

# Assignment 3: Data Exploration

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## OVERVIEW

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

## Directions

1. Change “Student Name, Section #” on line 3 (above) with your name and section number.
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., “FirstLast\_A03\_DataExploration.Rmd”) prior to submission.

The completed exercise is due on <>.

## 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. **Be sure to add the `stringsAsFactors = TRUE` parameter to the function when reading in the CSV files.**

```
getwd() #check working directory

## [1] "/Users/samsaltman/Documents/R/Environmental_Data_Analytics_2022/Assignments"

library(tidyverse) # load necessary package

Neonics <- read.csv("../Data/Raw/ECOTOX_Neonicotinoids_Insects_raw.csv", stringsAsFactors = TRUE)
Litter <- read.csv("../Data/Raw/NEON_NIWO_Litter_massdata_2018-08_raw.csv", stringsAsFactors = TRUE)
```

## 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: We may want to understand how this type of insecticide affects insects. Insects can harm crops; however, some insects can be good for agricultural purposes by pollinating crops and/or preying on harmful insects in the field. Data analysis on neonicotinoids can help us understand if an insecticide is successful at targeting harmful insects while not causing harms to insects that are beneficial to the agricultural process.

3. 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: We may want to study the litter and woody debris in forests to determine the health of the forest. This kind of debris will decompose and provide nutrients to the soil. Litter will decompose faster than woody debris. Analyzing litter and woody debris can help researchers understand the replenishment rate of nutrients to the soil and the general lifecycle of a forest.

4. 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: \* The woody debris and litter samples were collected using both elevated and ground traps. \* The research used a spatial sampling design to randomly select plot sites. The sites had to contain woody vegetation taller than 2 meters. \* Also, the research had a temporal sampling design. Ground traps were measured once a year. Sampling of elevated traps occurred frequently throughout the year but varied depending on the vegetation in the sample.

## Obtain basic summaries of your data (Neonics)

5. What are the dimensions of the dataset?

```
dim(Neonics) # dimensions
```

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

6. Using the `summary` function on the “Effect” column, determine the most common effects that are studied. Why might these effects specifically be of interest?

```
Neonics_effects <- summary(Neonics$Effect)
Neonics_effects
```

```
##      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: Population (1803) & Mortality (1493) are the most common effects studied. Studying population may be of interest to see if the insecticide increases, decreases or has no effect on a population size over the course of the study. Studying mortality could help researchers understand the effectiveness of the insecticide as well as understand why population size may have changed.

7. 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: Top 6: Honey Bees, Parasitic Wasp, Buff Tailed Bumblebee, Carniolan Honey Bee, Bumble Bee, Italian Bee. Bees are the most studied because a healthy garden needs pollinators. Researchers want to make sure that these insects are not harmed by the insecticide. The Asian Lady Beetle is also frequently studied because it is beneficial to a farm by preying on harmful insects. The insecticide should not harm this species of insect either. On the other hand, the Japanese Beetle is studied frequently as they are a pest. The insecticide should be effective at reducing this insect population.

- 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.) #it's a factor
```

