

Assignment 3: Data Exploration

Rachel Gonsenhauser

OVERVIEW

This exercise accompanies the lessons in Environmental Data Analytics on Data Exploration.

Directions

1. Change “Student Name” on line 3 (above) with your name.
2. Work through the steps, **creating code and output** that fulfill each instruction.
3. Be sure to **answer the questions** in this assignment document.
4. When you have completed the assignment, **Knit** the text and code into a single PDF file.
5. After Knitting, submit the completed exercise (PDF file) to the dropbox in Sakai. Add your last name into the file name (e.g., “Salk_A03_DataExploration.Rmd”) prior to submission.

The completed exercise is due on Tuesday, January 28 at 1:00 pm.

Set up your R session

1. Check your working directory, load necessary packages (tidyverse), and upload two datasets: the ECOTOX neonicotinoid dataset (ECOTOX_Neonicotinoids_Insects_raw.csv) and the Niwot Ridge NEON dataset for litter and woody debris (NEON_NIWO_Litter_massdata_2018-08_raw.csv). Name these datasets “Neonics” and “Litter”, respectively.

```
getwd()

## [1] "/Users/rachelgonsenhauser/Documents/Environmental_Data_Analytics_2020/Assignments/Assignment 3"

library(tidyverse)
Neonics <- read.csv("~/Documents/Environmental_Data_Analytics_2020/Data/Raw/ECOTOX_Neonicotinoids_Insects_raw.csv")
# View(Neonics)
Litter <- read.csv("~/Documents/Environmental_Data_Analytics_2020/Data/Raw/NEON_NIWO_Litter_massdata_2018-08_raw.csv")
# View(Litter)
```

Learn about your system

2. The neonicotinoid dataset was collected from the Environmental Protection Agency’s ECOTOX Knowledgebase, a database for ecotoxicology research. Neonicotinoids are a class of insecticides used widely in agriculture. The dataset that has been pulled includes all studies published on insects. Why might we be interested in the ecotoxicology of neonicotinoids on insects? Feel free to do a brief internet search if you feel you need more background information.

Answer: The use of neonicotinoids has been associated with adverse ecological impacts, especially honey bee population collapse and bird population declines due to the reduction in insect populations. As such, understanding the ecotoxicology of neonicotinoids on insects is crucial in understanding how these biotic populations respond to certain dosages of the insecticide and, consequently, how best to manage these populations.

- The Niwot Ridge litter and woody debris dataset was collected from the National Ecological Observatory Network, which collectively includes 81 aquatic and terrestrial sites across 20 ecoclimatic domains. 32 of these sites sample forest litter and woody debris, and we will focus on the Niwot Ridge long-term ecological research (LTER) station in Colorado. Why might we be interested in studying litter and woody debris that falls to the ground in forests? Feel free to do a brief internet search if you feel you need more background information.

Answer: Litter and woody debris can provide many benefits, including nutrient cycling, providing habitat for forest species, and promoting soil stabilization and improved infiltration. However, large quantities of litter and woody debris on the ground of forests can provide fuel for wildfire events, leading to prolonged, and more severe forest fires.

- How is litter and woody debris sampled as part of the NEON network? Read the `NEON_Litterfall_UserGuide.pdf` document to learn more. List three pieces of salient information about the sampling methods here:

Answer: *Litter and fine woody debris is sampled at terrestrial NEON sites that house woody vegetation >2m tall, with sampling occurring in tower plots whose locations were selected randomly within the 90% flux footprint of primary and secondary airsheds. Trap placement within plots were targeted or randomized depending on vegetation (e.g. in sites with more than 50% aerial cover of woody vegetation >2m tall, placement of traps was randomized). *Ground traps are sampled once per year whereas sampling frequency for elevated traps varies by site vegetation, with deciduous forest sites being sampled more frequently than evergreen sites.*

Obtain basic summaries of your data (Neonics)

- What are the dimensions of the dataset?

```
dim(Neonics)
```

```
## [1] 4623 30
```

Answer: The dimensions of the dataset are 4,623 rows by 30 columns.

