Coding Challenge 5

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Contents

Data wrangling – 25 pts

PLEASE READ THIS BEFORE CONTINUING.

This assignment will help you practice integrating some of the tidyverse functions into your R scripts. It will also involve some more practice with GitHub. You may collaborate with a partner to enhance your learning experience. Please ensure the following:

• Collaboration: If you work with a partner, include both names on the final submission by editing the YAML header. • Submission: Only one person should submit the assignment to Canvas in a Word document or .pdf file generated through R markdown. Additionally, you should provide a link to your GitHub, where the assignment should be viewable by rendering it as a GitHub-flavored markdown file. • Setup: It is also assumed you already have a GitHub repository for this class. • Time: This should take you no longer than the class period to complete.

1. 3 pts. Download two .csv files from Canvas called Diversity-Data.csv and Metadata.csv, and read them into R using relative file paths.

```r
DiversityData <- read.csv("DiversityData.csv")  #loading data in R
DiversityData
```

```
##          Code  shannon invsimpson   simpson richness
## 1      S01_13 6.624921  210.72795 0.9952545     3319
## 2      S02_16 6.612413  206.86664 0.9951660     3079
## 3      S03_19 6.660853  213.01843 0.9953056     3935
## 4      S04_22 6.660671  204.69080 0.9951146     3922
## 5      S05_25 6.610965  200.25523 0.9950064     3196
## 6      S06_28 6.650812  199.32110 0.9949830     3481
## 7      S61_32 6.570679  200.23177 0.9950058     3250
## 8      S62_35 6.492227  171.27965 0.9941616     3170
## 9      S63_38 6.610986  192.08535 0.9947940     3657
## 10     S64_41 6.472259  163.99814 0.9939024     3177
## 11     S65_44 6.508824  181.69248 0.9944962     2985
## 12     S66_47 6.482495  176.90684 0.9943473     2770
## 13    S121_51 6.276073  126.56259 0.9920988     3040
## 14    S122_54 6.461118  152.98152 0.9934633     3192
## 15    S123_57 6.334648  138.92556 0.9928019     2673
## 16    S124_60 6.461988  171.13732 0.9941567     3180
## 17    S125_63 6.501973  172.97532 0.9942188     3320
## 18    S126_66 6.354387  142.61016 0.9929879     2773
## 19    S181_70 6.299381  142.64506 0.9929896     2806
## 20    S182_74 6.340644  145.48656 0.9931265     3047
## 21    S183_78 6.282807  150.39829 0.9933510     2190
## 22    S184_82 6.268316  141.14138 0.9929149     2488
## 23    S186_90 6.289000  140.45260 0.9928802     2684
## 24     C01_11 6.618126  220.66218 0.9954682     3076
## 25     C02_14 6.627206  211.03921 0.9952615     3180
## 26     C03_17 6.616958  216.06631 0.9953718     2938
## 27     C04_20 6.626465  215.93901 0.9953691     3371
## 28     C05_23 6.642822  211.08960 0.9952627     3435
## 29     C06_26 6.679131  216.31351 0.9953771     3629
## 30     C61_30 6.454741  170.03639 0.9941189     2767
## 31     C62_33 6.484032  172.35279 0.9941979     3377
## 32     C63_36 6.517958  173.41489 0.9942335     3804
## 33     C64_39 6.476069  167.13138 0.9940167     3204
## 34     C65_42 6.569722  197.01186 0.9949242     3250
## 35     C66_45 6.482145  172.96394 0.9942184     3009
## 36    C121_49 5.944568   71.55607 0.9860249     2779
## 37    C122_52 6.187755   96.43939 0.9896308     3193
## 38    C123_55 6.129460   81.26646 0.9876948     2859
## 39    C124_58 6.028523   75.49726 0.9867545     2950
## 40    C125_61 6.148179   98.94468 0.9898933     3018
## 41    C126_64 6.347332  150.05708 0.9933359     2946
## 42    C181_68 6.301392  132.36230 0.9924450     3266
## 43    C182_72 6.000205   83.90929 0.9880824     2969
```

```
## 44  C183_76 5.981284   82.44127 0.9878702      2636
## 45  C184_80 5.578566   50.73174 0.9802885      2043
## 46  C185_84 6.064655   87.82732 0.9886140      3113
## 47  SB01_12 6.644864  216.86110 0.9953888      3203
## 48  SB02_15 6.615662  211.32573 0.9952680      3055
## 49  SB03_18 6.693987  230.45439 0.9956607      3595
## 50  SB04_21 6.647502  234.80343 0.9957411      3253
## 51  SB05_24 6.605749  198.57265 0.9949641      3187
## 52  SB06_27 6.640696  215.26494 0.9953546      3190
## 53  SB61_31 6.044229   89.13912 0.9887816      2371
## 54  SB62_34 6.437589  154.21624 0.9935156      3248
## 55  SB63_37 6.194632   83.11681 0.9879687      2976
## 56  SB64_40 6.117393   87.20257 0.9885324      3006
## 57  SB65_43 5.439798   29.48338 0.9660826      2809
## 