 <- mutate(weather3, day = as.numeric(day))
as_tibble(weather4)
```

```
#>  # A tibble: 341 x 7
#>     id       year month symbol   day  tmax  tmin
#>     <chr>   <int> <int> <chr>  <dbl> <dbl> <dbl>
#>   1 MX17004  2010     1 d          1    NA    NA
#>   2 MX17004  2010     1 d         10    NA    NA
#>   3 MX17004  2010     1 d         11    NA    NA
#>   4 MX17004  2010     1 d         12    NA    NA
#>   5 MX17004  2010     1 d         13    NA    NA
#>   6 MX17004  2010     1 d         14    NA    NA
#>   7 MX17004  2010     1 d         15    NA    NA
#>   8 MX17004  2010     1 d         16    NA    NA
#>   9 MX17004  2010     1 d         17    NA    NA
#>  10 MX17004  2010     1 d         18    NA    NA
#>  # … with 331 more rows
```

mutate

`mutate` can also be used to deal with missing values, by replacing them with a value, for example

```
mutate(weather4, tmax = replace_na(tmax, 0))
```

You wouldn't want to do exactly this, of course

```
#>           id year month symbol day tmax tmin
#>  1   MX17004 2010     1      d   1  0.0   NA
#>  2   MX17004 2010     1      d  10  0.0   NA
#>  3   MX17004 2010     1      d  11  0.0   NA
#>  4   MX17004 2010     1      d  12  0.0   NA
#>  5   MX17004 2010     1      d  13  0.0   NA
#>  6   MX17004 2010     1      d  14  0.0   NA
#>  7   MX17004 2010     1      d  15  0.0   NA
#>  8   MX17004 2010     1      d  16  0.0   NA
#>  9   MX17004 2010     1      d  17  0.0   NA
#>  10  MX17004 2010     1      d  18  0.0   NA
#>  11  MX17004 2010     1      d  19  0.0   NA
#>  12  MX17004 2010     1      d   2  0.0   NA
#>  13  MX17004 2010     1      d  20  0.0   NA
#>  14  MX17004 2010     1      d  21  0.0   NA
#>  15  MX17004 2010     1      d  22  0.0   NA
#>  16  MX17004 2010     1      d  23  0.0   NA
#>  17  MX17004 2010     1      d  24  0.0   NA
#>  18  MX17004 2010     1      d  25  0.0   NA
#>  19  MX17004 2010     1      d  26  0.0   NA
#>  20  MX17004 2010     1      d  27  0.0   NA
#>  21  MX17004 2010     1      d  28  0.0   NA
#>  22  MX17004 2010     1      d  29  0.0   NA
#>  23  MX17004 2010     1      d   3  0.0   NA
#>  24  MX17004 2010     1      d  30 27.8 14.5
```

filter

`filter` extracts **rows** based on criteria

So if we wanted to just grab January data, we could use

```
january <- filter(weather4, month==1)
head(january)
```

```
#>         id year month symbol day tmax tmin
#>  1 MX17004 2010     1      d   1   NA   NA
#>  2 MX17004 2010     1      d  10   NA   NA
#>  3 MX17004 2010     1      d  11   NA   NA
#>  4 MX17004 2010     1      d  12   NA   NA
#>  5 MX17004 2010     1      d  13   NA   NA
#>  6 MX17004 2010     1      d  14   NA   NA
```

Filter

Some comparison operators for filtering

Operator	Meaning
==	Equals
!=	Not equals
> / <	Greater / less than
>= / <=	Greater or equal / Less or equal
!	Not
%in%	In a set

Combining comparisons

Operator	Meaning
&	And
|	Or

filter

Let's use the `mpg` dataset from the `ggplot2` package

```
mpg1 <- filter(mpg,
       (year==1999) &
         (class %in% c('minivan','suv')))
select(mpg1, manufacturer, cty, hwy, class, year)
```

