3: Data Exploration

Environmental Data Analytics | Kateri Salk

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Objectives

1. Import and explore datasets in R
2. Graphically explore datasets in R
3. Apply data exploration skills to a real-world example dataset

Opening discussion: why do we explore our data?

Why is data exploration our first step in analyzing a dataset? What information do we gain? How does data exploration aid in our decision-making for data analysis steps further down the pipeline?

Import data and view summaries

```
# 1. Set up your working directory
getwd()
```

```
## [1] "/home/guest/EDA/EDA-Spring2023"
```

```
# 2. Load packages
library(tidyverse)

# 3. Import datasets
USGS.flow.data <- read.csv("./Data/Processed/USGS_Site02085000_Flow_Processed.csv",stringsAsFactors = T

#View(USGS.flow.data)
# Alternate option: click on data frame in Environment tab

colnames(USGS.flow.data)
```

```
##  [1] "agency_cd"                "site_no"
##  [3] "datetime"                 "discharge.max"
##  [5] "discharge.max.approval"   "discharge.min"
##  [7] "discharge.min.approval"   "discharge.mean"
##  [9] "discharge.mean.approval"  "gage.height.max"
## [11] "gage.height.max.approval" "gage.height.min"
## [13] "gage.height.min.approval" "gage.height.mean"
## [15] "gage.height.mean.approval"
```

```
str(USGS.flow.data)
```

```
## 'data.frame':    33690 obs. of  15 variables:
##  $ agency_cd                : Factor w/ 1 level "USGS": 1 1 1 1 1 1 1 1 1 1 ...
##  $ site_no                  : int  2085000 2085000 2085000 2085000 2085000 2085000 2085000 2085000 20
##  $ datetime                 : Factor w/ 33690 levels "1927-10-01","1927-10-02",..: 1 2 3 4 5 6 7 8 9
##  $ discharge.max            : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ discharge.max.approval   : Factor w/ 3 levels "","A","P": 1 1 1 1 1 1 1 1 1 1 ...
##  $ discharge.min            : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ discharge.min.approval   : Factor w/ 3 levels "","A","P": 1 1 1 1 1 1 1 1 1 1 ...
##  $ discharge.mean           : num  39 39 39 39 39 39 39 39 39 39 ...
##  $ discharge.mean.approval  : Factor w/ 4 levels "","A","A:e","P": 2 2 2 2 2 2 2 2 2 2 ...
##  $ gage.height.max          : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ gage.height.max.approval : Factor w/ 3 levels "","A","P": 1 1 1 1 1 1 1 1 1 1 ...
##  $ gage.height.min          : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ gage.height.min.approval : Factor w/ 3 levels "","A","P": 1 1 1 1 1 1 1 1 1 1 ...
##  $ gage.height.mean         : num  NA NA NA NA NA NA NA NA NA NA ...
##  $ gage.height.mean.approval: Factor w/ 3 levels "","A","P": 1 1 1 1 1 1 1 1 1 1 ...
```

```
dim(USGS.flow.data)
```

```
## [1] 33690    15
```

```
# Check our date column
class(USGS.flow.data$datetime)
```

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

```
USGS.flow.data$datetime <- as.Date(USGS.flow.data$datetime, format = "%Y-%m-%d")
class(USGS.flow.data$datetime)
```