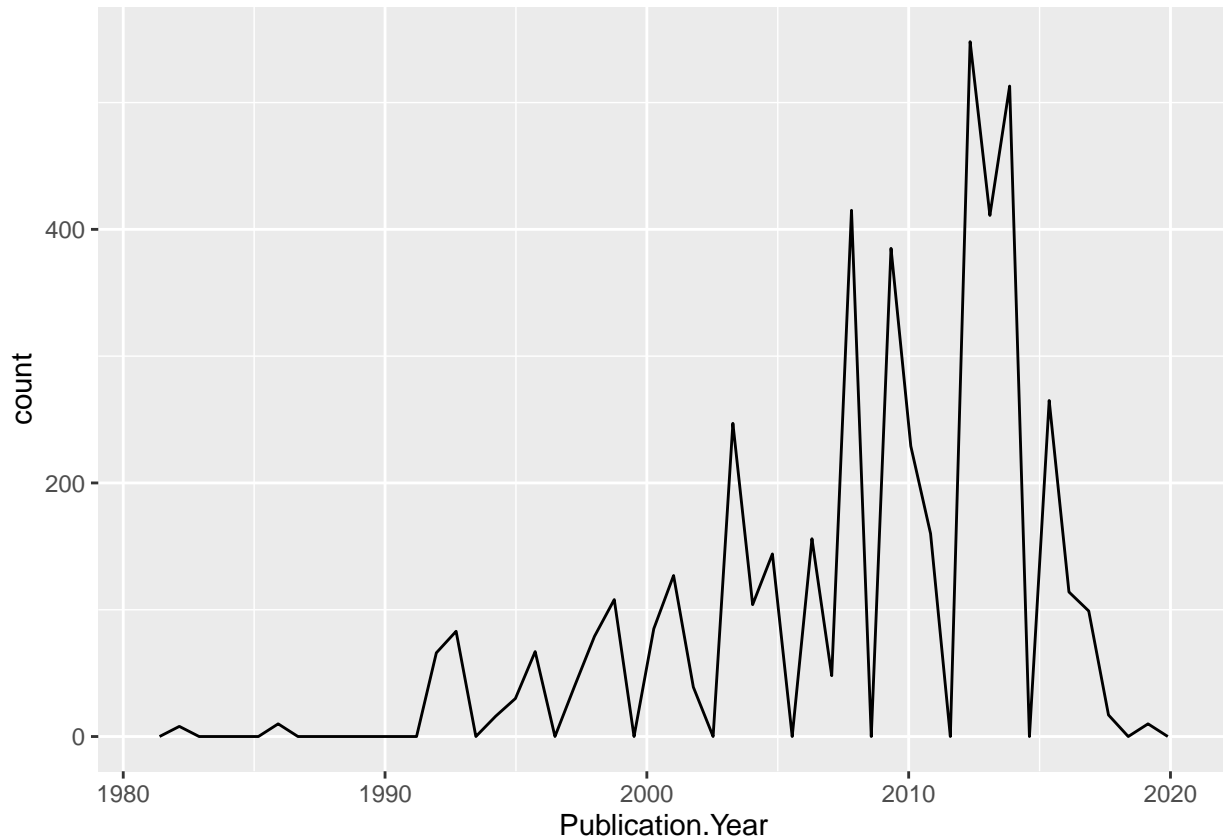
```
## [1] "factor"
```

Answer: It is not numeric because it contains both numbers and characters.

## Explore your data graphically (Neonics)

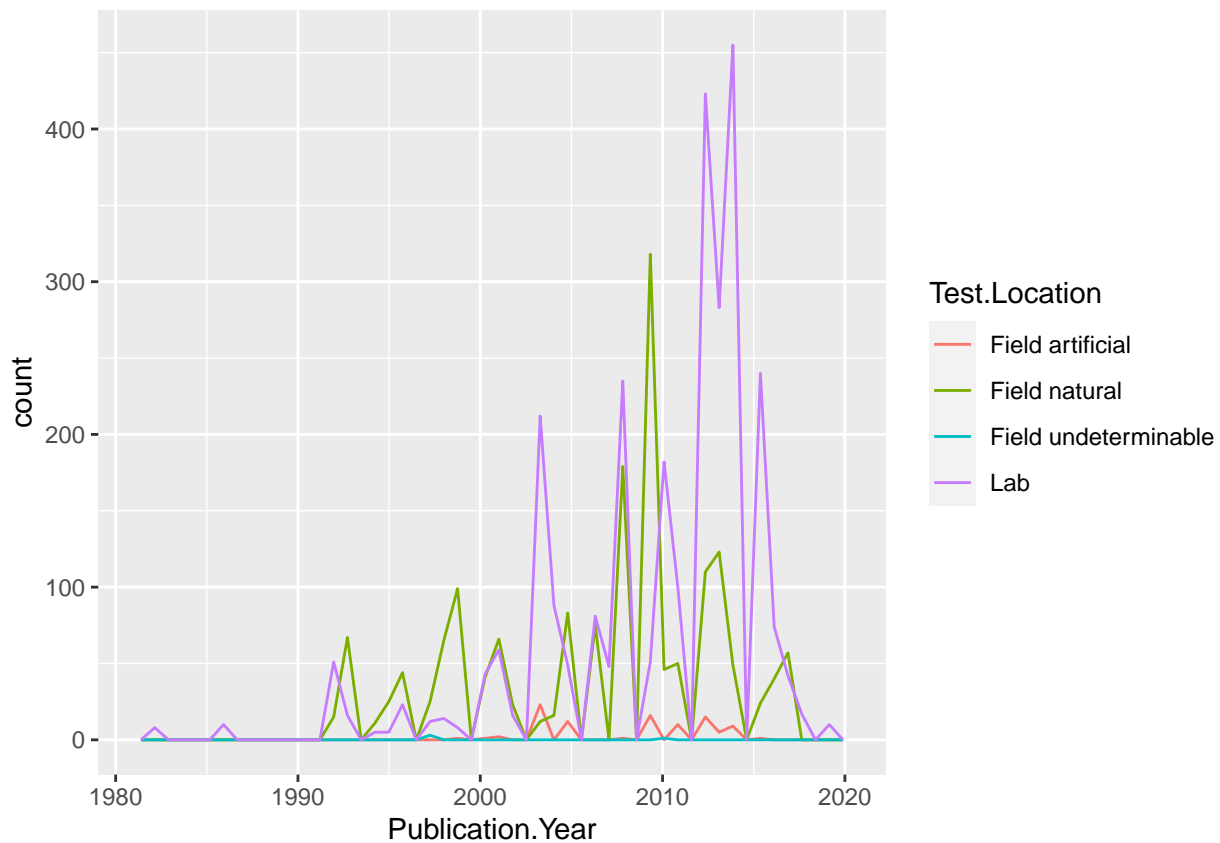
9. Using `geom_freqpoly`, generate a plot of the number of studies conducted by publication year.

```
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)
```

