

Data Wrangling II

QBS Bootcamp 2025

Lesson Objectives

At the end of this lecture you should be able to:

1. Use pipes in dplyr
2. Subset data using dplyr
3. Move between wide and long data frames in tidyr
4. Generate simple summary tables

Resources

Cheat Sheet for Functions in dplyr: <https://www.rstudio.com/wp-content/uploads/2015/02/data-wrangling-cheatsheet.pdf>

Pipes in tidyverse: <https://style.tidyverse.org/pipes.html>

```
# Install all tidyverse associated packages  
#install.packages('tidyverse')
```

```
# If you only want to install the packages we will use in this lecture:  
#install.packages('dplyr')  
#install.packages('tidyr')
```

```
# load tidyverse libraries  
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --  
## v dplyr      1.1.4      v readr      2.1.5  
## v forcats    1.0.0      v stringr    1.5.1  
## v ggplot2    3.5.1      v tibble     3.2.1  
## v lubridate  1.9.3      v tidyr      1.3.1  
## v purrr      1.0.2
```

```
## -- Conflicts ----- tidyverse_conflicts() --  
## x dplyr::filter() masks stats::filter()  
## x dplyr::lag()     masks stats::lag()  
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
library(dplyr)  
library(tidyr)
```

Data Set

We're going to start this lecture by generating the same random data set that we used in the last lecture. As always, don't forget to set a random seed so that our data is comparable across lectures.

```
# Set a random seed
set.seed(103)

# Define a data frame with our randomly generated data
randomData <- data.frame('SubjectID' = seq(1:1000),
                        'Systolic.BP' = rnorm(n = 1000, mean = 128, sd = 20),
                        'Diastolic.BP' = rnorm(n = 1000, mean = 71, sd = 10),
                        'Age' = trunc(runif(n = 1000, min = 18, max = 70)),
                        'Male' = rbinom(n = 1000, size = 1, prob = 0.5))

# Define binary variable for biological sex
randomData$BiologicalSex <- factor(ifelse(randomData$Male == 1, 'Male', 'Female'))

# Define variable specifying age above 65 (medicare eligible)
randomData$MedicareAge <- ifelse(randomData$Age < 65, F, T)

head(randomData, 5)
```

	SubjectID	Systolic.BP	Diastolic.BP	Age	Male	BiologicalSex	MedicareAge
## 1	1	112.28054	75.52894	52	0	Female	FALSE
## 2	2	129.09478	59.95778	56	0	Female	FALSE
## 3	3	104.54879	74.51568	25	1	Male	FALSE
## 4	4	124.65374	52.99577	41	0	Female	FALSE
## 5	5	90.69937	71.17388	41	0	Female	FALSE

Pipes

If you've looked at a lot of sample code online before, you've probably run into this syntax: `%>%`. This is a pipe! Pipes are used in tidyverse to keep code clean and prevent the defining of a lot of unnecessary intermediate variables. One of the main goals of this syntax is to keep a lot of white space in your code to help make it as readable as possible for anyone reading through your code.

Pipes will get more complex as we go through the lecture but first let's start with something simple to start to see what they do. First, let's define a subset of our data that reflects only individuals eligible for medicare. Last lecture, we used the following syntax:

```
# Subset to only those at medicare age using our binary variable
medicareData <- randomData[which(randomData$MedicareAge == T),]
head(medicareData)
```