- Using the `summary` function, determine the most common effects that are studied. Why might these effects specifically be of interest?

```
summary(Neonics$Effect)
```

```
##      Accumulation      Avoidance      Behavior      Biochemistry
##           12           102           360           11
##      Cell(s)      Development      Enzyme(s)      Feeding behavior
##           9           136           62           255
##      Genetics      Growth      Histology      Hormone(s)
##          82           38           5           1
##      Immunological      Intoxication      Morphology      Mortality
##          16           12           22           1493
##      Physiology      Population      Reproduction
##           7           1803           197
```

Answer: The most common effects studied include population, mortality, behavior, feeding behavior, reproduction, and development. These effects were measured by abundance, mortality, survival, progeny count, food consumption, and emergence, respectively. These effects might be of interest because testing these effects can reveal information about insect populations' responses to different doses of and means of exposure to neonicotinoids. Studying these effects in this context also allows cross-species comparisons of how the effects of different exposure manifest in different insects.

- Using the `summary` function, determine the six most commonly studied species in the dataset (common name). What do these species have in common, and why might they be of interest over other insects?

Feel free to do a brief internet search for more information if needed.

```
summary(Neonics$Species.Common.Name)
```

##	Honey Bee	Parasitic Wasp
##	667	285
##	Buff Tailed Bumblebee	Carniolan Honey Bee
##	183	152
##	Bumble Bee	Italian Honeybee
##	140	113
##	Japanese Beetle	Asian Lady Beetle
##	94	76
##	Euonymus Scale	Wireworm
##	75	69
##	European Dark Bee	Minute Pirate Bug
##	66	62
##	Asian Citrus Psyllid	Parastic Wasp
##	60	58
##	Colorado Potato Beetle	Parasitoid Wasp
##	57	51
##	Erythrina Gall Wasp	Beetle Order
##	49	47
##	Snout Beetle Family, Weevil	Sevenspotted Lady Beetle
##	47	46
##	True Bug Order	Buff-tailed Bumblebee
##	45	39
##	Aphid Family	Cabbage Looper
##	38	38
##	Sweetpotato Whitefly	Braconid Wasp
##	37	33
##	Cotton Aphid	Predatory Mite
##	33	33
##	Ladybird Beetle Family	Parasitoid
##	30	30
##	Scarab Beetle	Spring Tiphia
##	29	29
##	Thrip Order	Ground Beetle Family
##	29	27
##	Rove Beetle Family	Tobacco Aphid
##	27	27
##	Chalcid Wasp	Convergent Lady Beetle
##	25	25
##	Stingless Bee	Spider/Mite Class
##	25	24
##	Tobacco Flea Beetle	Citrus Leafminer
##	24	23
##	Ladybird Beetle	Mason Bee
##	23	22
##	Mosquito	Argentine Ant
##	22	21
##	Beetle	Flatheaded Appletree Borer
##	21	20
##	Horned Oak Gall Wasp	Leaf Beetle Family
##	20	20
##	Potato Leafhopper	Tooth-necked Fungus Beetle

##	20	20
##	Codling Moth	Black-spotted Lady Beetle
##	19	18
##	Calico Scale	Fairyfly Parasitoid
##	18	18
##	Lady Beetle	Minute Parasitic Wasps
##	18	18
##	Mirid Bug	Mulberry Pyralid
##	18	18
##	Silkworm	Vedalia Beetle
##	18	18
##	Araneoid Spider Order	Bee Order
##	17	17
##	Egg Parasitoid	Insect Class
##	17	17
##	Moth And Butterfly Order	Oystershell Scale Parasitoid
##	17	17
##	Hemlock Woolly Adelgid Lady Beetle	Hemlock Woolly Adelgid
##	16	16
##	Mite	Onion Thrip
##	16	16
##	Western Flower Thrips	Corn Earworm
##	15	14
##	Green Peach Aphid	House Fly
##	14	14
##	Ox Beetle	Red Scale Parasite
##	14	14
##	Spined Soldier Bug	Armoured Scale Family
##	14	13
##	Diamondback Moth	Eulophid Wasp
##	13	13
##	Monarch Butterfly	Predatory Bug
##	13	13
##	Yellow Fever Mosquito	Braconid Parasitoid
##	13	12
##	Common Thrip	Eastern Subterranean Termite
##	12	12
##	Jassid	Mite Order
##	12	12
##	Pea Aphid	Pond Wolf Spider
##	12	12
##	Spotless Ladybird Beetle	Glasshouse Potato Wasp
##	11	10
##	Lacewing	Southern House Mosquito
##	10	10
##	Two Spotted Lady Beetle	Ant Family
##	10	9
##	Apple Maggot	(Other)
##	9	670