```
#>  # A tibble: 35 x 5
#>    manufacturer   cty   hwy class    year
#>    <chr>        <int> <int> <chr>   <int>
#>  1 chevrolet       13    17 suv      1999
#>  2 chevrolet       11    15 suv      1999
#>  3 chevrolet       14    17 suv      1999
#>  4 dodge           18    24 minivan  1999
#>  5 dodge           17    24 minivan  1999
#>  6 dodge           16    22 minivan  1999
#>  7 dodge           16    22 minivan  1999
#>  8 dodge           15    22 minivan  1999
#>  9 dodge           15    21 minivan  1999
#>  10 dodge          13    17 suv      1999
#>  # … with 25 more rows
```

filter

A common use of `filter` is to remove rows with missing values from your dataset

```
weather5 <- filter(weather4,
                   !is.na(tmax) & !is.na(tmin))
head(weather5, 20)
```

`is.na` is a *function* that tests whether a value is missing or not.

So `!is.na` is the opposite of that.

```
#>          id year month symbol day tmax tmin
#>  1  MX17004 2010     1      d  30 27.8 14.5
#>  2  MX17004 2010     2      d  11 29.7 13.4
#>  3  MX17004 2010     2      d   2 27.3 14.4
#>  4  MX17004 2010     2      d  23 29.9 10.7
#>  5  MX17004 2010     2      d   3 24.1 14.4
#>  6  MX17004 2010     3      d  10 34.5 16.8
#>  7  MX17004 2010     3      d  16 31.1 17.6
#>  8  MX17004 2010     3      d   5 32.1 14.2
#>  9  MX17004 2010     4      d  27 36.3 16.7
#>  10 MX17004 2010     5      d  27 33.2 18.2
#>  11 MX17004 2010     6      d  17 28.0 17.5
#>  12 MX17004 2010     6      d  29 30.1 18.0
#>  13 MX17004 2010     7      d  14 29.9 16.5
#>  14 MX17004 2010     7      d   3 28.6 17.5
#>  15 MX17004 2010     8      d  13 29.8 16.5
#>  16 MX17004 2010     8      d  23 26.4 15.0
#>  17 MX17004 2010     8      d  25 29.7 15.6
#>  18 MX17004 2010     8      d  29 28.0 15.3
#>  19 MX17004 2010     8      d  31 25.4 15.4
#>  20 MX17004 2010     8      d   5 29.6 15.8
```

arrange

`arrange` reorders **rows** of a data set according to the values of one or more variables

```
arrange(weather5, day)
```

Not quite.

```
#>          id year month symbol day tmax tmin
#>  1  MX17004 2010    12      d   1 29.9 13.8
#>  2  MX17004 2010     2      d   2 27.3 14.4
#>  3  MX17004 2010    11      d   2 31.3 16.3
#>  4  MX17004 2010     2      d   3 24.1 14.4
#>  5  MX17004 2010     7      d   3 28.6 17.5
#>  6  MX17004 2010    11      d   4 27.2 12.0
#>  7  MX17004 2010     3      d   5 32.1 14.2
#>  8  MX17004 2010     8      d   5 29.6 15.8
#>  9  MX17004 2010    10      d   5 27.0 14.0
#>  10 MX17004 2010    11      d   5 26.3  7.9
#>  11 MX17004 2010    12      d   6 27.8 10.5
#>  12 MX17004 2010    10      d   7 28.1 12.9
#>  13 MX17004 2010     8      d   8 29.0 17.3
#>  14 MX17004 2010     3      d  10 34.5 16.8
#>  15 MX17004 2010     2      d  11 29.7 13.4
#>  16 MX17004 2010     8      d  13 29.8 16.5
#>  17 MX17004 2010     7      d  14 29.9 16.5
#>  18 MX17004 2010    10      d  14 29.5 13.0
#>  19 MX17004 2010    10      d  15 28.7 10.5
#>  20 MX17004 2010     3      d  16 31.1 17.6
#>  21 MX17004 2010     6      d  17 28.0 17.5
#>  22 MX17004 2010     2      d  23 29.9 10.7
#>  23 MX17004 2010     8      d  23 26.4 15.0
#>  24 MX17004 2010     8      d  25 29.7 15.6
```

arrange