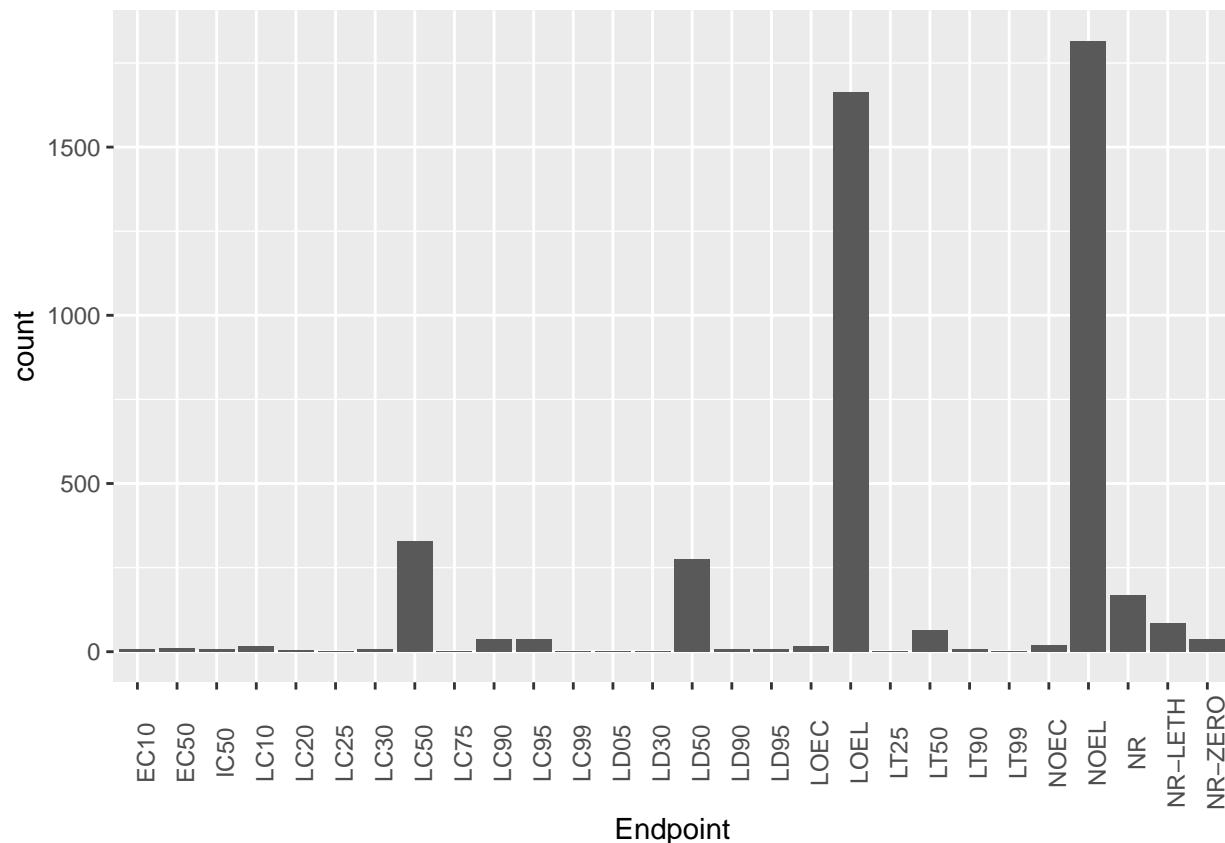


Interpret this graph. What are the most common test locations, and do they differ over time?