	SubjectID	Systolic.BP	Diastolic.BP	Age	Male	BiologicalSex	MedicareAge
## 7	7	144.5196	66.34599	69	0	Female	TRUE
## 8	8	151.8032	51.76280	67	0	Female	TRUE
## 23	23	123.0903	61.61668	67	0	Female	TRUE
## 28	28	151.7242	73.91189	66	0	Female	TRUE
## 33	33	139.8668	84.28383	66	0	Female	TRUE
## 40	40	133.1999	61.29819	67	1	Male	TRUE

```
# Subset to only those at medicare age using a continuous variable
medicareData <- randomData[randomData$Age >= 65,]
head(medicareData)
```

```
##      SubjectID Systolic.BP Diastolic.BP Age Male BiologicalSex MedicareAge
## 7             7    144.5196     66.34599 69   0         Female          TRUE
## 8             8    151.8032     51.76280 67   0         Female          TRUE
## 23            23    123.0903     61.61668 67   0         Female          TRUE
## 28            28    151.7242     73.91189 66   0         Female          TRUE
## 33            33    139.8668     84.28383 66   0         Female          TRUE
## 40            40    133.1999     61.29819 67   1           Male          TRUE
```

Now, we can generate the same data set using a pipe and the filter function in dplyr.

```
# Subset without pipe
medicareData <- filter(randomData, Age >= 65)

head(medicareData)
```

```
##      SubjectID Systolic.BP Diastolic.BP Age Male BiologicalSex MedicareAge
## 1             7    144.5196     66.34599 69   0         Female          TRUE
## 2             8    151.8032     51.76280 67   0         Female          TRUE
## 3            23    123.0903     61.61668 67   0         Female          TRUE
## 4            28    151.7242     73.91189 66   0         Female          TRUE
## 5            33    139.8668     84.28383 66   0         Female          TRUE
## 6            40    133.1999     61.29819 67   1           Male          TRUE
```

```
# Subset with a pipe
medicareData <- randomData %>%
  filter(Age >= 65)

head(medicareData)
```

```
##      SubjectID Systolic.BP Diastolic.BP Age Male BiologicalSex MedicareAge
## 1             7    144.5196     66.34599 69   0         Female          TRUE
## 2             8    151.8032     51.76280 67   0         Female          TRUE
## 3            23    123.0903     61.61668 67   0         Female          TRUE
## 4            28    151.7242     73.91189 66   0         Female          TRUE
## 5            33    139.8668     84.28383 66   0         Female          TRUE
## 6            40    133.1999     61.29819 67   1           Male          TRUE
```

Based on the the use of the filter function above, can you describe the syntax of how a pipe works?

Pipes might not seem too useful when we are only providing it a single function, but what if we want it to work through multiple steps?

```
medicareData <- randomData %>%
  dplyr::filter(Age >= 65) %>%
  dplyr::select(SubjectID,Systolic.BP,Diastolic.BP,BiologicalSex,Age)

head(medicareData)
```

```
##   SubjectID Systolic.BP Diastolic.BP BiologicalSex Age
## 1         7    144.5196     66.34599      Female  69
## 2         8    151.8032     51.76280      Female  67
## 3        23    123.0903     61.61668      Female  67
## 4        28    151.7242     73.91189      Female  66
## 5        33    139.8668     84.28383      Female  66
## 6        40    133.1999     61.29819       Male  67
```

What is the select function doing?

```
medicareData <- randomData %>%
  filter(Age >= 65) %>%
  select(SubjectID,Systolic.BP,Diastolic.BP,BiologicalSex,Age) %>%
  mutate(MedicareID = row_number()) %>%
  mutate(BP.Diff = Systolic.BP - Diastolic.BP)

head(medicareData)
```

```
##   SubjectID Systolic.BP Diastolic.BP BiologicalSex Age MedicareID  BP.Diff
## 1         7    144.5196     66.34599      Female  69         1  78.17358
## 2         8    151.8032     51.76280      Female  67         2 100.04039
## 3        23    123.0903     61.61668      Female  67         3  61.47363
## 4        28    151.7242     73.91189      Female  66         4  77.81236
## 5        33    139.8668     84.28383      Female  66         5  55.58301
## 6        40    133.1999     61.29819       Male  67         6  71.90172
```

Based on these examples, what is the mutate function doing?