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

Visualization for Data Exploration

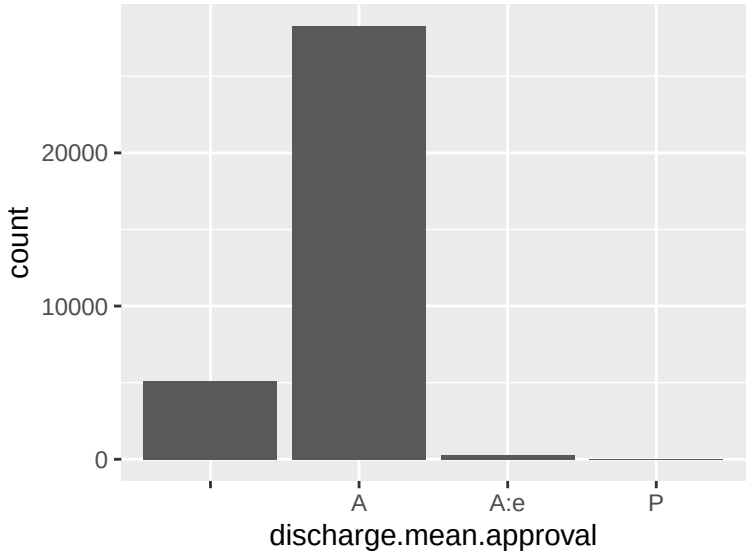
Although the `summary()` function is helpful in getting an idea of the spread of values in a numeric dataset, it can be useful to create visual representations of the data to help form hypotheses and direct downstream data analysis. Below is a summary of the useful types of graphs for data exploration.

Note: each of these approaches utilize the package "ggplot2". We will be covering the syntax of ggplot in a later lesson, but for now you should familiarize yourself with the functionality of what each command is doing.

Bar Chart (function: geom_bar)

Visualize count data for categorical variables.

```
ggplot(USGS.flow.data, aes(x = discharge.mean.approval)) +
  geom_bar()
```



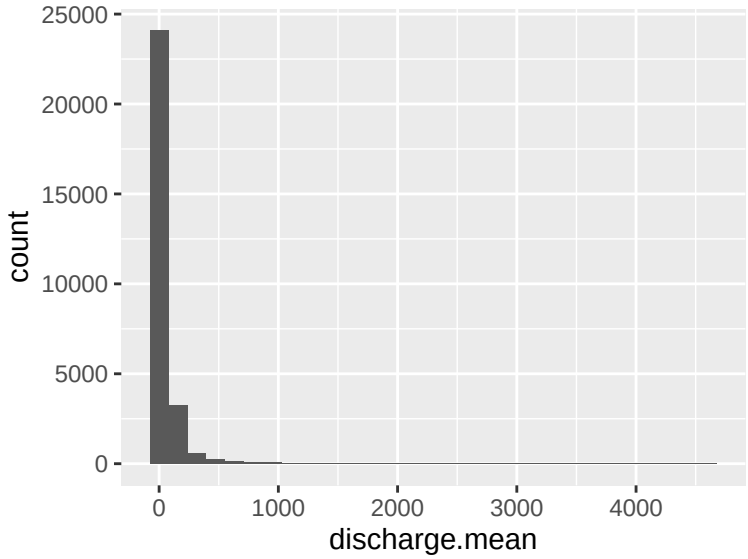
Histogram (function: geom_histogram)

Visualize distributions of values for continuous numerical variables. What is happening in each line of code? Insert a comment above each line.

```
#
ggplot(USGS.flow.data) +
  geom_histogram(aes(x = discharge.mean))
```