58  SB66_46 6.195816  108.22394 0.9907599      2680
## 59 SB121_50 4.393341   12.39587 0.9193280      2508
## 60 SB122_53 5.630929   52.97931 0.9811247      2403
## 61 SB123_56 5.579523   48.59842 0.9794232      2752
## 62 SB124_59 5.406651   34.08685 0.9706632      2946
## 63 SB125_62 5.863941   63.33020 0.9842097      3165
## 64 SB126_65 5.738025   57.88780 0.9827252      2705
## 65 SB181_69 5.671024   57.37726 0.9825715      2642
## 66 SB182_73 5.489406   43.16854 0.9768350      2773
## 67 SB183_77 5.713960   60.47882 0.9834653      2454
## 68 SB184_81 5.467076   44.06798 0.9773078      2365
## 69 SB185_85 5.729473   55.95864 0.9821297      2789
## 70 SB186_89 5.556356   54.34527 0.9815991      2050
```

```
Metadata <- read.csv("Metadata.csv",na.strings ="na") #loading data in R
Metadata
```

```
##           Code   Crop Time_Point Replicate Water_Imbibed
## 1        S01_13   Soil          0         1            NA
## 2        S02_16   Soil          0         2            NA
## 3        S03_19   Soil          0         3            NA
## 4        S04_22   Soil          0         4            NA
## 5        S05_25   Soil          0         5            NA
## 6        S06_28   Soil          0         6            NA
## 7        S61_32   Soil          6         1            NA
## 8        S62_35   Soil          6         2            NA
## 9        S63_38   Soil          6         3            NA
## 10       S64_41   Soil          6         4            NA
## 11       S65_44   Soil          6         5            NA
## 12       S66_47   Soil          6         6            NA
## 13      S121_51   Soil         12         1            NA
## 14      S122_54   Soil         12         2            NA
## 15      S123_57   Soil         12         3            NA
## 16      S124_60   Soil         12         4            NA
## 17      S125_63   Soil         12         5            NA
## 18      S126_66   Soil         12         6            NA
## 19      S181_70   Soil         18         1            NA
## 20      S182_74   Soil         18         2            NA
## 21      S183_78   Soil         18         3            NA
## 22      S184_82   Soil         18         4            NA
```

```
## 23   S186_90    Soil     18    6        NA
## 24   C01_11   Cotton      0    1    0.0042
## 25   C02_14   Cotton      0    2    0.0091
## 26   C03_17   Cotton      0    3    0.0013
## 27   C04_20   Cotton      0    4    0.0087
## 28   C05_23   Cotton      0    5    0.0075
## 29   C06_26   Cotton      0    6    0.0046
## 30   C61_30   Cotton      6    1    0.0580
## 31   C62_33   Cotton      6    2    0.0440
## 32   C63_36   Cotton      6    3    0.0569
## 33   C64_39   Cotton      6    4    0.0841
## 34   C65_42   Cotton      6    5    0.0535
## 35   C66_45   Cotton      6    6    0.0029
## 36  C121_49   Cotton     12    1    0.0651
## 37  C122_52   Cotton     12    2    0.0527
## 38  C123_55   Cotton     12    3    0.0675
## 39  C124_58   Cotton     12    4    0.0545
## 40  C125_61   Cotton     12    5    0.0623
## 41  C126_64   Cotton     12    6    0.0021
## 42  C181_68   Cotton     18    1    0.0034
## 43  C182_72   Cotton     18    2    0.0632
## 44  C183_76   Cotton     18    3    0.0514
## 45  C184_80   Cotton     18    4    0.0577
## 46  C185_84   Cotton     18    5    0.0554
## 47  SB01_12  Soybean      0    1    0.1664
## 48  SB02_15  Soybean      0    2    0.0942
## 49  SB03_18  Soybean      0    3    0.1248
## 50  SB04_21  Soybean      0    4    0.1150
## 51  SB05_24  Soybean      0    5    0.0993
## 52  SB06_27  Soybean      0    6    0.1005
## 53  SB61_31  Soybean      6    1    0.2308
## 54  SB62_34  Soybean      6    2    0.2603
## 55  SB63_37  Soybean      6    3    0.2111
## 56  SB64_40  Soybean      6    4    0.2808
## 57  SB65_43  Soybean      6    5    0.2712
## 58  SB66_46  Soybean      6    6    0.2887
## 59 SB121_50  Soybean     12    1    0.2822
## 60 SB122_53  Soybean     12    2    0.2557
## 61 SB123_56  Soybean     12    3    0.2982
## 62 SB124_59  Soybean     12    4    0.2489
## 63 SB125_62  Soybean     12    5    0.2573
## 64 SB126_65  Soybean     12    6    0.2285
## 65 SB181_69  Soybean     18    1    0.2528
## 66 SB182_73  Soybean     18    2    0.2706
## 67 SB183_77  Soybean     18    3    0.3196
## 68 SB184_81  Soybean     18    4    0.2437
## 69 SB185_85  Soybean     18    5    0.2461
## 70 SB186_89  Soybean     18    6    0.3010
```