Answer: The six most commonly studied species in the dataset are the honey bee, parasitic wasp, buff tailed bumblebee, carniolan honey bee, bumblee bee, and italian honeybee. These species are all bees and wasps and may be of particular interest over other insect species because neonicotinoids can kill bees and parasitic wasps as they can contaminate pollen and nectar that

these insects feed on. As such, it makes sense that these species would be of particular interest in neonicotinoid ecotoxicity studies over other insect species such as beetles and spiders who do not feed on pollen and nectar.

8. Concentrations are always a numeric value. What is the class of `Conc.1..Author.` in the dataset, and why is it not numeric?

```
class(Neonics$Conc.1..Author.)
```

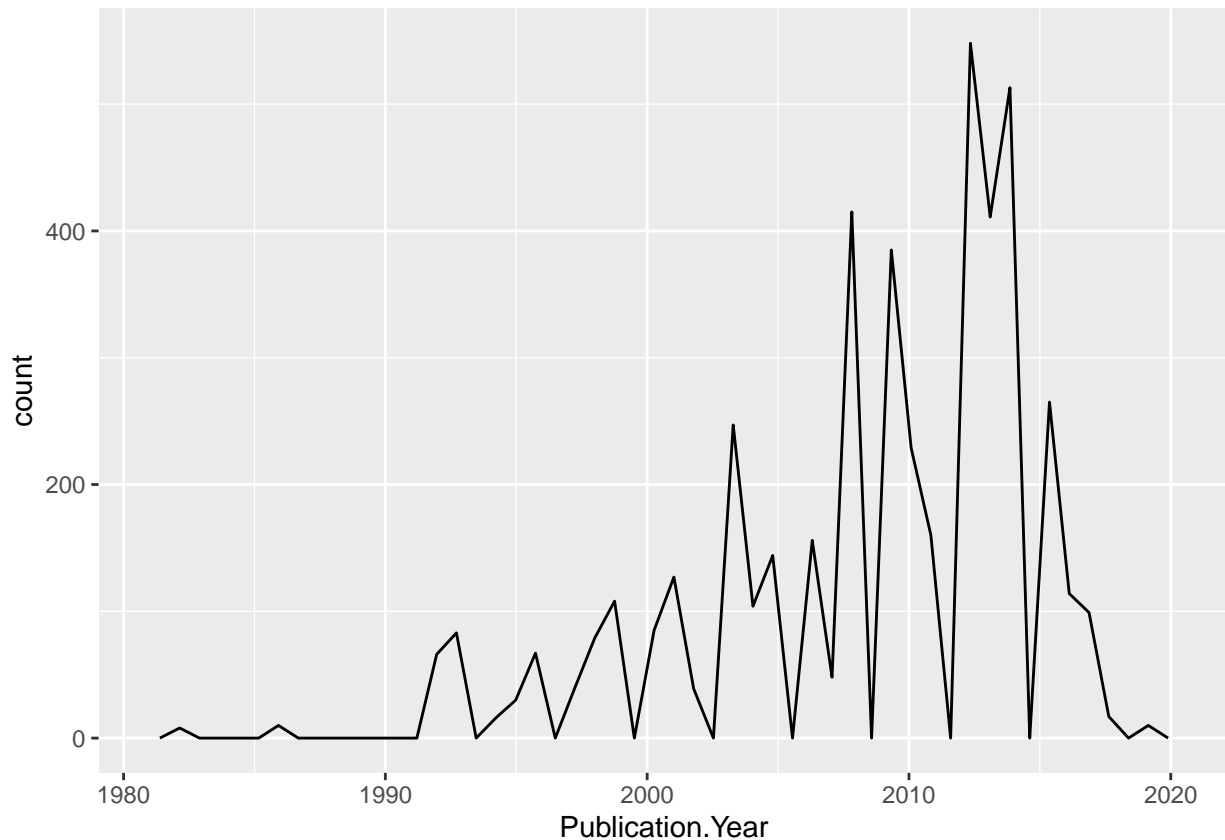
```
## [1] "factor"
```

Answer: The class of `Conc.1..Author.` in the dataset is “factor”. The class of these values is not numeric because the data in this column contains non-numeric information (e.g. slashes and letters). As such, this column cannot be made a numeric class of data.