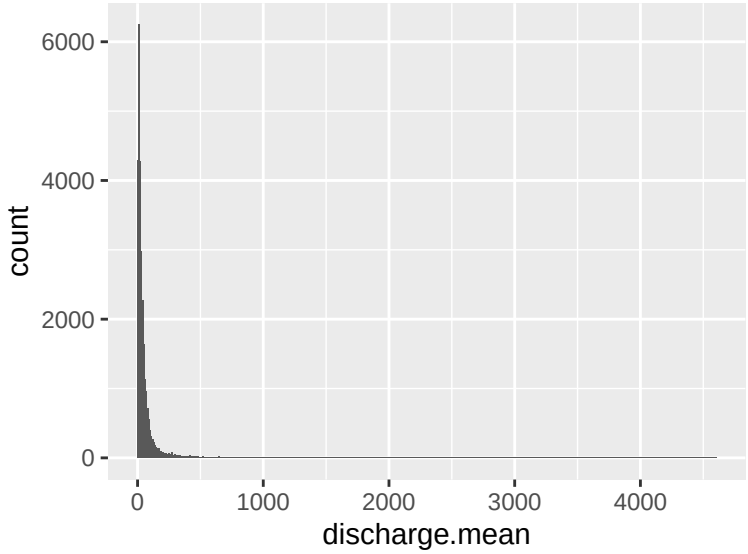
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 5108 rows containing non-finite values (`stat_bin()`).
```



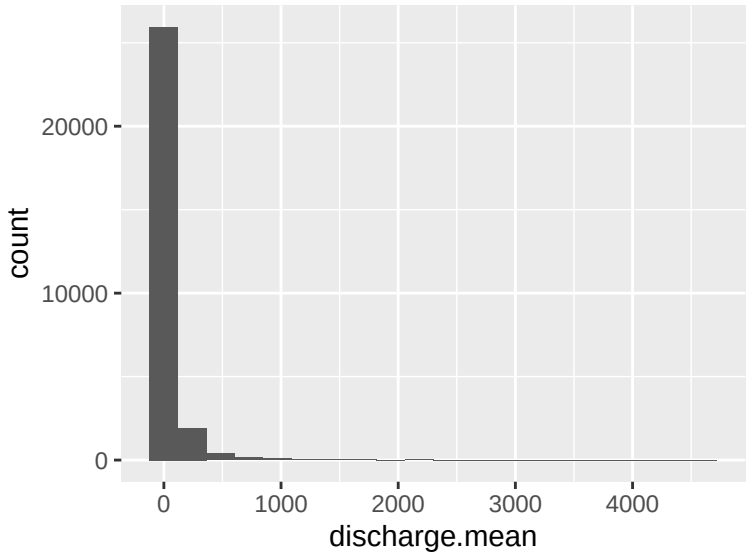
```
#
ggplot(USGS.flow.data) +
  geom_histogram(aes(x = discharge.mean), binwidth = 10)
```

```
## Warning: Removed 5108 rows containing non-finite values (‘stat_bin()‘).
```




```
#
ggplot(USGS.flow.data) +
  geom_histogram(aes(x = discharge.mean), bins = 20)
```

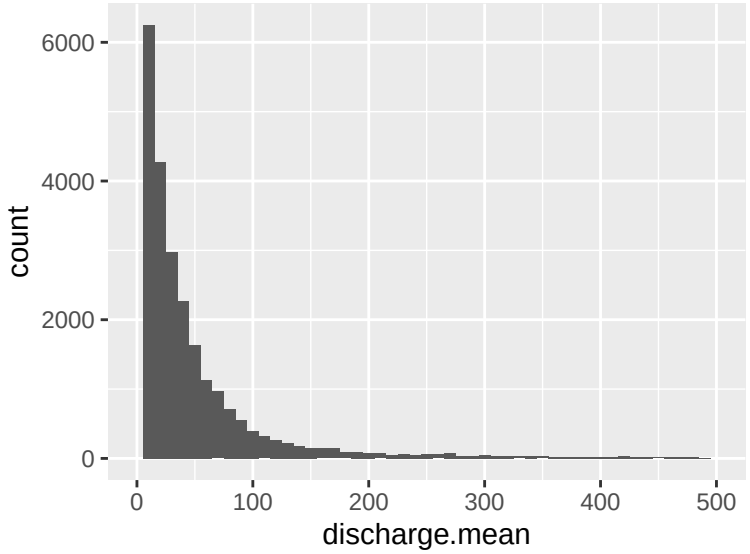
```
## Warning: Removed 5108 rows containing non-finite values (‘stat_bin()‘).
```



```
#
ggplot(USGS.flow.data, aes(x = discharge.mean)) +
  geom_histogram(binwidth = 10) +
  scale_x_continuous(limits = c(0, 500))
```

