Madison Wozniak: Assignment 3

Assignment 3

You are asked to submit both the R Markdown file and its pdf output.

Q1. Write an if-else statement:

1. If the number is greater than 0 and less than 10, print: "This number is between 0 and 10"
2. If the number is greater than 10, print: "This number is greater than 10"
3. If the number is less than 0, print: "This number is a negative number"
4. Otherwise print: "This number is either 0 or 10"

```
x<-12
if(x>0){
  print("This number is between 0 and 10")
}else if(x<10){
  print("This number is between 0 and 10")
} else if(x>10){
  print("This number is greater than 10")
}else if(x<0){
  print("This number is a negative number")
}else{
  print("This number is either 0 or 10")
}
```

```
## [1] "This number is between 0 and 10"
```

Q2. Write a function that gets a vector as its input and returns the mean and the standard deviation of the vector using the formula below:

$$\left(\frac{\sum(x_i - \bar{x})^2}{n-1}\right)^{1/2}$$

where $\bar{x}$ is the mean and n is the length of the vector.

```
x<-c(1,5,4,9,1)
 n<-length(x)
((sum(x-mean(x))^2)/(n-1))^(1/2)
```

```
## [1] 0
```

```
sd_by_hand<-function(x){

  x_bar<-mean(x)
  n<-length(x)
  sd_<-(((sum(x-x_bar^2))/(n-1))^(1/2))
  mean_<-mean(x)
  c(mean_,sd_)
```

```
}
sd_by_hand(c(1,5,4,9,1))
```

```
## [1]   4 NaN
```

Q3.

(a) Write a function that returns Euclidian Distance between two k-dimensional vectors:

$$d = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + ... + (x_k - y_k)^2}$$

```
Euclidian_Distance<-function(x){
  sqrt((sum(x-y))^2)
}
x<-c(4,5,7,3,56)
y<-c(3,4,5,6,7)
Euclidian_Distance(x)
```

```
## [1] 50
```

(b) Write a function that will input the vectors x, y and p and will return the distance between two k-dimensional vectors:

$$d_p(x, y) = ((x_1 - y_1)^p + (x_2 - y_2)^p + ... + (x_k - y_k)^p)^{1/p}$$

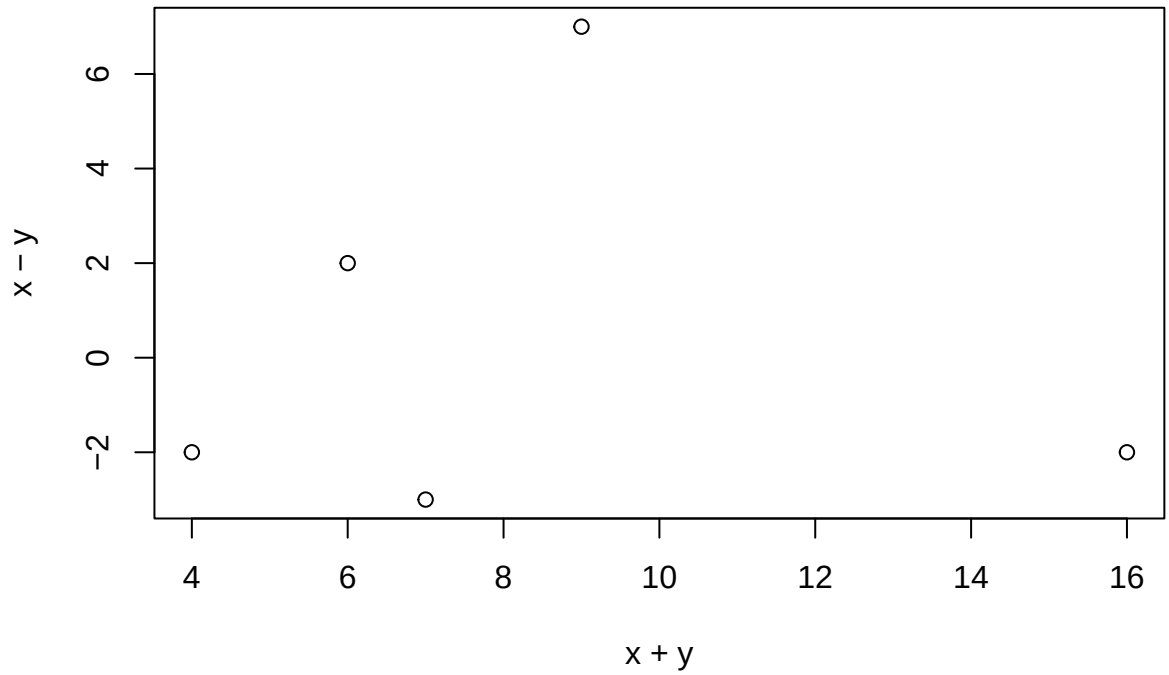
Pick the default value for p as 2.

```
distance_function<-function(x,y,p){
  p<-2
  x<-c(3,4,5,6,7)
y<-c(1,2,3,4,5)
x_k<-length(x)
y_k<-length(y)
(sum((x-y)^p))^(1/p)
}
distance_function(x,y,p)
```

```
## [1] 4.472136
```