Explore your data graphically (Neonics)

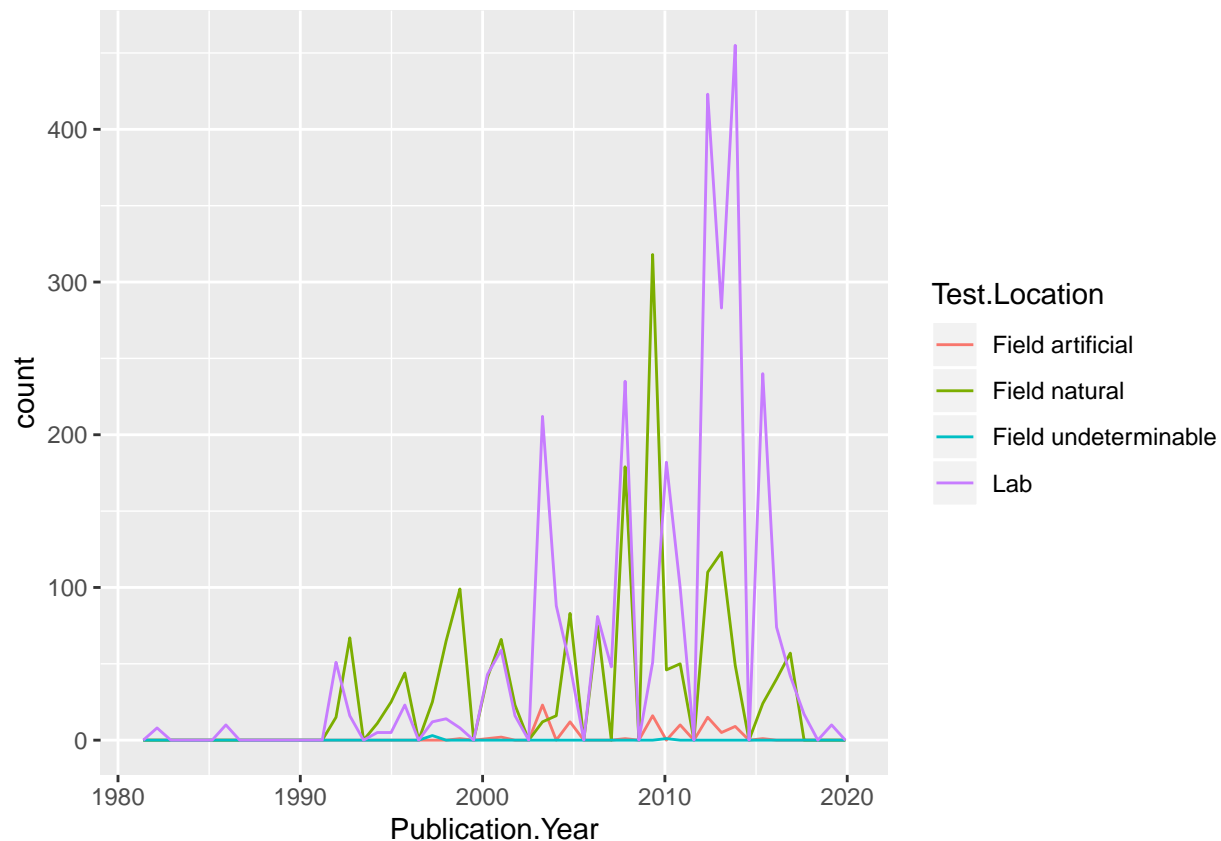
9. Using `geom_freqpoly`, generate a plot of the number of studies conducted by publication year.

```
ggplot(Neonics) +  
  geom_freqpoly(aes(x = Publication.Year), bins = 50)
```