2. 4 pts. Join the two dataframes together by the common column 'Code'. Name the resulting dataframe alpha.

```r
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
```

```r
library(ggplot2)
library(knitr)
library(markdown)
alpha <- left_join(DiversityData, Metadata, by = "Code") #combining two dataframes together by common c
alpha
```

```
##         Code  shannon invsimpson   simpson richness   Crop Time_Point Replicate
## 1     S01_13 6.624921  210.72795 0.9952545     3319   Soil          0         1
## 2     S02_16 6.612413  206.86664 0.9951660     3079   Soil          0         2
## 3     S03_19 6.660853  213.01843 0.9953056     3935   Soil          0         3
## 4     S04_22 6.660671  204.69080 0.9951146     3922   Soil          0         4
## 5     S05_25 6.610965  200.25523 0.9950064     3196   Soil          0         5
## 6     S06_28 6.650812  199.32110 0.9949830     3481   Soil          0         6
## 7     S61_32 6.570679  200.23177 0.9950058     3250   Soil          6         1
## 8     S62_35 6.492227  171.27965 0.9941616     3170   Soil          6         2
## 9     S63_38 6.610986  192.08535 0.9947940     3657   Soil          6         3
## 10    S64_41 6.472259  163.99814 0.9939024     3177   Soil          6         4
## 11    S65_44 6.508824  181.69248 0.9944962     2985   Soil          6         5
## 12    S66_47 6.482495  176.90684 0.9943473     2770   Soil          6         6
## 13   S121_51 6.276073  126.56259 0.9920988     3040   Soil         12         1
## 14   S122_54 6.461118  152.98152 0.9934633     3192   Soil         12         2
## 15   S123_57 6.334648  138.92556 0.9928019     2673   Soil         12         3
## 16   S124_60 6.461988  171.13732 0.9941567     3180   Soil         12         4
## 17   S125_63 6.501973  172.97532 0.9942188     3320   Soil         12         5
## 18   S126_66 6.354387  142.61016 0.9929879     2773   Soil         12         6
## 19   S181_70 6.299381  142.64506 0.9929896     2806   Soil         18         1
## 20   S182_74 6.340644  145.48656 0.9931265     3047   Soil         18         2
## 21   S183_78 6.282807  150.39829 0.9933510     2190   Soil         18         3
## 22   S184_82 6.268316  141.14138 0.9929149     2488   Soil         18         4
## 23   S186_90 6.289000  140.45260 0.9928802     2684   Soil         18         6
## 24    C01_11 6.618126  220.66218 0.9954682     3076 Cotton          0         1
## 25    C02_14 6.627206  211.03921 0.9952615     3180 Cotton          0         2
## 26    C03_17 6.616958  216.06631 0.9953718     2938 Cotton          0         3
## 27    C04_20 6.626465  215.93901 0.9953691     3371 Cotton          0         4
## 28    C05_23 6.642822  211.08960 0.9952627     3435 Cotton          0         5
```

```
## 29   C06_26 6.679131 216.31351 0.9953771 3629   Cotton  0  6
## 30   C61_30 6.454741 170.03639 0.9941189 2767   Cotton  6  1
## 31   C62_33 6.484032 172.35279 0.9941979 3377   Cotton  6  2
## 32   C63_36 6.517958 173.41489 0.9942335 3804   Cotton  6  3
## 33   C64_39 6.476069 167.13138 0.9940167 3204   Cotton  6  4
## 34   C65_42 6.569722 197.01186 0.9949242 3250   Cotton  6  5
## 35   C66_45 6.482145 172.96394 0.9942184 3009   Cotton  6  6
## 36  C121_49 5.944568  71.55607 0.9860249 2779   Cotton 12  1
## 37  C122_52 6.187755  96.43939 0.9896308 3193   Cotton 12  2
## 38  C123_55 6.129460  81.26646 0.9876948 2859   Cotton 