Q4. Create a function altman_plot that takes two arguments, `x` and `y`, and plots the difference against the sum.

```
altman_plot<-function(x,y){
  plot(x+y,x-y)
}
x<-c(1,2,4,7,8)
y<-c(3,5,2,9,1)
altman_plot(x,y)
```



Q5. Write a function `compute_s_n_2` that for any given n, computes the sum:

$$1^2 + 2^2 + 3^2 + 4^2 + ... + (n-1)^2 + n^2$$

```
compute_s_n_2<-function(n){
  x<-1:n
  sum(x)
}
```

(a) Find `compute_s_n_2(30)`.

```
compute_s_n_2<-function(n){
  x<-1:n
  sum(x)
}
compute_s_n_2(30)
```

```
## [1] 465
```

(b) Confirm that the formula for this sum is $= \frac{n(n+1)(2n+1)}{6}$.

Q6. Which of the following built-in datasets is tidy (you can pick more than one):

(a) BJsales
(b) EuStockMarkets
(c) DNase
(d) Formaldehyde
(e) Orange
(f) UCBAdmissions

```
head(BJsales)
```

```
## [1] 200.1 199.5 199.4 198.9 199.0 200.2
```

```
# not tidy
head(EuStockMarkets)
```

```
##          DAX    SMI    CAC   FTSE
## [1,] 1628.75 1678.1 1772.8 2443.6
## [2,] 1613.63 1688.5 1750.5 2460.2
## [3,] 1606.51 1678.6 1718.0 2448.2
## [4,] 1621.04 1684.1 1708.1 2470.4
## [5,] 1618.16 1686.6 1723.1 2484.7
## [6,] 1610.61 1671.6 1714.3 2466.8
```

```
#not tidy
head(DNase)
```

```
##   Run       conc density
## 1   1 0.04882812   0.017
## 2   1 0.04882812   0.018
## 3   1 0.19531250   0.121
## 4   1 0.19531250   0.124
## 5   1 0.39062500   0.206
## 6   1 0.39062500   0.215
```

```
#tidy
head(Formaldehyde)
```

```
##   carb optden
## 1  0.1  0.086
## 2  0.3  0.269
## 3  0.5  0.446
## 4  0.6  0.538
## 5  0.7  0.626
## 6  0.9  0.782
```

```
#tidy
head(Orange)
```

```
##   Tree  age circumference
## 1    1  118            30
## 2    1  484            58
## 3    1  664            87
## 4    1 1004           115
## 5    1 1231           120
## 6    1 1372           142
```

```
#tidy
head(UCBAdmissions)
```

```
## , , Dept = A
##
##           Gender
## Admit      Male Female
##   Admitted  512     89
##   Rejected  313     19
##
## , , Dept = B
##
##           Gender
## Admit      Male Female
##   Admitted  353     17
##   Rejected  207      8
```

```
##
## , , Dept = C
##
##           Gender
## Admit      Male Female
##   Admitted  120    202
##   Rejected  205    391
##
## , , Dept = D
##
##           Gender
## Admit      Male Female
##   Admitted  138    131
##   Rejected  279    244
##
## , , Dept = E
##
##           Gender
## Admit      Male Female
##   Admitted   53     94
##   Rejected  138    299
##
## , , Dept = F
##
##           Gender
## Admit      Male Female
##   Admitted   22     24
##   Rejected  351    317
```

```
#tidy
```