10. Reproduce the same graph but now add a color aesthetic so that different `Test.Location` are displayed as different colors.

```
ggplot(Neonics) +  
  geom_freqpoly(aes(x = Publication.Year, color = Test.Location), bins = 50)
```

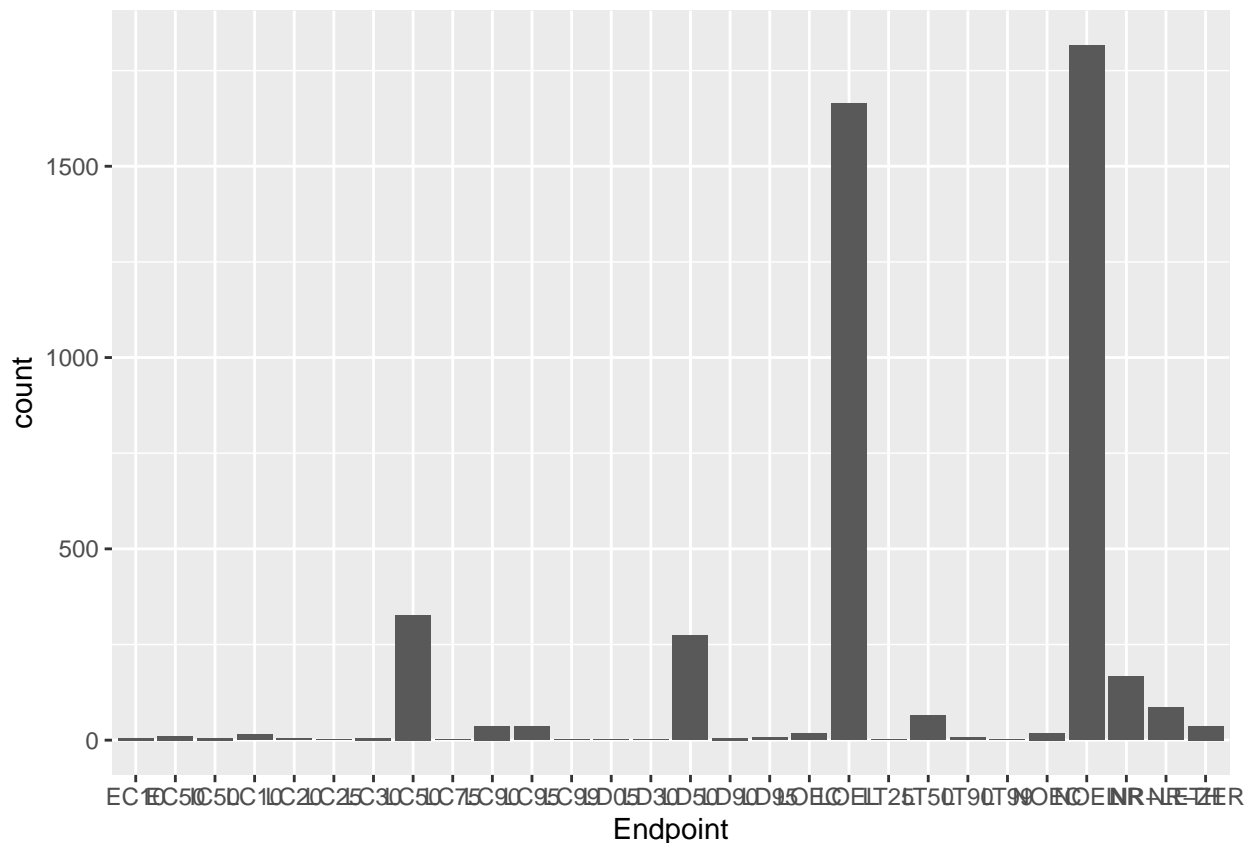


Interpret this graph. What are the most common test locations, and do they differ over time?

Answer: The most common test locations are “field natural” and “lab”. The frequency of testing in the “field natural” location peaks around 2008, with less frequent testing before and after this period. By contrast, testing in “lab” locations increases dramatically with time, peaking around 2012 and 2014, tapering slightly after this, but still remaining quite high until around 2017.