```
## Warning: Removed 5577 rows containing non-finite values (‘stat_bin()‘).
```

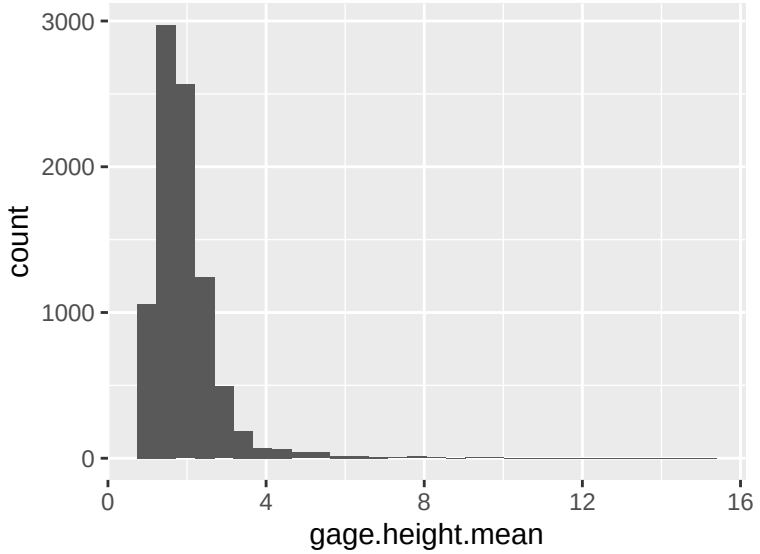
```
## Warning: Removed 2 rows containing missing values (‘geom_bar()‘).
```




```
#
ggplot(USGS.flow.data) +
  geom_histogram(aes(x = gage.height.mean))
```

```
## ‘stat_bin()‘ using ‘bins = 30‘. Pick better value with ‘binwidth‘.
```

```
## Warning: Removed 24870 rows containing non-finite values (‘stat_bin()‘).
```



Frequency line graph (function:

geom_freqpoly)

An alternate to a histogram is a frequency polygon graph (distributions of values for continuous numerical variables). Instead of displaying bars, counts of continuous variables are displayed as lines. This is advantageous if you want to display multiple variables or categories of variables at once.

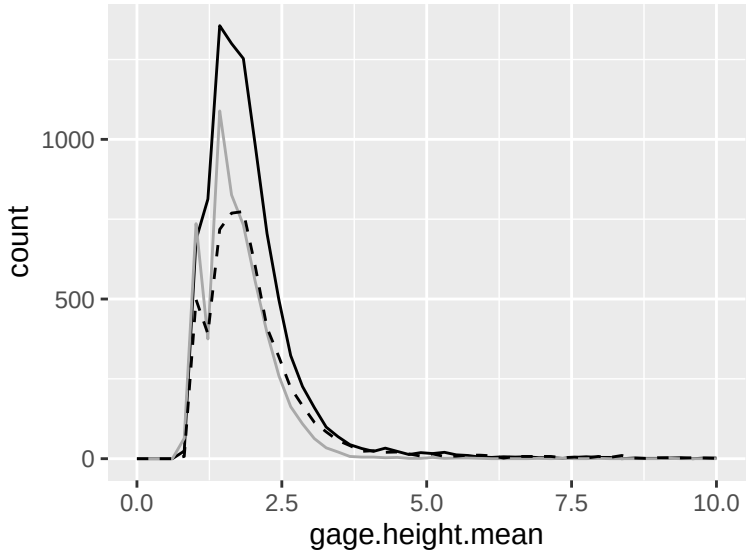
```
#
ggplot(USGS.flow.data) +
  geom_freqpoly(aes(x = gage.height.mean), bins = 50) +
  geom_freqpoly(aes(x = gage.height.min), bins = 50, color = "darkgray") +
  geom_freqpoly(aes(x = gage.height.max), bins = 50,  lty = 2) +
  scale_x_continuous(limits = c(0, 10))
```

```
## Warning: Removed 24887 rows containing non-finite values (‘stat_bin()‘).
```

```
## Warning: Removed 28229 rows containing non-finite values (‘stat_bin()‘).
```