Q7. Load the `dplyr` package and the `murders` dataset.

```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --
```

```
## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.4     v dplyr   1.0.7
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   2.0.1     v forcats 0.5.1
```

```
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(dslabs)
murders
```

```
##                  state abb        region population total
## 1              Alabama  AL         South    4779736   135
## 2               Alaska  AK          West     710231    19
## 3              Arizona  AZ          West    6392017   232
## 4             Arkansas  AR         South    2915918    93
## 5           California  CA          West   37253956  1257
## 6             Colorado  CO          West    5029196    65
## 7          Connecticut  CT     Northeast    3574097    97
```

```
## 8              Delaware  DE         South     897934    38
## 9  District of Columbia  DC         South     601723    99
## 10              Florida  FL         South   19687653   669
## 11              Georgia  GA         South    9920000   376
## 12               Hawaii  HI          West    1360301     7
## 13                Idaho  ID          West    1567582    12
## 14             Illinois  IL North Central   12830632   364
## 15              Indiana  IN North Central    6483802   142
## 16                 Iowa  IA North Central    3046355    21
## 17               Kansas  KS North Central    2853118    63
## 18             Kentucky  KY         South    4339367   116
## 19            Louisiana  LA         South    4533372   351
## 20                Maine  ME     Northeast    1328361    11
## 21             Maryland  MD         South    5773552   293
## 22        Massachusetts  MA     Northeast    6547629   118
## 23             Michigan  MI North Central    9883640   413
## 24            Minnesota  MN North Central    5303925    53
## 25          Mississippi  MS         South    2967297   120
## 26             Missouri  MO North Central    5988927   321
## 27              Montana  MT          West     989415    12
## 28             Nebraska  NE North Central    1826341    32
## 29               Nevada  NV          West    2700551    84
## 30        New Hampshire  NH     Northeast    1316470     5
## 31           New Jersey  NJ     Northeast    8791894   246
## 32           New Mexico  NM          West    2059179    67
## 33             New York  NY     Northeast   19378102   517
## 34       North Carolina  NC         South    9535483   286
## 35         North Dakota  ND North Central     672591     4
## 36                 Ohio  OH North Central   11536504   310
## 37             Oklahoma  OK         South    3751351   111
## 38               Oregon  OR          West    3831074    36
## 39         Pennsylvania  PA     Northeast   12702379   457
## 40         Rhode Island  RI     Northeast    1052567    16
## 41       South Carolina  SC         South    4625364   207
## 42         South Dakota  SD North Central     814180     8
## 43            Tennessee  TN         South    6346105   219
## 44                Texas  TX         South   25145561   805
## 45                 Utah  UT          West    2763885    22
## 46              Vermont  VT     Northeast     625741     2
## 47             Virginia  VA         South    8001024   250
## 48           Washington  WA          West    6724540    93
## 49        West Virginia  WV         South    1852994    27
## 50            Wisconsin  WI North Central    5686986    97
## 51              Wyoming  WY          West     563626     5
```

(a) By using dplyr's `mutate` function, add a new column:

`population_in_millions = population / 10^6`

```
murders_added<-mutate(murders,population_in_millions=population/(10^6))
murders_added
```

```
##                  state abb        region population total
## 1              Alabama  AL         South    4779736   135
## 2               Alaska  AK          West     710231    19
## 3              Arizona  AZ          West    6392017   232
```

```
## 4              Arkansas  AR         South    2915918    93
## 5            California  CA          West   37253956  1257
## 6              Colorado  CO          West    5029196    65
## 7           Connecticut  CT     Northeast    3574097    97
## 8              Delaware  DE         South     897934    38
## 9  District of Columbia  DC         South     601723    99
## 10              Florida  FL         South   19687653   669
## 11              Georgia  GA         South    9920000   376
## 12               Hawaii  HI          West    1360301     7
## 13                Idaho  ID          West    1567582    12
## 14             Illinois  IL North Central   12830632   364
## 15              Indiana  IN North Central    6483802   142
## 16                 Iowa  IA North Central    3046355    21
## 17               Kansas  KS North Central    2853118    63
## 18             Kentucky  KY         South    4339367   116
## 19            Louisiana  LA         South    4533372   351
## 20                Maine  ME     Northeast    1328361    11
## 21             Maryland  MD         South    5773552   293
## 22        Massachusetts  MA     Northeast    6547629   118
## 23             Michigan  MI North Central    9883640   413
## 24            Minnesota  MN North Central    5303925    53
## 25          Mississippi  MS         South    2967297   120
## 26             Missouri  MO North Central    5988927   321
## 27              Montana  MT          West     989415    12
## 28             Nebraska  NE North Central    1826341    32
## 29               Nevada  NV          West    2700551    84
## 30        New Hampshire  NH     Northeast    1316470     5
## 31           New Jersey  NJ     Northeast    8791894   246
## 32           New Mexico  NM          West    2059179    67
## 33             New York  NY     Northeast   19378102   517
## 34       North Carolina  NC         South    9535483   286
## 35         North Dakota  ND North Central     672591     4
## 36                 Ohio  OH North Central   11536504   310
## 37             Oklahoma  OK         South    3751351   111
## 38               Oregon  OR          West    3831074    36
## 39         Pennsylvania  PA     Northeast   12702379   457
## 40         Rhode Island  RI     Northeast    1052567    16
## 41       South Carolina  SC         South    4625364   207
## 42         South Dakota  SD North Central     814180     8
## 43            Tennessee  TN         South    6346105   219
## 44                Texas  TX         South   25145561   805
## 45                 Utah  UT          West    2763885    22
## 46              Vermont  VT     Northeast     625741     2
## 47             Virginia  VA         South    8001024   250
## 48           Washington  WA          West    6724540    93
## 49        West Virginia  WV         South    1852994    27
## 50            Wisconsin  WI North Central    5686986    97
## 51              Wyoming  WY          West     563626     5
##    population_in_millions
## 1                4.779736
## 2                0.710231
## 3                6.392017
## 4                2.915918
## 5               37.253956
```

```
## 6                5.029196
## 7                3.574097
## 8                0.897934
## 9                0.601723
## 10              19.687653
## 11               9.920000
## 12               1.360301
## 13               1.567582
## 14              12.830632
## 15               6.483802
## 16               3.046355
## 17               2.853118
## 18               4.339367
## 19               4.533372
## 20               1.328361
## 21               5.773552
## 22               6.547629
## 23               9.883640
## 24               5.303925
## 25               2.967297
## 26               5.988927
## 27               0.989415
## 28               1.826341
## 29               2.700551
## 30               1.316470
## 31               8.791894
## 32               2.059179
## 33              19.378102
## 34               9.535483
## 35               0.672591
## 36              11.536504
## 37               3.751351
## 38               3.831074
## 39              12.702379
## 40               1.052567
## 41               4.625364
## 42               0.814180
## 43               6.346105
## 44              25.145561
## 45               2.763885
## 46               0.625741
## 47               8.001024
## 48               6.724540
## 49               1.852994
## 50               5.686986
## 51               0.563626
```