Answer: Labs and field natural test locations are most commonly used. There is variability over time, but it appears that these locations have been used more often since the first recorded publish date in this dataset.

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)) +
  geom_bar(aes(x = Endpoint)) +
  theme(axis.text.x = element_text(angle = 90)) # used this code to make x axis labels visible
```



Answer: LOEL is the “lowest-observable-effect-level,” and it is defined as the lowest dose that would produce a significantly different response from the controls. NOEL is “no-observable-effect-level,” and it is defined as the highest dose that does not cause a significantly different response from the controls.

## 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) #it's a factor to start. Can run this code again to see if conversion worked
```

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

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

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

```
unique(Litter$collectDate) #samples were collected on August 2nd and 30th in 2018
```

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

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`?

```
unique(Litter$plotID)
```

```
## [1] NIWO_061 NIWO_064 NIWO_067 NIWO_040 NIWO_041 NIWO_063 NIWO_047 NIWO_051
```

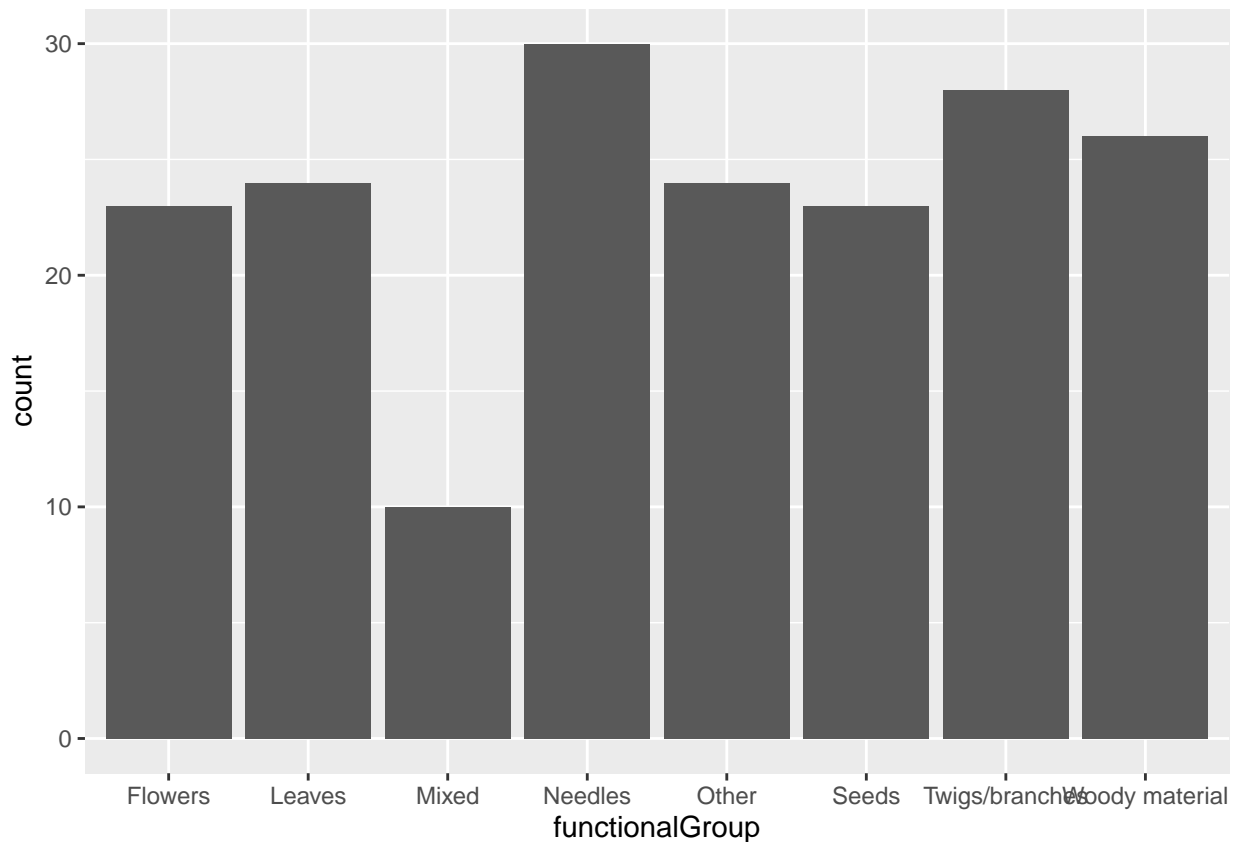
```
## [9] NIWO_058 NIWO_046 NIWO_062 NIWO_057
```

```
## 12 Levels: NIWO_040 NIWO_041 NIWO_046 NIWO_047 NIWO_051 NIWO_057 ... NIWO_067
```