12  3
## 39  C124_58 6.028523  75.49726 0.9867545 2950   Cotton 12  4
## 40  C125_61 6.148179  98.94468 0.9898933 3018   Cotton 12  5
## 41  C126_64 6.347332 150.05708 0.9933359 2946   Cotton 12  6
## 42  C181_68 6.301392 132.36230 0.9924450 3266   Cotton 18  1
## 43  C182_72 6.000205  83.90929 0.9880824 2969   Cotton 18  2
## 44  C183_76 5.981284  82.44127 0.9878702 2636   Cotton 18  3
## 45  C184_80 5.578566  50.73174 0.9802885 2043   Cotton 18  4
## 46  C185_84 6.064655  87.82732 0.9886140 3113   Cotton 18  5
## 47  SB01_12 6.644864 216.86110 0.9953888 3203  Soybean  0  1
## 48  SB02_15 6.615662 211.32573 0.9952680 3055  Soybean  0  2
## 49  SB03_18 6.693987 230.45439 0.9956607 3595  Soybean  0  3
## 50  SB04_21 6.647502 234.80343 0.9957411 3253  Soybean  0  4
## 51  SB05_24 6.605749 198.57265 0.9949641 3187  Soybean  0  5
## 52  SB06_27 6.640696 215.26494 0.9953546 3190  Soybean  0  6
## 53  SB61_31 6.044229  89.13912 0.9887816 2371  Soybean  6  1
## 54  SB62_34 6.437589 154.21624 0.9935156 3248  Soybean  6  2
## 55  SB63_37 6.194632  83.11681 0.9879687 2976  Soybean  6  3
## 56  SB64_40 6.117393  87.20257 0.9885324 3006  Soybean  6  4
## 57  SB65_43 5.439798  29.48338 0.9660826 2809  Soybean  6  5
## 58  SB66_46 6.195816 108.22394 0.9907599 2680  Soybean  6  6
## 59 SB121_50 4.393341  12.39587 0.9193280 2508  Soybean 12  1
## 60 SB122_53 5.630929  52.97931 0.9811247 2403  Soybean 12  2
## 61 SB123_56 5.579523  48.59842 0.9794232 2752  Soybean 12  3
## 62 SB124_59 5.406651  34.08685 0.9706632 2946  Soybean 12  4
## 63 SB125_62 5.863941  63.33020 0.9842097 3165  Soybean 12  5
## 64 SB126_65 5.738025  57.88780 0.9827252 2705  Soybean 12  6
## 65 SB181_69 5.671024  57.37726 0.9825715 2642  Soybean 18  1
## 66 SB182_73 5.489406  43.16854 0.9768350 2773  Soybean 18  2
## 67 SB183_77 5.713960  60.47882 0.9834653 2454  Soybean 18  3
## 68 SB184_81 5.467076  44.06798 0.9773078 2365  Soybean 18  4
## 69 SB185_85 5.729473  55.95864 0.9821297 2789  Soybean 18  5
## 70 SB186_89 5.556356  54.34527 0.9815991 2050  Soybean 18  6
##    Water_Imbibed
## 1             NA
## 2             NA
## 3             NA
## 4             NA
## 5             NA
## 6             NA
## 7             NA
## 8             NA
## 9             NA
## 10            NA
## 11            NA
```

```
## 12          NA
## 13          NA
## 14          NA
## 15          NA
## 16          NA
## 17          NA
## 18          NA
## 19          NA
## 20          NA
## 21          NA
## 22          NA
## 23          NA
## 24      0.0042
## 25      0.0091
## 26      0.0013
## 27      0.0087
## 28      0.0075
## 29      0.0046
## 30      0.0580
## 31      0.0440
## 32      0.0569
## 33      0.0841
## 34      0.0535
## 35      0.0029
## 36      0.0651
## 37      0.0527
## 38      0.0675
## 39      0.0545
## 40      0.0623
## 41      0.0021
## 42      0.0034
## 43      0.0632
## 44      0.0514
## 45      0.0577
## 46      0.0554
## 47      0.1664
## 48      0.0942
## 49      0.1248
## 50      0.1150
## 51      0.0993
## 52      0.1005
## 53      0.2308
## 54      0.2603
## 55      0.2111
## 56      0.2808
## 57      0.2712
## 58      0.2887
## 59      0.2822
## 60      0.2557
## 61      0.2982
## 62      0.2489
## 63      0.2573
## 64      0.2285
## 65      0.2528
```

```
## 66          0.2706
## 67          0.3196
## 68          0.2437
## 69          0.2461
## 70          0.3010
```