```
arrange(weather5, month, day)
```

```
#>          id year month symbol day tmax tmin
#>  1  MX17004 2010     1      d  30 27.8 14.5
#>  2  MX17004 2010     2      d   2 27.3 14.4
#>  3  MX17004 2010     2      d   3 24.1 14.4
#>  4  MX17004 2010     2      d  11 29.7 13.4
#>  5  MX17004 2010     2      d  23 29.9 10.7
#>  6  MX17004 2010     3      d   5 32.1 14.2
#>  7  MX17004 2010     3      d  10 34.5 16.8
#>  8  MX17004 2010     3      d  16 31.1 17.6
#>  9  MX17004 2010     4      d  27 36.3 16.7
#>  10 MX17004 2010     5      d  27 33.2 18.2
#>  11 MX17004 2010     6      d  17 28.0 17.5
#>  12 MX17004 2010     6      d  29 30.1 18.0
#>  13 MX17004 2010     7      d   3 28.6 17.5
#>  14 MX17004 2010     7      d  14 29.9 16.5
#>  15 MX17004 2010     8      d   5 29.6 15.8
#>  16 MX17004 2010     8      d   8 29.0 17.3
#>  17 MX17004 2010     8      d  13 29.8 16.5
#>  18 MX17004 2010     8      d  23 26.4 15.0
#>  19 MX17004 2010     8      d  25 29.7 15.6
#>  20 MX17004 2010     8      d  29 28.0 15.3
#>  21 MX17004 2010     8      d  31 25.4 15.4
#>  22 MX17004 2010    10      d   5 27.0 14.0
#>  23 MX17004 2010    10      d   7 28.1 12.9
#>  24 MX17004 2010    10      d  14 29.5 13.0
#>  25 MX17004 2010    10      d  15 28.7 10.5
#>  26 MX17004 2010    10      d  28 31.2 15.0
#>  27 MX17004 2010    11      d   2 31.3 16.3
```

arrange

1. I use `arrange` sparingly in my workflow
    - For spiffying up final presentation tables
    - If order is **really** important
2. Sorting data is one of the most computationally expensive operations you can do
    - It can crash your computer for big data

Cluttering up our workspace

We've done a bit, but lets see all the objects we've created

```
ls()
```

```
#>   [1] "dat"          "f"            "fname"        "january"
#>   [5] "mpg1"         "outdir"       "pdfname"      "weather_data"
#>   [9] "weather1"     "weather2"     "weather3"     "weather4"
#>  [13] "weather5"
```

We see a lot of intermediate datasets we've created, that we aren't going to really use anymore

Workflow pipes in the tidyverse

Intermediate data sets

Recall how we cleaned the weather dataset yesterday

```
weather <- as_tibble(weather)
weather1 <- tidyr::gather(weather, key='day', value = 'temp', starts_with('d'))
weather2 <- spread(weather1, element, temp)
weather3 <- separate(weather2, day, c('symbol','day'), sep = 1)
weather4 <- select(weather3, -symbol)
weather5 <- mutate(weather4, day = as.numeric(day),
                   tmax = replace_na(tmax, 0),
                   tmin = replace_na(tmin, 0))
weather6 <- arrange(weather5,year,month,day)
```

This required us to create and keep track of several intermediate datasets

These datasets are essentially temporary datasets which do not hold the final result

What we did is a series of sequential steps to process the data

The tidyverse pipe

The pipe operator `%>%` was first introduced in the `magrittr` package.

The idea behind the pipe is to take the result of one function and insert that as an input of another function

In the tidyverse, we start with a tibble, and every intermediate result is also a tibble

The tidyverse pipe

1. The result of each function needs to be a tibble

2. You can omit the input for the data in the code for the function on the right side of the pipe operator, since we know that tits the output from the function to the left of the operator

The tidyverse pipe

Old School	Piping school
`mutate(mpg, differ = hwy-city))`	`mpg %>% mutate(differ=hyw-cty)`
`select(mpg, cyl, cty, hwy)`	`mpg %>% select(cyl, cty, hyw)`

There is a handy shortcut in RStudio to type the pipe operator. It is Ctrl-Shift-M on Windows/Linux and Cmd-Shift-M on Mac.

Reading a pipe