(b) If `rank(x)` gives you the ranks of `x` from lowest to highest, `rank(-x)` gives you the ranks from highest to lowest. Use the function mutate to add a column rank containing the rank, from highest to lowest murder rate. Make sure you redefine murders so we can keep using this variable.

```
murders_ranked<-murders%>%mutate(murd_rank=rank(-(total/(population)*100000)))
murders_ranked
```

```
##                  state abb        region population total murd_rank
```

```
##  1               Alabama  AL         South    4779736   135        23
##  2                Alaska  AK          West     710231    19        27
##  3               Arizona  AZ          West    6392017   232        10
##  4              Arkansas  AR         South    2915918    93        17
##  5            California  CA          West   37253956  1257        14
##  6              Colorado  CO          West    5029196    65        38
##  7           Connecticut  CT     Northeast    3574097    97        25
##  8              Delaware  DE         South     897934    38         6
##  9  District of Columbia  DC         South     601723    99         1
## 10               Florida  FL         South   19687653   669        13
## 11               Georgia  GA         South    9920000   376         9
## 12                Hawaii  HI          West    1360301     7        49
## 13                 Idaho  ID          West    1567582    12        46
## 14              Illinois  IL North Central   12830632   364        22
## 15               Indiana  IN North Central    6483802   142        31
## 16                  Iowa  IA North Central    3046355    21        47
## 17                Kansas  KS North Central    2853118    63        30
## 18              Kentucky  KY         South    4339367   116        28
## 19             Louisiana  LA         South    4533372   351         2
## 20                 Maine  ME     Northeast    1328361    11        44
## 21              Maryland  MD         South    5773552   293         4
## 22         Massachusetts  MA     Northeast    6547629   118        32
## 23              Michigan  MI North Central    9883640   413         7
## 24             Minnesota  MN North Central    5303925    53        40
## 25           Mississippi  MS         South    2967297   120         8
## 26              Missouri  MO North Central    5988927   321         3
## 27               Montana  MT          West     989415    12        39
## 28              Nebraska  NE North Central    1826341    32        33
## 29                Nevada  NV          West    2700551    84        19
## 30         New Hampshire  NH     Northeast    1316470     5        50
## 31            New Jersey  NJ     Northeast    8791894   246        24
## 32            New Mexico  NM          West    2059179    67        15
## 33              New York  NY     Northeast   19378102   517        29
## 34        North Carolina  NC         South    9535483   286        20
## 35          North Dakota  ND North Central     672591     4        48
## 36                  Ohio  OH North Central   11536504   310        26
## 37              Oklahoma  OK         South    3751351   111        21
## 38                Oregon  OR          West    3831074    36        42
## 39          Pennsylvania  PA     Northeast   12702379   457        11
## 40          Rhode Island  RI     Northeast    1052567    16        35
## 41        South Carolina  SC         South    4625364   207         5
## 42          South Dakota  SD North Central     814180     8        41
## 43             Tennessee  TN         South    6346105   219        12
## 44                 Texas  TX         South   25145561   805        16
## 45                  Utah  UT          West    2763885    22        45
## 46               Vermont  VT     Northeast     625741     2        51
## 47              Virginia  VA         South    8001024   250        18
## 48            Washington  WA          West    6724540    93        37
## 49         West Virginia  WV         South    1852994    27        36
## 50             Wisconsin  WI North Central    5686986    97        34
## 51               Wyoming  WY          West     563626     5        43
```

(c) Select the columns `state`, `population` and give it a name `new_df`.

```
library(tidyverse)
new_df<-murders%>%
  select(state,population)
new_df
```

```
##                   state population
## 1               Alabama    4779736
## 2                Alaska     710231
## 3               Arizona    6392017
## 4              Arkansas    2915918
## 5            California   37253956
## 6              Colorado    5029196
## 7           Connecticut    3574097
## 8              Delaware     897934
## 9  District of Columbia     601723
## 10              Florida   19687653
## 11              Georgia    9920000
## 12               Hawaii    1360301
## 13                Idaho    1567582
## 14             Illinois   12830632
## 15              Indiana    6483802
## 16                 Iowa    3046355
## 17               Kansas    2853118
## 18             Kentucky    4339367
## 19            Louisiana    4533372
## 20                Maine    1328361
## 21             Maryland    5773552
## 22        Massachusetts    6547629
## 23             Michigan    9883640
## 24            Minnesota    5303925
## 25          Mississippi    2967297
## 26             Missouri    5988927
## 27              Montana     989415
## 28             Nebraska    1826341
## 29               Nevada    2700551
## 30        New Hampshire    1316470
## 31           New Jersey    8791894
## 32           New Mexico    2059179
## 33             New York   19378102
## 34       North Carolina    9535483
## 35         North Dakota     672591
## 36                 Ohio   11536504
## 37             Oklahoma    3751351
## 38               Oregon    3831074
## 39         Pennsylvania   12702379
## 40         Rhode Island    1052567
## 41       South Carolina    4625364
## 42         South Dakota     814180
## 43            Tennessee    6346105
## 44                Texas   25145561
## 45                 Utah    2763885
## 46              Vermont     625741
## 47             Virginia    8001024
## 48           Washington    6724540
```

```
## 49        West Virginia    1852994
## 50            Wisconsin    5686986
## 51              Wyoming     563626
```

(d) Filter the observations with only `state== 'New York'` and call it as `murders_ny`.

```
murders_ny<-murders%>%
  filter(state=="New York")
murders_ny
```

```
##      state abb    region population total
## 1 New York  NY Northeast   19378102   517
```