3. 4 pts. Calculate Pielou's evenness index: Pielou's evenness is an ecological parameter calculated by the Shannon diversity index (column Shannon) divided by the log of the richness column.

    a. Using mutate, create a new column to calculate Pielou's evenness index.
    b. Name the resulting dataframe alpha_even.

```
alpha_even <- alpha %>%
mutate(logRich = log(richness)) %>%  #adding a column named logRich containing log values of richness c
mutate(alpha, Pielouseveennessindex = shannon/logRich) #adding a column Pielouseveennessindex by calculat

alpha_even
```

```
##          Code  shannon invsimpson    simpson richness    Crop Time_Point Replicate
## 1     S01_13 6.624921  210.72795 0.9952545     3319    Soil          0         1
## 2     S02_16 6.612413  206.86664 0.9951660     3079    Soil          0         2
## 3     S03_19 6.660853  213.01843 0.9953056     3935    Soil          0         3
## 4     S04_22 6.660671  204.69080 0.9951146     3922    Soil          0         4
## 5     S05_25 6.610965  200.25523 0.9950064     3196    Soil          0         5
## 6     S06_28 6.650812  199.32110 0.9949830     3481    Soil          0         6
## 7     S61_32 6.570679  200.23177 0.9950058     3250    Soil          6         1
## 8     S62_35 6.492227  171.27965 0.9941616     3170    Soil          6         2
## 9     S63_38 6.610986  192.08535 0.9947940     3657    Soil          6         3
## 10    S64_41 6.472259  163.99814 0.9939024     3177    Soil          6         4
## 11    S65_44 6.508824  181.69248 0.9944962     2985    Soil          6         5
## 12    S66_47 6.482495  176.90684 0.9943473     2770    Soil          6         6
## 13   S121_51 6.276073  126.56259 0.9920988     3040    Soil         12         1
## 14   S122_54 6.461118  152.98152 0.9934633     3192    Soil         12         2
## 15   S123_57 6.334648  138.92556 0.9928019     2673    Soil         12         3
## 16   S124_60 6.461988  171.13732 0.9941567     3180    Soil         12         4
## 17   S125_63 6.501973  172.97532 0.9942188     3320    Soil         12         5
## 18   S126_66 6.354387  142.61016 0.9929879     2773    Soil         12         6
## 19   S181_70 6.299381  142.64506 0.9929896     2806    Soil         18         1
## 20   S182_74 6.340644  145.48656 0.9931265     3047    Soil         18         2
## 21   S183_78 6.282807  150.39829 0.9933510     2190    Soil         18         3
## 22   S184_82 6.268316  141.14138 0.9929149     2488    Soil         18         4
## 23   S186_90 6.289000  140.45260 0.9928802     2684    Soil         18         6
## 24    C01_11 6.618126  220.66218 0.9954682     3076  Cotton          0         1
## 25    C02_14 6.627206  211.03921 0.9952615     3180  Cotton          0         2
## 26    C03_17 6.616958  216.06631 0.9953718     2938  Cotton          0         3
## 27    C04_20 6.626465  215.93901 0.9953691     3371  Cotton          0         4
## 28    C05_23 6.642822  211.08960 0.9952627     3435  Cotton          0         5
## 29    C06_26 6.679131  216.31351 0.9953771     3629  Cotton          0         6
## 30    C61_30 6.454741  170.03639 0.9941189     2767  Cotton          6         1
## 31    C62_33 6.484032  172.35279 0.9941979     3377  Cotton          6         2
```

```
## 32    C63_36 6.517958  173.41489 0.9942335   3804   Cotton         6      3
## 33    C64_39 6.476069  167.13138 0.9940167   3204   Cotton         6      4
## 34    C65_42 6.569722  197.01186 0.9949242   3250   Cotton         6      5
## 35    C66_45 6.482145  172.96394 0.9942184   3009   Cotton         6      6
## 36   C121_49 5.944568   71.55607 0.9860249   2779   Cotton        12      1
## 37   C122_52 6.187755   96.43939 0.9896308   3193   Cotton        12      2
## 38   C123_55 6.129460   81.26646 0.9876948   2859   Cotton        12      3
## 39   C124_58 6.028523   75.49726 0.9867545   2950   Cotton        12      4
## 40   C125_61 6.148179   98.94468 0.9898933   3018   Cotton        12      5
## 41   C126_64 6.347332  150.05708 0.9933359   2946   Cotton        12      6
## 42   C181_68 6.301392  132.36230 0.9924450   3266   Cotton        18      1
## 43   C182_72 6.000205   83.90929 0.9880824   2969   Cotton        18      2
## 44   C183_76 5.981284   82.44127 0.9878702   2636   Cotton        18      3
## 45   C184_80 5.578566   50.73174 0.9802885   2043   Cotton        18      4
## 46   C185_84 6.064655   87.82732 0.9886140   3113   Cotton        18      5
## 47   SB01_12 6.644864  216.86110 0.9953888   3203  Soybean         0      1
## 48   SB02_15 6.615662  211.32573 0.9952680   3055  Soybean         0      2
## 49   SB03_18 6.693987  230.45439 0.9956607   3595  Soybean         0      3
## 50   SB04_21 6.647502  234.80343 0.9957411   3253  Soybean         0      4
## 51   SB05_24 6.605749  198.57265 0.9949641   3187  Soybean         0      5
## 52   