```
mpg %>%
  mutate(differ = hwy - cty) %>%
  group_by(cyl) %>%
  summarize(difference = mean(differ)) %>%
  ungroup()
```

```
#>  # A tibble: 4 x 2
#>      cyl difference
#>    <int>      <dbl>
#>  1     4       7.79
#>  2     5       8.25
#>  3     6       6.61
#>  4     8       5.06
```

You can verbalize the pipe operator as **then**

Reading a pipe

Since the end result of a pipe is a tibble, we can assign a name to store it

```
summary_mpg <- mpg %>%
  mutate(differ = hwy - cty) %>%
  group_by(cyl) %>%
  summarize(difference = mean(differ)) %>%
  ungroup()
summary_mpg
```

```
#>  # A tibble: 4 x 2
#>      cyl difference
#>    <int>      <dbl>
#>  1     4       7.79
#>  2     5       8.25
#>  3     6       6.61
#>  4     8       5.06
```

Exercise

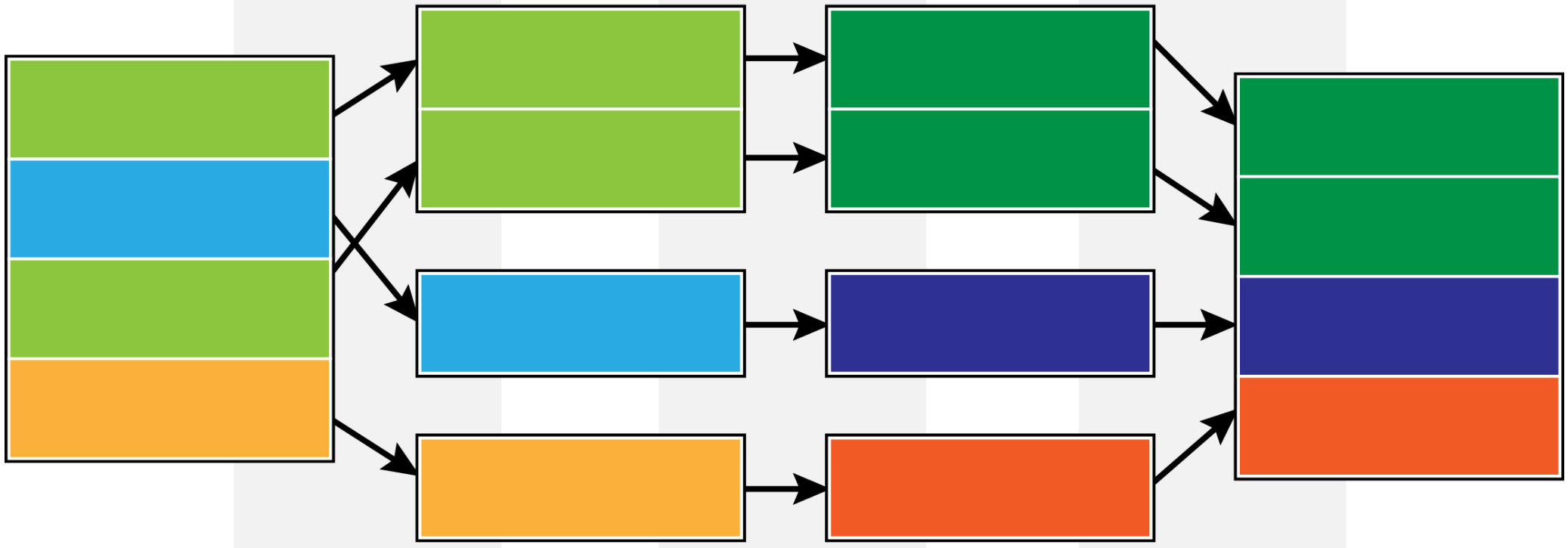
Transform the process of tidyfing the weather data into a pipe format

10:00

`group_by` and `summarize`

The `group_by` and `summarize` functions work together, in a principle called

split-apply-combine


SPLIT
based on a common criteria
APPLY
a change to each group
COMBINE
the newly processed groups

{

Split-apply-combine

Let's find the average city mileage from the `mpg` dataset by vehicle class