(e) Remove all the observations with `state=='Florida'` and call that dataframe as `murders_no_fl`.

```
murders_no_fl<-murders%>%
filter(state!="Florida")
murders_no_fl
```

```
##                   state abb        region population total
## 1               Alabama  AL         South    4779736   135
## 2                Alaska  AK          West     710231    19
## 3               Arizona  AZ          West    6392017   232
## 4              Arkansas  AR         South    2915918    93
## 5            California  CA          West   37253956  1257
## 6              Colorado  CO          West    5029196    65
## 7           Connecticut  CT     Northeast    3574097    97
## 8              Delaware  DE         South     897934    38
## 9  District of Columbia  DC         South     601723    99
## 10               Georgia  GA         South    9920000   376
## 11                Hawaii  HI          West    1360301     7
## 12                 Idaho  ID          West    1567582    12
## 13              Illinois  IL North Central   12830632   364
## 14               Indiana  IN North Central    6483802   142
## 15                  Iowa  IA North Central    3046355    21
## 16                Kansas  KS North Central    2853118    63
## 17              Kentucky  KY         South    4339367   116
## 18             Louisiana  LA         South    4533372   351
## 19                 Maine  ME     Northeast    1328361    11
## 20              Maryland  MD         South    5773552   293
## 21         Massachusetts  MA     Northeast    6547629   118
## 22              Michigan  MI North Central    9883640   413
## 23             Minnesota  MN North Central    5303925    53
## 24           Mississippi  MS         South    2967297   120
## 25              Missouri  MO North Central    5988927   321
## 26               Montana  MT          West     989415    12
## 27              Nebraska  NE North Central    1826341    32
## 28                Nevada  NV          West    2700551    84
## 29         New Hampshire  NH     Northeast    1316470     5
## 30            New Jersey  NJ     Northeast    8791894   246
## 31            New Mexico  NM          West    2059179    67
## 32              New York  NY     Northeast   19378102   517
## 33        North Carolina  NC         South    9535483   286
## 34          North Dakota  ND North Central     672591     4
## 35                  Ohio  OH North Central   11536504   310
## 36              Oklahoma  OK         South    3751351   111
```

```
## 37              Oregon  OR          West    3831074    36
## 38        Pennsylvania  PA     Northeast   12702379   457
## 39        Rhode Island  RI     Northeast    1052567    16
## 40      South Carolina  SC         South    4625364   207
## 41        South Dakota  SD North Central     814180     8
## 42           Tennessee  TN         South    6346105   219
## 43               Texas  TX         South   25145561   805
## 44                Utah  UT          West    2763885    22
## 45             Vermont  VT     Northeast     625741     2
## 46            Virginia  VA         South    8001024   250
## 47          Washington  WA          West    6724540    93
## 48       West Virginia  WV         South    1852994    27
## 49           Wisconsin  WI North Central    5686986    97
## 50             Wyoming  WY          West     563626     5
```

(f) Filter the murders dataset using `%in%` to filter the observations with `state=='New York'` or `state=='Texas'`.

```
murders_tex_ny<-murders%>%
  filter(state%in%c("New York"))
murders_tex_ny
```

```
##      state abb    region population total
## 1 New York  NY Northeast   19378102   517
```

(g) Suppose you want to live in the Northeast or West and want the murder rate to be less than 1. How many options do you have?

```
safe_northeast_west<-murders%>%
  mutate(rate=(total/population*100000))%>%
  filter((region%in%c("Northeast","West")&(rate<1)))
safe_northeast_west
```

```
##           state abb    region population total      rate
## 1        Hawaii  HI      West    1360301     7 0.5145920
## 2         Idaho  ID      West    1567582    12 0.7655102
## 3         Maine  ME Northeast    1328361    11 0.8280881
## 4 New Hampshire  NH Northeast    1316470     5 0.3798036
## 5        Oregon  OR      West    3831074    36 0.9396843
## 6          Utah  UT      West    2763885    22 0.7959810
## 7       Vermont  VT Northeast     625741     2 0.3196211
## 8       Wyoming  WY      West     563626     5 0.8871131
```

Q8. Use a pipe to create a new data frame called my_states that considers only states in the Northeast or West which have a murder rate lower than 1, and contains only the state, rate and rank columns.

```
my_states <- murders %>%
 mutate(rate=(total/population*100000),murd_rank=rank(-(total/population*100000))) %>%
filter((region%in%c("Northeast","West")&(rate<1))) %>%
select(state,rate,murd_rank)
my_states
```

```
##           state      rate murd_rank
## 1        Hawaii 0.5145920        49
## 2         Idaho 0.7655102        46
## 3         Maine 0.8280881        44
## 4 New Hampshire 0.3798036        50
## 5        Oregon 0.9396843        42
```

```
## 6          Utah 0.7959810        45
## 7       Vermont 0.3196211        51
## 8       Wyoming 0.8871131        43
```

Q9. Install the NHANES package, load the data `NHANES`.

```
#install.packages("NHANES")
library(NHANES)
data(NHANES)
```

Observe that `NHANES` data has many missing values.