SB06_27 6.640696  215.26494 0.9953546   3190  Soybean         0      6
## 53   SB61_31 6.044229   89.13912 0.9887816   2371  Soybean         6      1
## 54   SB62_34 6.437589  154.21624 0.9935156   3248  Soybean         6      2
## 55   SB63_37 6.194632   83.11681 0.9879687   2976  Soybean         6      3
## 56   SB64_40 6.117393   87.20257 0.9885324   3006  Soybean         6      4
## 57   SB65_43 5.439798   29.48338 0.9660826   2809  Soybean         6      5
## 58   SB66_46 6.195816  108.22394 0.9907599   2680  Soybean         6      6
## 59  SB121_50 4.393341   12.39587 0.9193280   2508  Soybean        12      1
## 60  SB122_53 5.630929   52.97931 0.9811247   2403  Soybean        12      2
## 61  SB123_56 5.579523   48.59842 0.9794232   2752  Soybean        12      3
## 62  SB124_59 5.406651   34.08685 0.9706632   2946  Soybean        12      4
## 63  SB125_62 5.863941   63.33020 0.9842097   3165  Soybean        12      5
## 64  SB126_65 5.738025   57.88780 0.9827252   2705  Soybean        12      6
## 65  SB181_69 5.671024   57.37726 0.9825715   2642  Soybean        18      1
## 66  SB182_73 5.489406   43.16854 0.9768350   2773  Soybean        18      2
## 67  SB183_77 5.713960   60.47882 0.9834653   2454  Soybean        18      3
## 68  SB184_81 5.467076   44.06798 0.9773078   2365  Soybean        18      4
## 69  SB185_85 5.729473   55.95864 0.9821297   2789  Soybean        18      5
## 70  SB186_89 5.556356   54.34527 0.9815991   2050  Soybean        18      6
##     Water_Imbibed  logRich Pielousevennessindex
## 1              NA 8.107419            0.8171431
## 2              NA 8.032360            0.8232216
## 3              NA 8.277666            0.8046776
## 4              NA 8.274357            0.8049774
## 5              NA 8.069655            0.8192376
## 6              NA 8.155075            0.8155427
## 7              NA 8.086410            0.8125582
## 8              NA 8.061487            0.8053387
## 9              NA 8.204398            0.8057856
## 10             NA 8.063693            0.8026420
## 11             NA 8.001355            0.8134652
## 12             NA 7.926603            0.8178151
## 13             NA 8.019613            0.7825905
## 14             NA 8.068403            0.8007927
```

```
## 15          NA 7.890957          0.8027732
## 16          NA 8.064636          0.8012745
## 17          NA 8.107720          0.8019483
## 18          NA 7.927685          0.8015438
## 19          NA 7.939515          0.7934213
## 20          NA 8.021913          0.7904154
## 21          NA 7.691657          0.8168340
## 22          NA 7.819234          0.8016534
## 23          NA 7.895063          0.7965737
## 24      0.0042 8.031385          0.8240330
## 25      0.0091 8.064636          0.8217613
## 26      0.0013 7.985484          0.8286233
## 27      0.0087 8.122965          0.8157692
## 28      0.0075 8.141772          0.8158938
## 29      0.0046 8.196712          0.8148549
## 30      0.0580 7.925519          0.8144250
## 31      0.0440 8.124743          0.7980600
## 32      0.0569 8.243808          0.7906489
## 33      0.0841 8.072155          0.8022726
## 34      0.0535 8.086410          0.8124399
## 35      0.0029 8.009363          0.8093209
## 36      0.0651 7.929846          0.7496447
## 37      0.0527 8.068716          0.7668822
## 38      0.0675 7.958227          0.7702042
## 39      0.0545 7.989560          0.7545500
## 40      0.0623 8.012350          0.7673379
## 41      0.0021 7.988204          0.7945881
## 42      0.0034 8.091321          0.7787840
## 43      0.0632 7.995980          0.7504026
## 44      0.0514 7.877018          0.7593336
## 45      0.0577 7.622175          0.7318864
## 46      0.0554 8.043342          0.7539969
## 47      0.1664 8.071843          0.8232153
## 48      0.0942 8.024535          0.8244294
## 49      0.1248 8.187299          0.8176063
## 50      0.1150 8.087333          0.8219646
## 51      0.0993 8.066835          0.8188774
## 52      0.1005 8.067776          0.8231136
## 53      0.2308 7.771067          0.7777862
## 54      0.2603 8.085795          0.7961603
## 55      0.2111 7.998335          0.7744902
## 56      0.2808 8.008366          0.7638754
## 57      0.2712 7.940584          0.6850627
## 58      0.2887 7.893572          0.7849191
## 59      0.2822 7.827241          0.5612885
## 60      0.2557 7.784473          0.7233538
## 61      0.2982 7.920083          0.7044778
## 62      0.2489 7.988204          0.6768294
## 63      0.2573 8.059908          0.7275444
## 64      0.2285 7.902857          0.7260697
## 65      0.2528 7.879291          0.7197378
## 66      0.2706 7.927685          0.6924349
## 67      0.3196 7.805475          0.7320451
## 68      0.2437 7.768533          0.7037462
```

```
## 69         0.2461 7.933438          0.7221929
## 70         0.3010 7.625595          0.7286456
```