```
mpg %>%
  group_by(class) %>%
  summarize(avgMPG = mean(cty))
```

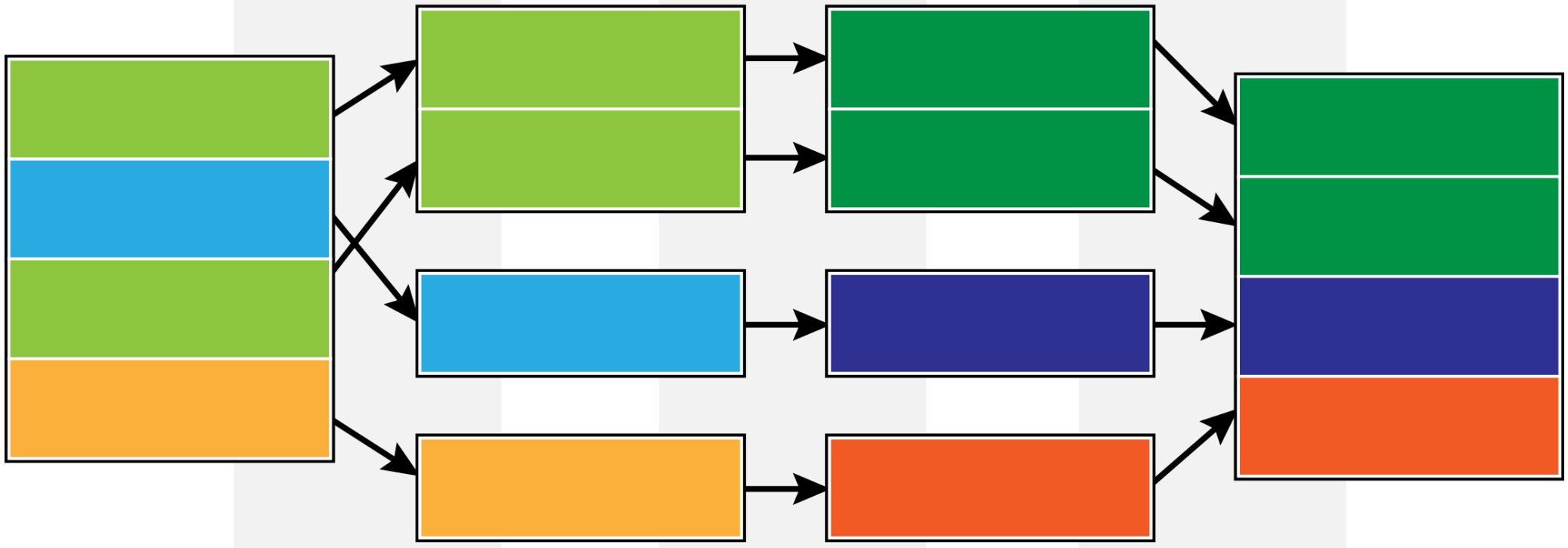
```
#>  # A tibble: 7 x 2
#>    class      avgMPG
#>    <chr>       <dbl>
#>  1 2seater      15.4
#>  2 compact      20.1
#>  3 midsize      18.8
#>  4 minivan      15.8
#>  5 pickup       13
#>  6 subcompact   20.4
#>  7 suv          13.5
```

Split-apply-combine

Let's find the average city mileage from the `mpg` dataset by vehicle class

```
mpg %>%
  group_by(class) %>%
  summarize(avgMPG = mean(cty)) %>%
  knitr::kable(format='html')
```

class	avgMPG
2seater	15.40000
compact	20.12766
midsize	18.75610
minivan	15.81818
pickup	13.00000
subcompact	20.37143
suv	13.50000



SPLIT
based on a common criteria

APPLY
a change to each group

COMBINE
the newly processed groups

Split-apply-combine

We can compute the monthly average minimum and maximum temperatures from the weather dataset

```
weather5 %>%
  arrange(month, day) %>%
  group_by(month) %>%
  summarize(avgMin = mean(tmin, na.rm=T), avgMax = mean(tmax, na.rm=T))
```