11. Create a bar graph of Endpoint counts. What are the two most common end points, and how are they defined? Consult the ECOTOX_CodeAppendix for more information.

```
ggplot(Neonics, aes(x = Endpoint)) +  
  geom_bar()
```



Answer: The two most common endpoints are LOEL and NOEL. As per the ECO-TOX_CodeAppendix, LOEL is defined as the “lowest-observable-effect-level”, or the lowest dose producing effects that were significantly different from responses of controls. NOEL is defined as “no-observable-effect-level”, or the highest dose producing effects not significantly different from responses of controls according to author’s reported statistical test.

Explore your data (Litter)

12. Determine the class of `collectDate`. Is it a date? If not, change to a date and confirm the new class of the variable. Using the `unique` function, determine which dates litter was sampled in August 2018.

```
class(Litter$collectDate)
```

```
## [1] "factor"
```

```
Litter$collectDate <- as.Date(Litter$collectDate, format = "%Y-%m-%d")
Litter$collectDate <- format(Litter$collectDate, "%Y-%m-%d")
Litter$collectDate <- as.Date(Litter$collectDate, format = "%Y-%m-%d")
class(Litter$collectDate)
```

```
## [1] "Date"
```

```
collection_date <- Litter$collectDate
collection_date
```

```
## [1] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [6] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [11] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [16] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
```

```
## [21] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [26] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [31] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [36] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [41] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [46] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [51] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [56] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [61] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [66] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [71] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [76] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [81] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [86] "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02" "2018-08-02"
## [91] "2018-08-02" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [96] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [101] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [106] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [111] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [116] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [121] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [126] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [131] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [136] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [141] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [146] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [151] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [156] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [161] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [166] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [171] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [176] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [181] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
## [186] "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30" "2018-08-30"
```

```
length(collection_date)
```

```
## [1] 188
```

```
unique_collection_date <- unique(collection_date)
unique_collection_date
```

```
## [1] "2018-08-02" "2018-08-30"
```

```
length(unique_collection_date)
```

```
## [1] 2
```

Answer: Litter was sampled on August 2, 2018 and August 30, 2018.

13. Using the `unique` function, determine how many plots were sampled at Niwot Ridge. How is the information obtained from `unique` different from that obtained from `summary`?

```
plots <- Litter$plotID
length(plots)
```

```
## [1] 188
```



```

unique_plots <- unique(plots)
unique_plots

## [1] NIWO_061 NIWO_064 NIWO_067 NIWO_040 NIWO_041 NIWO_063 NIWO_047 NIWO_051
## [9] NIWO_058 NIWO_046 NIWO_062 NIWO_057
## 12 Levels: NIWO_040 NIWO_041 NIWO_046 NIWO_047 NIWO_051 NIWO_057 ... NIWO_067

length(unique_plots)

## [1] 12

summary(unique_plots)

## NIWO_040 NIWO_041 NIWO_046 NIWO_047 NIWO_051 NIWO_057 NIWO_058 NIWO_061
##      1      1      1      1      1      1      1      1
## NIWO_062 NIWO_063 NIWO_064 NIWO_067
##      1      1      1      1

summary(plots)

## NIWO_040 NIWO_041 NIWO_046 NIWO_047 NIWO_051 NIWO_057 NIWO_058 NIWO_061
##      20      19      18      15      14      8      16      17
## NIWO_062 NIWO_063 NIWO_064 NIWO_067
##      14      14      16      17

```

Answer: The ‘unique’ function reveals that 12 plots were sampled at Niwot Ridge. The ‘unique’ function presents a list of site numbers, explaining that they exist at 12 levels. Conversely, the ‘summary’ function provides a list of site numbers accompanied by counts of each plot name.