4. 4. Pts. Using tidyverse language of functions and the pipe, use the summarise function and tell me the mean and standard error evenness grouped by crop over time.

a. Start with the alpha_even dataframe
b. Group the data: group the data by Crop and Time_Point.
c. Summarize the data: Calculate the mean, count, standard deviation, and standard error for the even variable within each group.
d. Name the resulting dataframe alpha_average

```r
alpha_average <- alpha_even %>%
  group_by(Crop, Time_Point) %>%     #grouping the data by Crop and Time point
  summarise(Mean = mean(Pielousevennessindex),  #calculating mean of evenness by group
            n = n(),     #counting number of rows based on group
            sd.dev = sd(Pielousevennessindex)) %>%  #calculating standard deviation of the evenness by
  mutate(std.err = sd.dev/sqrt(n))   #calculating standard error by group
```

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

```
alpha_average
```

```
## # A tibble: 12 x 6
## # Groups:   Crop [3]
##    Crop    Time_Point  Mean     n  sd.dev std.err
##    <chr>        <int> <dbl> <int>   <dbl>   <dbl>
##  1 Cotton           0 0.820     6 0.00556 0.00227
##  2 Cotton           6 0.805     6 0.00920 0.00376
##  3 Cotton          12 0.767     6 0.0157  0.00640
##  4 Cotton          18 0.755     5 0.0169  0.00755
##  5 Soil             0 0.814     6 0.00765 0.00312
##  6 Soil             6 0.810     6 0.00587 0.00240
##  7 Soil            12 0.798     6 0.00782 0.00319
##  8 Soil            18 0.800     5 0.0104  0.00465
##  9 Soybean          0 0.822     6 0.00270 0.00110
## 10 Soybean          6 0.764     6 0.0400  0.0163
## 11 Soybean         12 0.687     6 0.0643  0.0263
## 12 Soybean         18 0.716     6 0.0153  0.00626
```

5. 4. Pts. Calculate the difference between the soybean column, the soil column, and the difference between the cotton column and the soil column