Answer: The unique function lists every unique plot ID and gives the total of the different sites which is 12 in this case. We can infer the same info from the summary function; however, this function does not explicitly state how many unique plots there are. It's main function is to provide stats on each plot.

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.

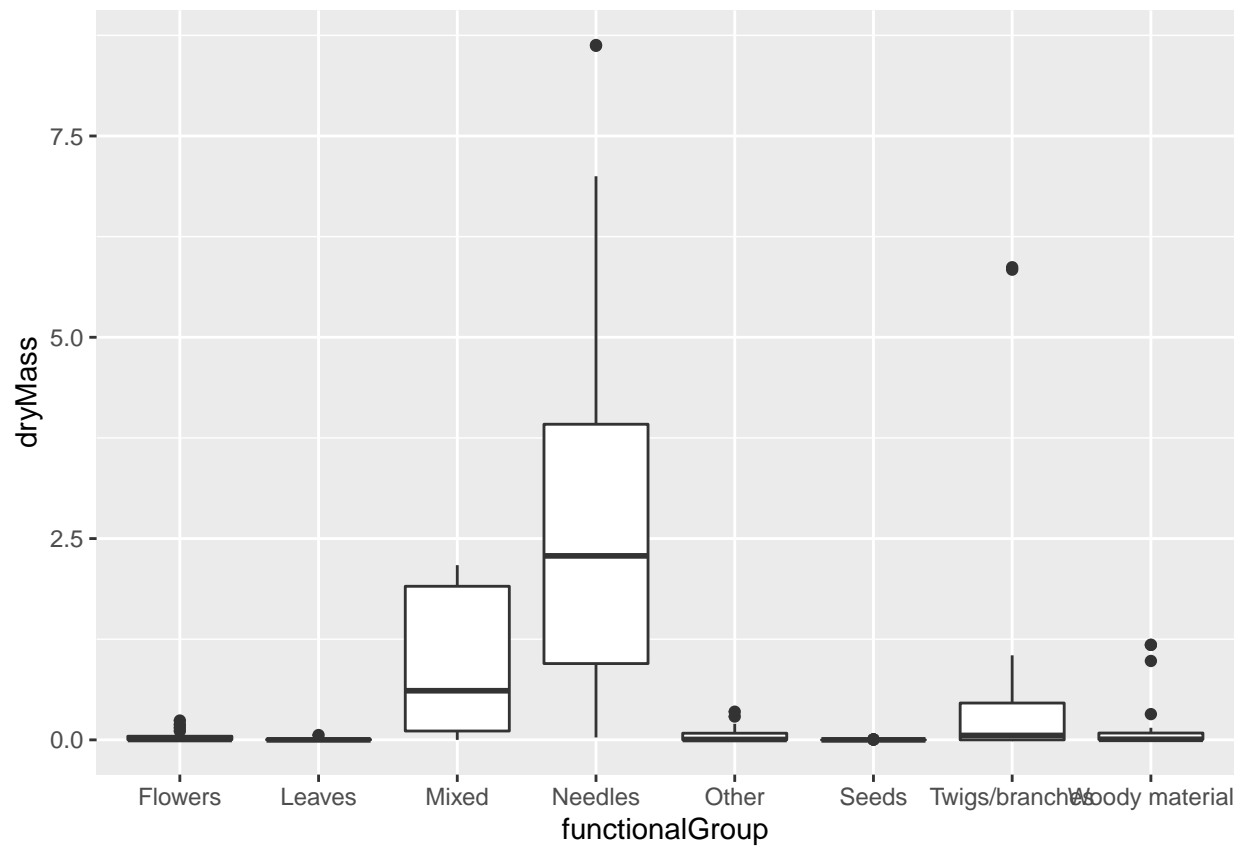
```
ggplot(Litter) +  
  geom_bar(aes(x = functionalGroup))
```