14. Create a bar graph of functionalGroup counts. This shows you what type of litter is collected at the Niwot Ridge sites. Notice that litter types are fairly equally distributed across the Niwot Ridge sites.

```

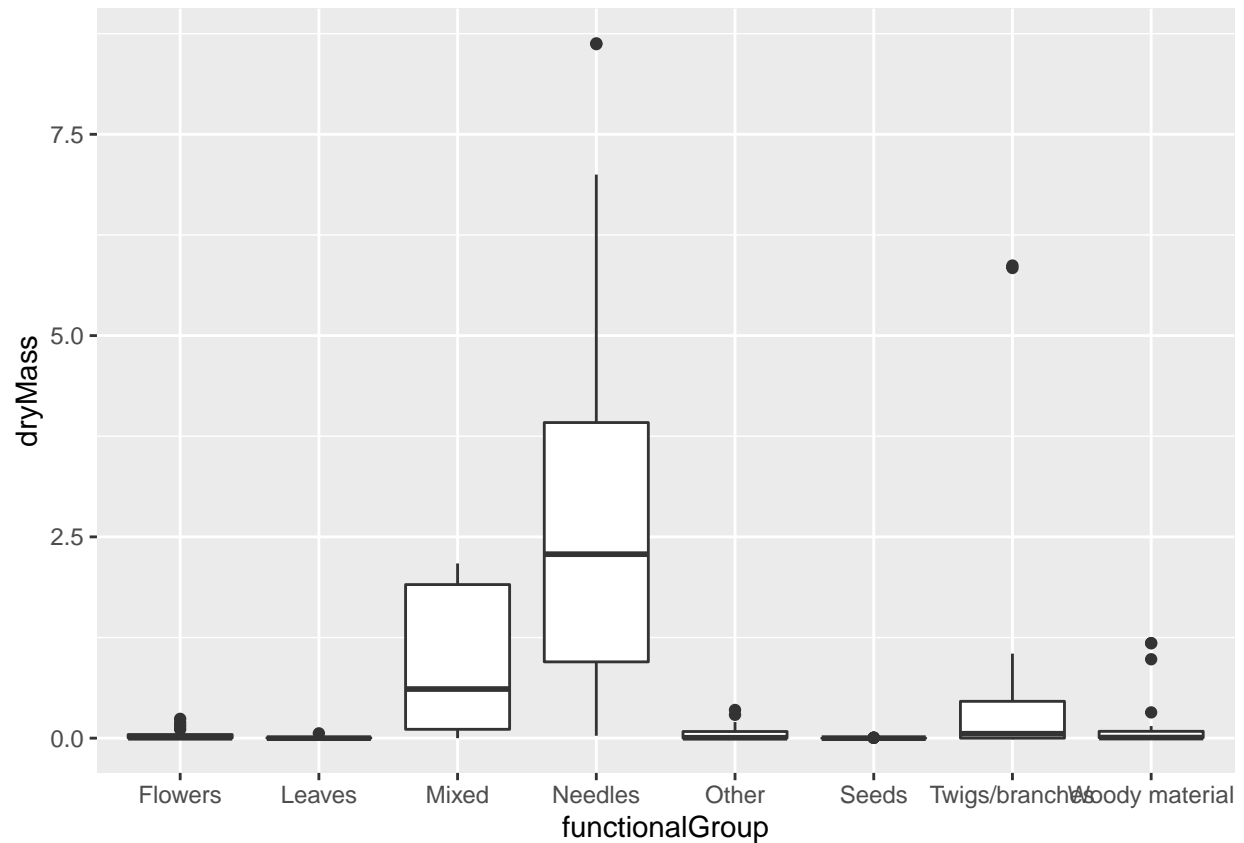
ggplot(Litter, aes(x = functionalGroup)) +
  geom_bar()

```



15. Using `geom_boxplot` and `geom_violin`, create a boxplot and a violin plot of `dryMass` by `functionalGroup`.

```
ggplot(Litter) +  
  geom_boxplot(aes(x = functionalGroup, y = dryMass))
```