Wide -> Long Data in *tidyverse*

Last class, we moved from a wide to a long data frame using the *melt* function in *reshape2*.

```
# Melt the data frame into a long form
longData <- reshape2::melt(randomData[,c('SubjectID','Systolic.BP','Diastolic.BP','Age','BiologicalSex')],
  id.vars = c('SubjectID','Age','BiologicalSex'),value.name = 'BP',
  variable.name = 'BP.Type')

head(longData)
```

```
##   SubjectID Age BiologicalSex  BP.Type      BP
## 1         1  52      Female Systolic.BP 112.28054
## 2         2  56      Female Systolic.BP 129.09478
## 3         3  25       Male Systolic.BP 104.54879
## 4         4  41      Female Systolic.BP 124.65374
## 5         5  41      Female Systolic.BP  90.69937
## 6         6  31      Female Systolic.BP 125.59120
```

In *dplyr*, we will use the *gather* function or the *pivot_longer*.

```
# use gather()
longData2 <- randomData %>%
  tidyr::gather(Systolic.BP,Diastolic.BP,key = BP.Type, value = BP)

head(randomData)
```

	SubjectID	Systolic.BP	Diastolic.BP	Age	Male	BiologicalSex	MedicareAge
## 1	1	112.28054	75.52894	52	0	Female	FALSE
## 2	2	129.09478	59.95778	56	0	Female	FALSE
## 3	3	104.54879	74.51568	25	1	Male	FALSE
## 4	4	124.65374	52.99577	41	0	Female	FALSE
## 5	5	90.69937	71.17388	41	0	Female	FALSE
## 6	6	125.59120	69.50961	31	0	Female	FALSE

```
head(longData2)
```

	SubjectID	Age	Male	BiologicalSex	MedicareAge	BP.Type	BP
## 1	1	52	0	Female	FALSE	Systolic.BP	112.28054
## 2	2	56	0	Female	FALSE	Systolic.BP	129.09478
## 3	3	25	1	Male	FALSE	Systolic.BP	104.54879
## 4	4	41	0	Female	FALSE	Systolic.BP	124.65374
## 5	5	41	0	Female	FALSE	Systolic.BP	90.69937
## 6	6	31	0	Female	FALSE	Systolic.BP	125.59120

```
# use pivot_longer()
longData3 <- randomData %>%
  pivot_longer(cols = c(Systolic.BP,Diastolic.BP),
               names_to = 'BP.Type',
               values_to = 'BP')
```

```
head(longData3)
```

```
## # A tibble: 6 x 7
##   SubjectID Age Male BiologicalSex MedicareAge BP.Type      BP
##   <int> <dbl> <int> <fct>      <lgl>      <chr>      <dbl>
## 1     1     52     0 Female     FALSE     Systolic.BP 112.
## 2     1     52     0 Female     FALSE     Diastolic.BP 75.5
## 3     2     56     0 Female     FALSE     Systolic.BP 129.
## 4     2     56     0 Female     FALSE     Diastolic.BP 60.0
## 5     3     25     1 Male       FALSE     Systolic.BP 105.
## 6     3     25     1 Male       FALSE     Diastolic.BP 74.5
```

What is different about the syntax we used here vs. what we used in the last class?

We can also use some more pipes to clean this up even more:

```
longData <- randomData %>%
  # Convert to long format
  tidyr::gather(key = BP.Type, value = BP,c('Systolic.BP','Diastolic.BP')) %>%
  # Split into two separate variables
  tidyr::separate(col = BP.Type, into = c('BP.Type','Bad.ID')) %>%
  # Remove the bad ID variable
```