(a) Find the mean and the standard deviation of the variable `Age`. Remember the exclude the missing values. Hint: Add `na.rm = TRUE` inside the mean and the sd functions.

```
mean(NHANES$Age,na.rm=TRUE)
```

```
## [1] 36.7421
```

```
sd(NHANES$Age,na.rm=TRUE)
```

```
## [1] 22.39757
```

(b) First select the group as 20-to-29-year-old females. `AgeDecade` is a categorical variable with these ages. Note that the category is coded like " 20-29", with a space in front! What is the average and standard deviation of systolic blood pressure as saved in the `BPSysAve` variable? Save it to a variable called `ref`.

```
filtered_age<-NHANES%>%
  filter(AgeDecade==" 20-29")
filtered_age
```

```
## # A tibble: 1,356 x 76
##       ID SurveyYr Gender   Age AgeDecade AgeMonths Race1    Race3 Education
##    <int> <fct>    <fct>  <int> <fct>         <int> <fct>    <fct> <fct>
##  1 51710 2009_10  female    26 " 20-29"        319 White    <NA>  College Grad
##  2 51723 2009_10  male      28 " 20-29"        336 Black    <NA>  Some College
##  3 51731 2009_10  female    28 " 20-29"        346 Black    <NA>  High School
##  4 51734 2009_10  male      25 " 20-29"        310 White    <NA>  High School
##  5 51741 2009_10  female    21 " 20-29"        253 Black    <NA>  Some College
##  6 51741 2009_10  female    21 " 20-29"        253 Black    <NA>  Some College
##  7 51760 2009_10  female    27 " 20-29"        334 Hispanic <NA>  9 - 11th Grade
##  8 51764 2009_10  female    29 " 20-29"        357 White    <NA>  College Grad
##  9 51764 2009_10  female    29 " 20-29"        357 White    <NA>  College Grad
## 10 51764 2009_10  female    29 " 20-29"        357 White    <NA>  College Grad
## # ... with 1,346 more rows, and 67 more variables: MaritalStatus <fct>,
## #   HHIncome <fct>, HHIncomeMid <int>, Poverty <dbl>, HomeRooms <int>,
## #   HomeOwn <fct>, Work <fct>, Weight <dbl>, Length <dbl>, HeadCirc <dbl>,
## #   Height <dbl>, BMI <dbl>, BMICatUnder20yrs <fct>, BMI_WHO <fct>,
## #   Pulse <int>, BPSysAve <int>, BPDiaAve <int>, BPSys1 <int>, BPDia1 <int>,
## #   BPSys2 <int>, BPDia2 <int>, BPSys3 <int>, BPDia3 <int>, Testosterone <dbl>,
## #   DirectChol <dbl>, TotChol <dbl>, UrineVol1 <int>, UrineFlow1 <dbl>, ...
```

```
ref<-filtered_age%>%
  filter(BPSysAve!="NA")%>%
  summarize(avg=mean(BPSysAve,na.rm=TRUE),standev=sd(BPSysAve,na.rm=TRUE))
ref
```

```
## # A tibble: 1 x 2
##     avg standev
```

```
##   <dbl>   <dbl>
## 1  113.    11.7
```

Hint: Use `filter` and `summarize` and use the `na.rm = TRUE` argument when computing the average and standard deviation. You can also `filter` the NA values using `filter`.