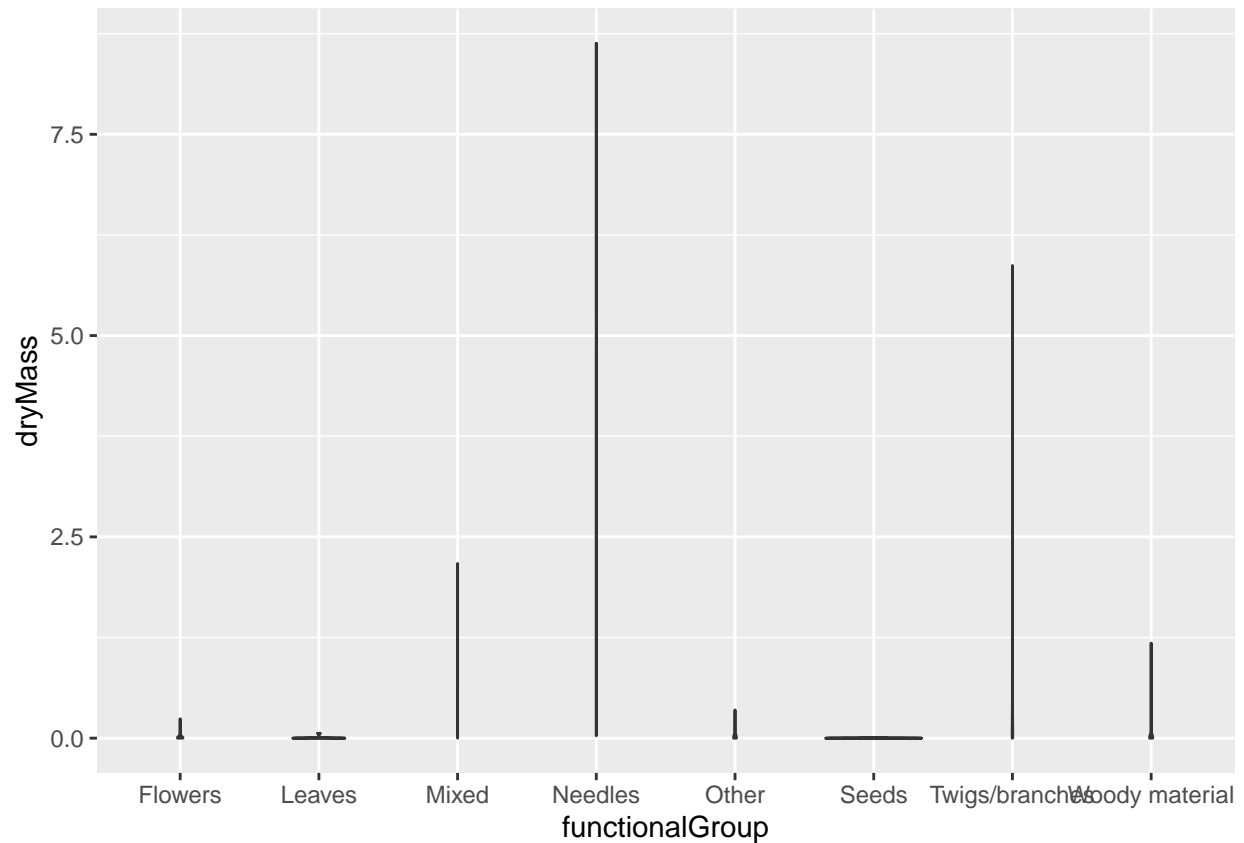


```
ggplot(Litter) +
  geom_violin(aes(x = functionalGroup, y = dryMass),
    draw_quantiles = c(0.25, 0.5, 0.75),
    scale = "count")
```

```
## Warning in regularize.values(x, y, ties, missing(ties)): collapsing to unique
## 'x' values
```

```
## Warning in regularize.values(x, y, ties, missing(ties)): collapsing to unique
## 'x' values
```

```
## Warning in regularize.values(x, y, ties, missing(ties)): collapsing to unique
## 'x' values
```



Why is the boxplot a more effective visualization option than the violin plot in this case?

Answer: The boxplot is able to show the distribution of dryMass for each functional group, wherein the median and spread of dryMass in each case can be compared side by side. By contrast, the violin plot is only able to show the spread of dryMass values for each group in this case; since the data is skewed it's very hard to see the data in the violin plot format.

What type(s) of litter tend to have the highest biomass at these sites?

Answer: The mixed and needles functional groups have the highest biomass at these sites. Additionally, the twigs/branches group has an outlier with a particularly high biomass value.