```
#>  # A tibble: 11 x 3
#>     month avgMin avgMax
#>     <int>  <dbl>  <dbl>
#>   1     1   14.5   27.8
#>   2     2   13.2   27.8
#>   3     3   16.2   32.6
#>   4     4   16.7   36.3
#>   5     5   18.2   33.2
#>   6     6   17.8   29.0
#>   7     7   17     29.2
#>   8     8   15.8   28.3
#>   9    10   13.1   28.9
#>  10    11   12.5   28.1
#>  11    12   12.2   28.8
```

Split-apply-combine

The split-apply-combine method is also useful in `mutate`.

In the weather dataset, let's impute the monthly averages for the missing values

```
weather4 %>% # weather4 still has missing values
  arrange(month,day) %>%
  group_by(month) %>%
  mutate(tmax = replace_na(tmax, mean(tmax, na.rm=T)),
         tmin = replace_na(tmin, mean(tmin, na.rm=T)))
```

```
#>  # A tibble: 341 x 7
#>  # Groups:   month [11]
#>     id       year month symbol   day  tmax  tmin
#>     <chr>   <int> <int> <chr>  <dbl> <dbl> <dbl>
#>   1 MX17004  2010     1 d          1  27.8  14.5
#>   2 MX17004  2010     1 d          2  27.8  14.5
#>   3 MX17004  2010     1 d          3  27.8  14.5
#>   4 MX17004  2010     1 d          4  27.8  14.5
#>   5 MX17004  2010     1 d          5  27.8  14.5
#>   6 MX17004  2010     1 d          6  27.8  14.5
#>   7 MX17004  2010     1 d          7  27.8  14.5
#>   8 MX17004  2010     1 d          8  27.8  14.5
#>   9 MX17004  2010     1 d          9  27.8  14.5
#>  10 MX17004  2010     1 d         10  27.8  14.5
#>  # … with 331 more rows
```

Split-apply-combine

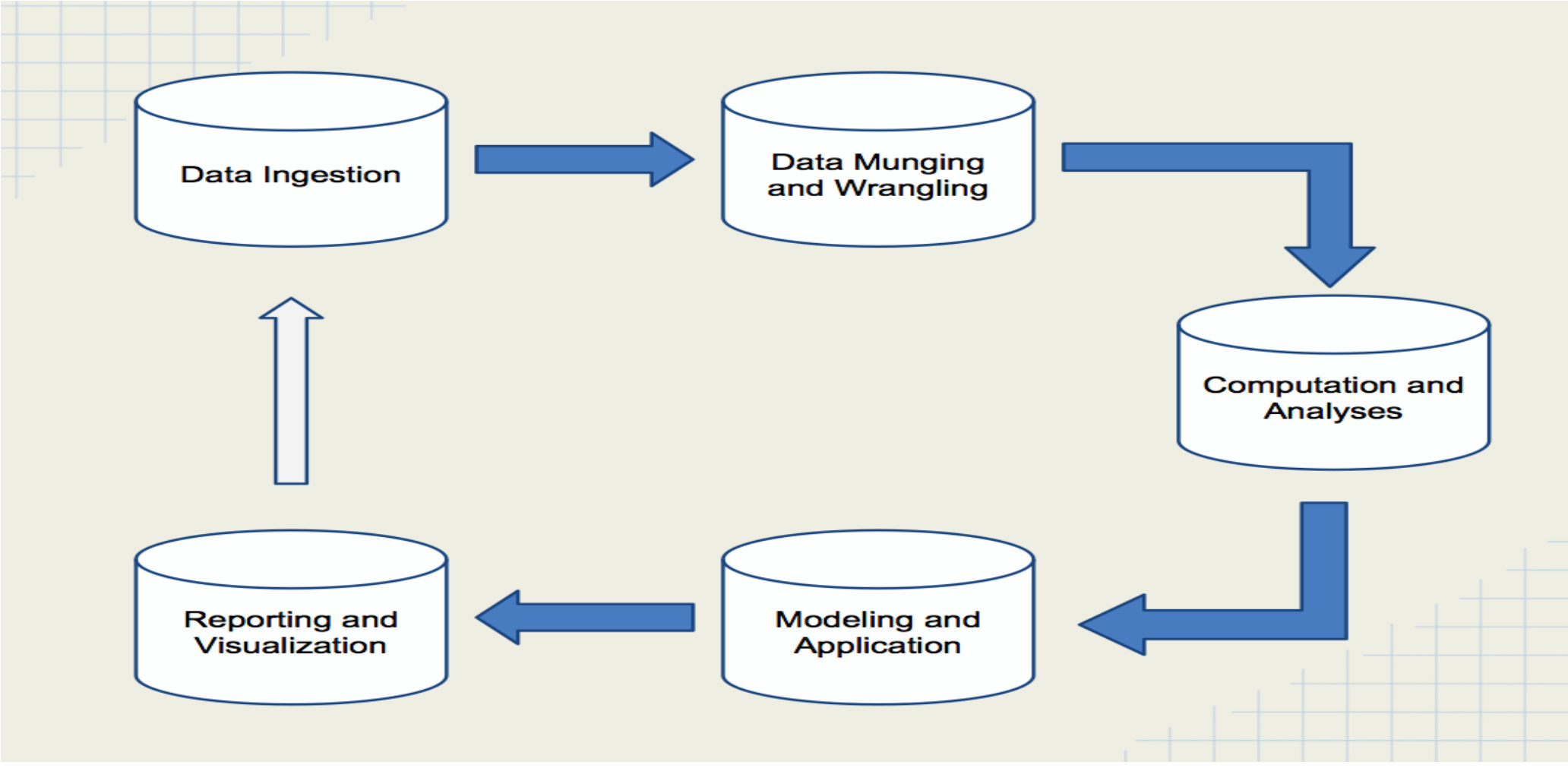
We can even use this principle for some filtering