a. Start with the alpha_average dataframe

b. Select relevant columns: select the columns Time_Point, Crop, and mean.even.
c. Reshape the data: Use the pivot_wider function to transform the data from long to wide format, creating new columns for each Crop with values from mean.even.
d. Calculate differences: Create new columns named diff.cotton.even and diff.soybean.even by calculating the difference between Soil and Cotton, and Soil and Soybean, respectively.
e. Name the resulting dataframe alpha_average2

```r
alpha_average2 <- alpha_average %>%
  select(Time_Point, Crop, Mean) %>%     #selecting the relevant columns
  pivot_wider(names_from = Crop, values_from = Mean) %>%   #transforming data from longer format to wid
  mutate(diff.cotton.even = Soil - Cotton) %>%  #calculating difference in mean between soil and cotton
  mutate(diff.soybean.even = Soil - Soybean) #calculating difference in mean between soil and soybean a
alpha_average2
```

```
## # A tibble: 4 x 6
##   Time_Point Cotton  Soil Soybean diff.cotton.even diff.soybean.even
##        <int>  <dbl> <dbl>   <dbl>            <dbl>             <dbl>
## 1          0  0.820 0.814   0.822         -0.00602          -0.00740
## 2          6  0.805 0.810   0.764          0.00507           0.0459
## 3         12  0.767 0.798   0.687          0.0313            0.112
## 4         18  0.755 0.800   0.716          0.0449            0.0833
```
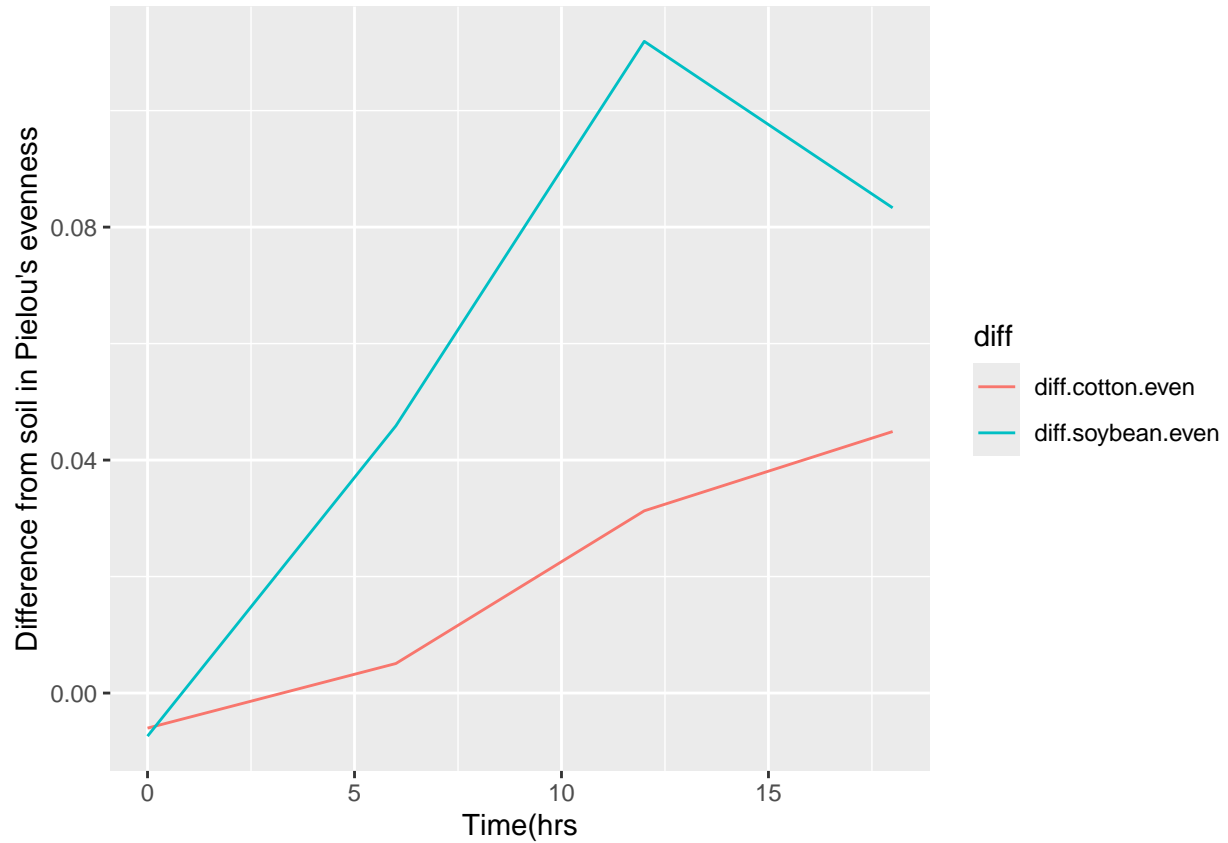
6. 4 pts. Connecting it to plots

a. Start with the alpha_average2 dataframe
b. Select relevant columns: select the columns Time_Point, diff.cotton.even, and diff.soybean.even.
c. Reshape the data: Use the pivot_longer function to transform the data from wide to long format, creating a new column named diff that contains the values from diff.cotton.even and diff.soybean.even.
d. This might be challenging, so I'll give you a break. The code is below.

pivot_longer(c(diff.cotton.even, diff.soybean.even), names_to = "diff")

d. Create the plot: Use ggplot and geom_line() with 'Time_Point' on the x-axis, the column 'values' on the y-axis, and different colors for each 'diff' category. The column named 'values' come from the pivot_longer. The resulting plot should look like the one to the right.

```r
alpha_average2 %>%
  select(Time_Point, diff.cotton.even, diff.soybean.even) %>% #selecting relevant columns
  pivot_longer(c(diff.cotton.even, diff.soybean.even), names_to = "diff") %>%  #transforming wide forma
  ggplot(aes(x= Time_Point, y = value, color = diff))+ #creating a line graph with time point as x axis
  geom_line()+
  xlab("Time(hrs")+ #labeling x axis
  ylab("Difference from soil in Pielou's evenness") #labeling y axis
```

7. 2 pts. Commit and push a gfm .md file to GitHub inside a directory called Coding Challenge 5. Provide me a link to your github written as a clickable link in your .pdf or .docx

Link to my GitHub