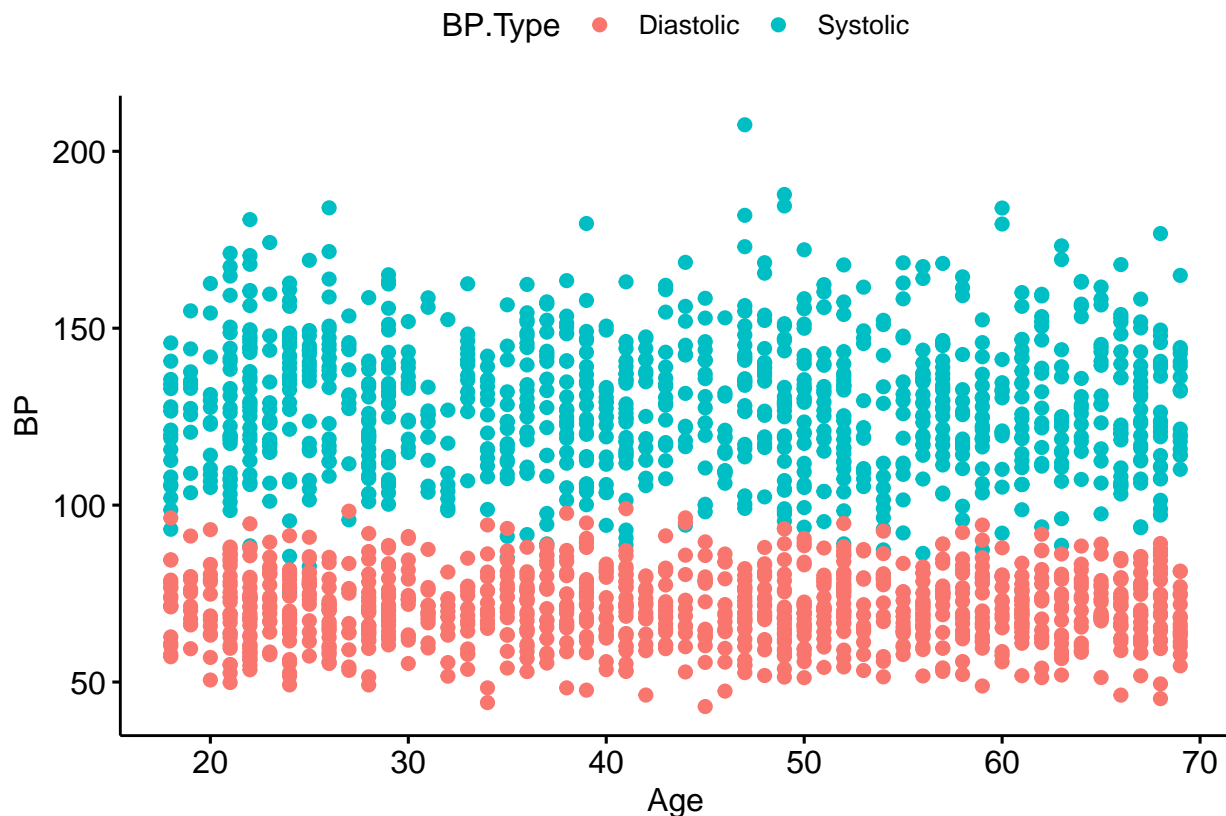
```
select(-Bad.ID)

head(longData)
```

```
##   SubjectID Age Male BiologicalSex MedicareAge BP.Type      BP
## 1         1  52   0      Female          FALSE Systolic 112.28054
## 2         2  56   0      Female          FALSE Systolic 129.09478
## 3         3  25   1        Male          FALSE Systolic 104.54879
## 4         4  41   0      Female          FALSE Systolic 124.65374
## 5         5  41   0      Female          FALSE Systolic  90.69937
## 6         6  31   0      Female          FALSE Systolic 125.59120
```