```
weather5 %>%
  arrange(month, day) %>%
  group_by(month) %>%
  filter(tmax >= mean(tmax, na.rm=T)) %>%
  ungroup()
```

```
#>  # A tibble: 16 x 7
#>     id       year month symbol   day  tmax  tmin
#>     <chr>   <int> <int> <chr>  <dbl> <dbl> <dbl>
#>   1 MX17004  2010     1 d         30  27.8  14.5
#>   2 MX17004  2010     2 d         11  29.7  13.4
#>   3 MX17004  2010     2 d         23  29.9  10.7
#>   4 MX17004  2010     3 d         10  34.5  16.8
#>   5 MX17004  2010     4 d         27  36.3  16.7
#>   6 MX17004  2010     5 d         27  33.2  18.2
#>   7 MX17004  2010     6 d         29  30.1  18
#>   8 MX17004  2010     7 d         14  29.9  16.5
#>   9 MX17004  2010     8 d          5  29.6  15.8
#>  10 MX17004  2010     8 d          8  29    17.3
#>  11 MX17004  2010     8 d         13  29.8  16.5
#>  12 MX17004  2010     8 d         25  29.7  15.6
#>  13 MX17004  2010    10 d         14  29.5  13
#>  14 MX17004  2010    10 d         28  31.2  15
#>  15 MX17004  2010    11 d          2  31.3  16.3
#>  16 MX17004  2010    12 d          1  29.9  13.8
```

Organizing data projects

The data science pipeline



RStudio Projects

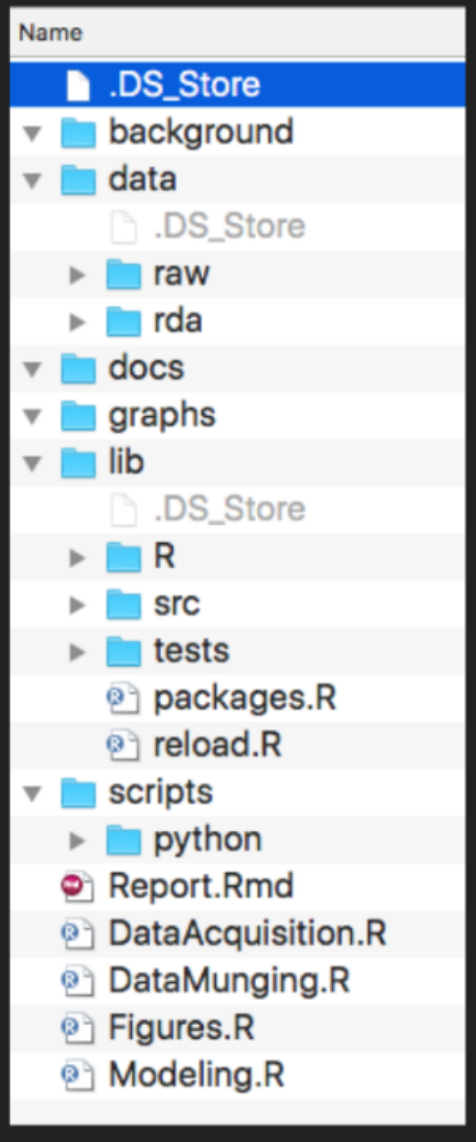
- RStudio allows you to create Projects
- These encapsulate individual projects

Use a template to organize your projects

Before you even get the data

- Set up a folder structure where
  - you know what goes where
  - you can have canned scripts/packages set things up
- Make sure it's the same structure every time
- Next time you visit the project, you don't have to go into desperate search mode

MY STRUCTURE



Background materials

Raw data (storage, not to be touched)

Intermediate and final R data sets

Generated documents (docx, html, pdf)

Graphs (pdf, png, tiff)

Custom R functions (all of them, without exception)

Custom C/C++ functions

Unit tests

List of R packages for the project

Automated loading of functions and packages in a separate environment

Scripts for file management and conversion

Storing data

1. Keep one copy of the raw data in the format you received it
2. Read in the data into R (see Lecture 7) -> `DataAcquisition.R`