(c) Using a pipe, assign the average to a numeric variable `ref_avg`. Hint: Use the code similar to above and then `pull`.

```
ref_avg<-filtered_age%>%
  filter(BPSysAve!="NA")%>%
  summarize(avg=mean(BPSysAve,na.rm=TRUE),standev=sd(BPSysAve,na.rm=TRUE))%>%
  pull(avg)
ref_avg
```

```
## [1] 113.1583
```

(d) Compute the average and standard deviation for females, but for each age group separately rather than a selected decade as in the earlier question. Note that the age groups are defined by AgeDecade. Hint: rather than filtering by age and gender, `filter` by *Gender* and then use `group_by`.

```
filtered_female_age<-NHANES%>%
  filter(Gender=="female")%>%
  group_by(AgeDecade)%>%
  filter(BPSysAve!="NA")%>%
  summarize(avg=mean(BPSysAve,na.rm=TRUE),standev=sd(BPSysAve,na.rm=TRUE))
filtered_female_age
```

```
## # A tibble: 9 x 3
##   AgeDecade   avg standev
##   <fct>     <dbl>   <dbl>
## 1 " 0-9"     100.    9.07
## 2 " 10-19"   104.    9.46
## 3 " 20-29"   108.   10.1
## 4 " 30-39"   111.   12.3
## 5 " 40-49"   115.   14.5
## 6 " 50-59"   122.   16.2
## 7 " 60-69"   127.   17.1
## 8 " 70+"     134.   19.8
## 9  <NA>      142.   22.9
```

(e) Repeat exercise (d) for males.

```
filtered_male_age<-NHANES%>%
  filter(Gender=="male")%>%
  group_by(AgeDecade)%>%
  filter(BPSysAve!="NA")%>%
  summarize(avg=mean(BPSysAve,na.rm=TRUE),standev=sd(BPSysAve,na.rm=TRUE))
filtered_male_age
```

```
## # A tibble: 9 x 3
##   AgeDecade   avg standev
##   <fct>     <dbl>   <dbl>
## 1 " 0-9"     97.4    8.32
## 2 " 10-19"  110.    11.2
## 3 " 20-29"  118.    11.3
## 4 " 30-39"  119.    12.3
## 5 " 40-49"  121.    14.0
```

```
## 6 " 50-59"  126.    17.8
## 7 " 60-69"  127.    17.5
## 8 " 70+"    130.    18.7
## 9  <NA>     136.    23.5
```

(f) We can actually combine both summaries for exercises 4 and 5 into one line of code. This is because `group_by` permits us to group by more than one variable. Obtain one big summary table using `group_by(AgeDecade, Gender)`.

```
combined_summary<-NHANES%>%
group_by(AgeDecade,Gender)%>%
  summarize(avg=mean(BPSysAve,na.rm=TRUE),standev=sd(BPSysAve,na.rm=TRUE))
```

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

```
combined_summary
```

```
## # A tibble: 18 x 4
## # Groups:   AgeDecade [9]
##    AgeDecade Gender   avg standev
##    <fct>     <fct>  <dbl>   <dbl>
##  1 " 0-9"    female 100.     9.07
##  2 " 0-9"    male    97.4    8.32
##  3 " 10-19"  female 104.     9.46
##  4 " 10-19"  male   110.    11.2
##  5 " 20-29"  female 108.    10.1
##  6 " 20-29"  male   118.    11.3
##  7 " 30-39"  female 111.    12.3
##  8 " 30-39"  male   119.    12.3
##  9 " 40-49"  female 115.    14.5
## 10 " 40-49"  male   121.    14.0
## 11 " 50-59"  female 122.    16.2
## 12 " 50-59"  male   126.    17.8
## 13 " 60-69"  female 127.    17.1
## 14 " 60-69"  male   127.    17.5
## 15 " 70+"    female 134.    19.8
## 16 " 70+"    male   130.    18.7
## 17  <NA>     female 142.    22.9
## 18  <NA>     male   136.    23.5
```

(g) For males between the ages of 40-49, compare systolic blood pressure `BPSysAve` across race as reported in the Race1 variable. Order the resulting table from lowest to highest average systolic blood pressure.

```
male_filter_age<-NHANES%>%
  filter(AgeDecade==" 40-49")
male_comparison<-male_filter_age%>%
  summarize(Race1,BPSysAve)%>%
  arrange(BPSysAve)
male_comparison
```

```
## # A tibble: 1,398 x 2
##    Race1 BPSysAve
##    <fct>    <int>
##  1 White       84
##  2 White       84
##  3 White       86
##  4 White       86
```

```
##  5 White       86
##  6 White       86
##  7 White       86
##  8 White       87
##  9 White       87
## 10 White       88
## # ... with 1,388 more rows
```