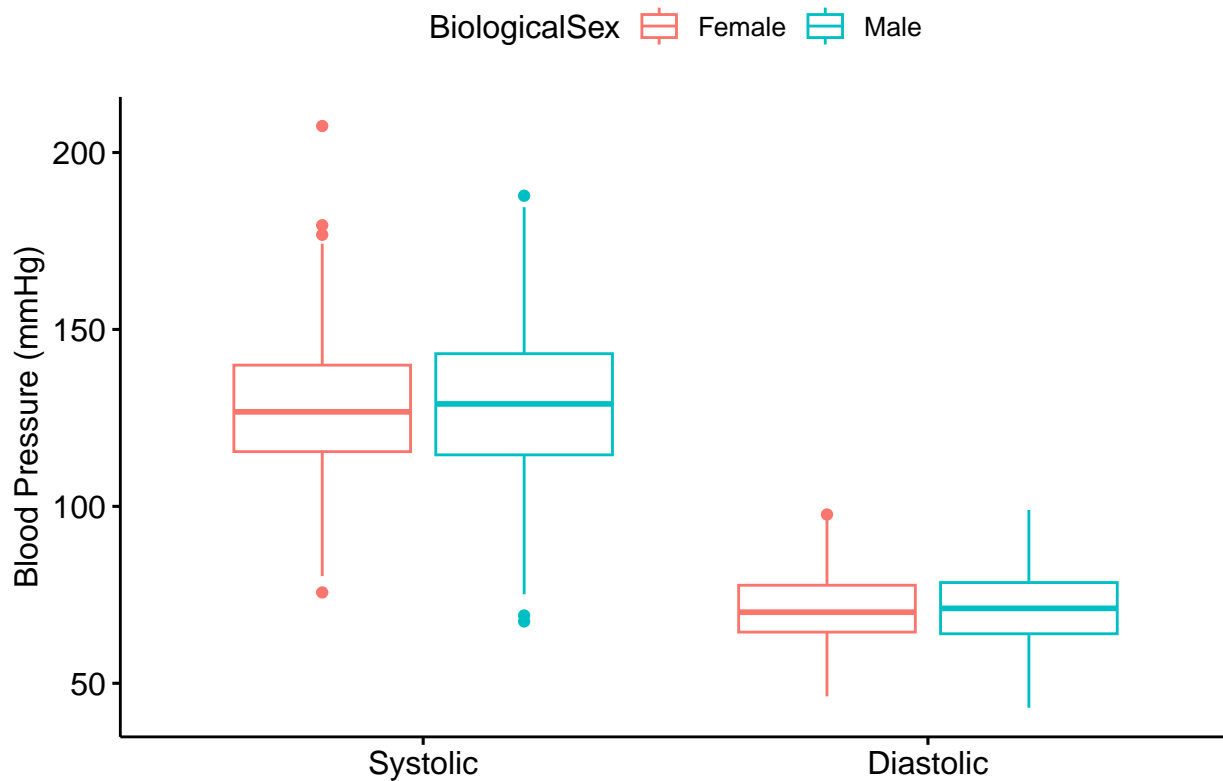
Now that our data is in a long format, we can generate plots with both measures of blood pressure in one plot.

```
# Generate a scatter plot of age by systolic blood pressure
ggpubr::ggscatter(longData,
  x = 'Age',
  y = 'BP',
  color = 'BP.Type')
```



```
# Generate a boxplot for diastolic blood pressure distribution by biological sex in our original dataset
ggpubr::ggboxplot(longData,
  x = 'BP.Type',
  y = 'BP',
  color = 'BiologicalSex',
```

```
ylab = 'Blood Pressure (mmHg)',
xlab = '')
```



Take a minute and comment what each step of this pipe is doing.