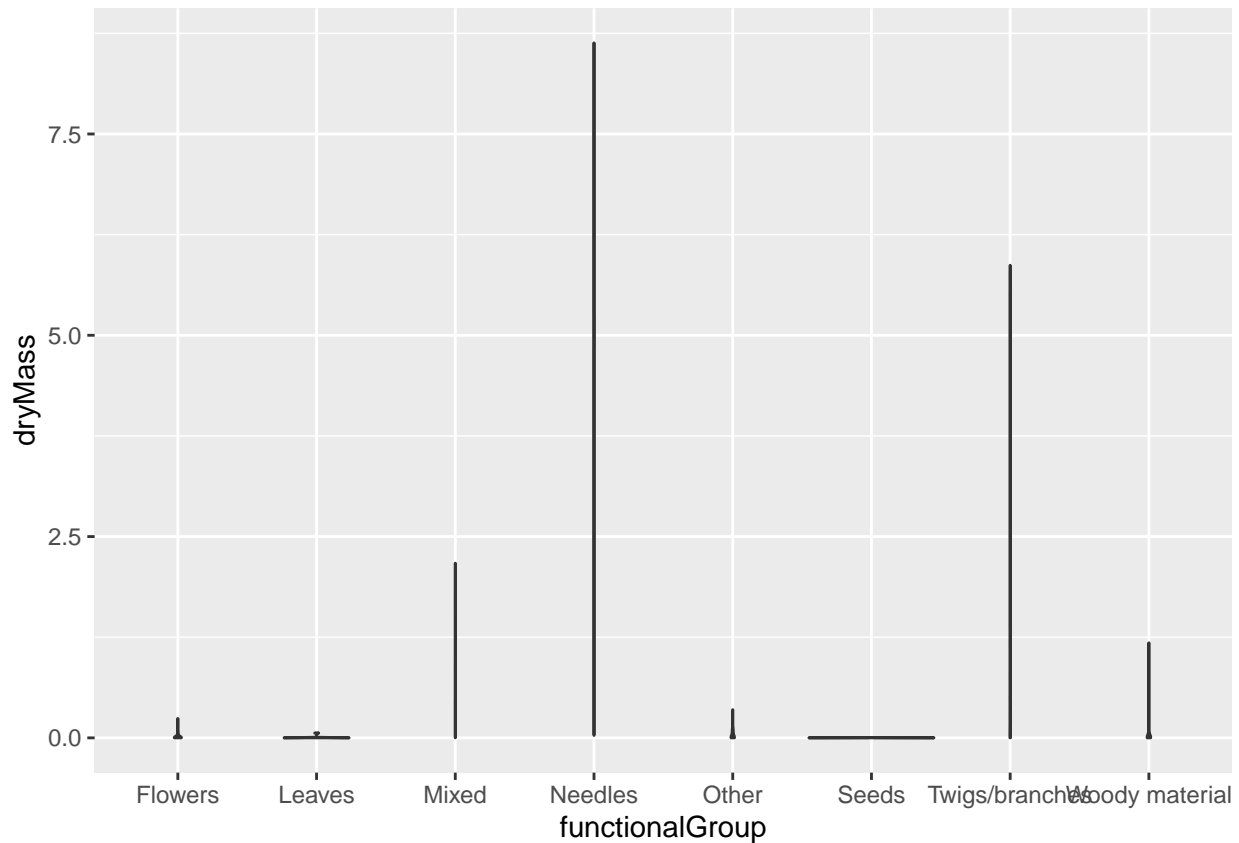
15. Using `geom_boxplot` and `geom_violin`, create a boxplot and a violin plot of `dryMass` by functionalGroup.

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





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



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

Answer: The boxplot helps us visualize the range of drymass between functionalgroups. We can clearly see the calculated averages between the samples. However, drymass accumulation in all functionalGroups varies between each sample. The violin is good for visually communicating if there is a certain range with many data points. This isn't the case in this chart, so the violin becomes less informative than the boxplot in this instance as a result.

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

Answer: Needles