3. Save a copy of this data in RDSformat (use endings .rds). We'll see how to do this in a few slides

Start working with the data

Summaries:

- `summary`
- `dplyr::summarise`
- `mean`, `sd`, `range`

Exploratory graphs

- `ggplot`
- `plot`

Maybe call this file `DataExploration.R`

Data munging

- Reshaping data
- Aggregating data
- Split-apply-combine

Maybe call this file `DataMunging.R`

Modeling

- Hypothesis testing
- Linear models
- Logistic regression
- Whatever model you need to run

This process requires a lot of exploration and trial-and-error, so it gets messy I'll usually create several files that look at different models, but once I'm done, my "final" models go in `Modeling.R`

> Coming soon

Packages to be used

You can use several packages in a particular project

It's good practice to load them first, and know what they are

- Makes sure packages are installed
- Makes sure package dependencies are met
- Makes sure package conflicts are known and fixed

Packages to be used

```
reqpackages <- c('dplyr', 'reshape2', 'readxl',
                 'ggplot2','stringr','ggthemes')
for(pkg in reqpackages){
  if(!(pkg %in% row.names(installed.packages()))){
    install.packages(pkg, repos='http://cran.r-project.org')
  }
}

library(dplyr)
library(reshape2)
library(readxl)
library(stringr)
library(ggplot2)
library(ggthemes)
```

This goes in `packages.R`

Creating a pipeline

Now you can ensure that your analyses are reproducible by creating a pipeline where code is run sequentially in a particular order

```
source('packages.R')
source('DataAcquistion.R')
source('DataExploration.R')
source('DataMunging.R')
source('Modeling.R')
```

Essentially, I'm doing modular programming

- Separate code by function
- Makes it easier to debug
- Try to write code for a particular function once

Saving your work

You would often like to store intermediate datasets, and final datasets, so that you can access them quickly.

There are several ways of saving even large datasets so that they can be quickly accessed.

Function	Package	Example	Re-loading the data
saveRDS	base	`saveRDS(weather, file = 'weather.rds')`	`weather <- readRDS('weather.rds')`
write_fst	fst	`write_fst(weather, file='weather.fst')`	`weather <- read_fst('weather.fst')`