Long -> Wide Data in *tidyverse*

We can go back to a wide format in *tidyr* using the *spread* or *pivot_wider* function.

```
# Convert using spread
wideData1 <- longData %>%
  tidyr::spread(key = BP.Type, value = BP)
head(wideData1)
```

```
##   SubjectID Age Male BiologicalSex MedicareAge Diastolic Systolic
## 1         1  52   0      Female      FALSE    75.52894 112.28054
## 2         2  56   0      Female      FALSE    59.95778 129.09478
## 3         3  25   1       Male      FALSE    74.51568 104.54879
## 4         4  41   0      Female      FALSE    52.99577 124.65374
## 5         5  41   0      Female      FALSE    71.17388  90.69937
## 6         6  31   0      Female      FALSE    69.50961 125.59120
```

```
# Convert using pivot_wider
wideData2 <- longData %>%
  tidyr::pivot_wider(names_from = BP.Type,
                     values_from = BP)
head(wideData2)
```

```
## # A tibble: 6 x 7
##   SubjectID Age Male BiologicalSex MedicareAge Systolic Diastolic
##   <int> <dbl> <int> <fct>          <lgl>          <dbl>    <dbl>
## 1         1  52     0 Female          FALSE         112.     75.5
## 2         2  56     0 Female          FALSE         129.     60.0
## 3         3  25     1 Male            FALSE         105.     74.5
## 4         4  41     0 Female          FALSE         125.     53.0
## 5         5  41     0 Female          FALSE          90.7     71.2
## 6         6  31     0 Female          FALSE         126.     69.5
```

And, just like in *reshape2* we can also create summary tables using the *group_by* and *summarise* functions.

```
summary <- longData %>%
  tidyr::spread(key = BP.Type, value = BP) %>%
  dplyr::mutate(MedicareAge = ifelse(Age >= 65, T, F)) %>%
  dplyr::group_by(BiologicalSex, MedicareAge) %>%
  dplyr::summarise(Mean.Age = mean(Age), Mean.Sys = mean(Systolic), Mean.Dias = mean(Diastolic))
```

```
## 'summarise()' has grouped output by 'BiologicalSex'. You can override using the
## '.groups' argument.
```

```
summary
```

```
## # A tibble: 4 x 5
## # Groups:   BiologicalSex [2]
##   BiologicalSex MedicareAge Mean.Age Mean.Sys Mean.Dias
##   <fct>          <lgl>          <dbl>    <dbl>    <dbl>
## 1 Female          FALSE         41.0     128.     70.6
## 2 Female          TRUE         67.1     129.     71.1
## 3 Male            FALSE         41.0     129.     71.4
## 4 Male            TRUE         66.9     127.     70.3
```

In Class Exercises

1. Generate Random Data

Generate a random data set (remember to set a random seed) of 10,000 pregnant women with the following characteristics:

1. Age is uniformly distributed between 18 and 35 years old (Variable Name: Age).
2. There is a probability of 0.5 that each mother is carrying a female infant (Variable Name: InfantSex). This variable should be formatted as a factor variable with levels “Male” and “Female”
3. Define fasting glucose measures (Variable Name: Glucose1) as normally distributed. Mothers carrying a male infant have a mean score of 85 and a standard deviation of 6 mg/dL. Mothers carrying a female infant have a mean score of 80 and a standard deviation of 6 mg/dL.
4. Define 1 hour glucose measures (Variable Name: Glucose2) as normally distributed. Mothers carrying a male infant have a mean score of 165 and a standard deviation of 9 mg/dL. Mothers carrying a female infant have a mean score of 155 and a standard deviation of 9 mg/dL.

5. Define a summary variable for gestational diabetes (Variable Name: Diagnosis) which is “Gestational Diabetes” if either Glucose1 is higher than 95 or Glucose2 is higher than 180 and “Healthy” otherwise.

```
# code here
```

2. Summarize Random Data

Generate a summary table including age, fasting glucose, and one hour glucose of all subjects by both disease status and infant sex.

Your table should have 4 rows in the following order: Healthy & Female, Gestational Diabetes & Female, Healthy & Male, Gestational Diabetes & Male and should summarize mean age, mean and sd fasting glucose, and mean and sd one hour glucose.

```
# code here
```

3. Visualize Data

Generate a boxplot of the distribution of Glucose (y axis) for all subjects where timepoint is on the x-axis and the plot is colored by Diagnosis.

```
# code here
```