```
## Warning: Removed 28266 rows containing non-finite values (‘stat_bin()‘).
```

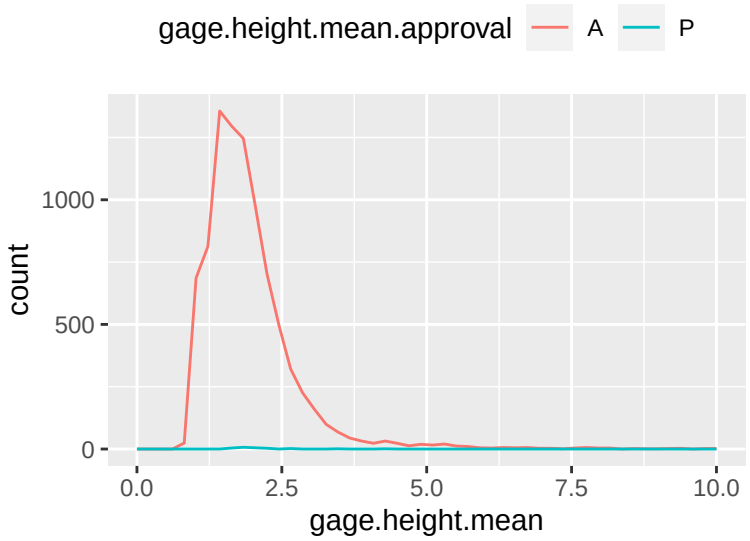
```
## Warning: Removed 2 rows containing missing values (‘geom_path()‘).
## Removed 2 rows containing missing values (‘geom_path()‘).
## Removed 2 rows containing missing values (‘geom_path()‘).
```




```
#
ggplot(USGS.flow.data) +
  geom_freqpoly(aes(x = gage.height.mean, color = gage.height.mean.approval), bins = 50) +
  scale_x_continuous(limits = c(0, 10)) +
  theme(legend.position = "top")
```

```
## Warning: Removed 24887 rows containing non-finite values (‘stat_bin()‘).
```

```
## Warning: Removed 4 rows containing missing values (‘geom_path()‘).
```



Box-and-whisker plots (function: geom_boxplot, geom_violin)

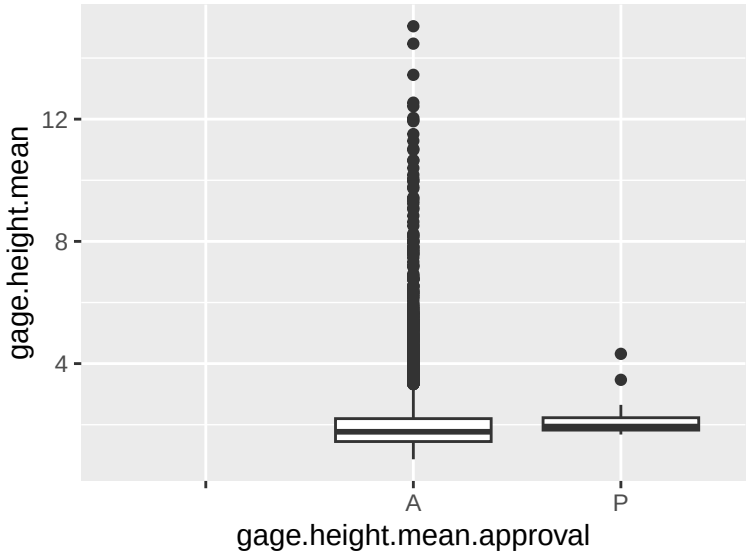
A box-and-whisker plot is yet another alternative to histograms (distributions of values for continuous numerical variables). These plots consist of:

- A box from the 25th to the 75th percentile of the data, called the interquartile range (IQR).
- A bold line inside the box representing the median value of the data. Whether the median is in the center or off to one side of the IQR will give you an idea about the skewness of your data.
- A line outside of the box representing values falling within 1.5 times the IQR.
- Points representing outliers, values that fall outside 1.5 times the IQR.

An alternate option is a violin plot, which displays density distributions, somewhat like a hybrid of the box-and-whiskers and the frequency polygon plot.

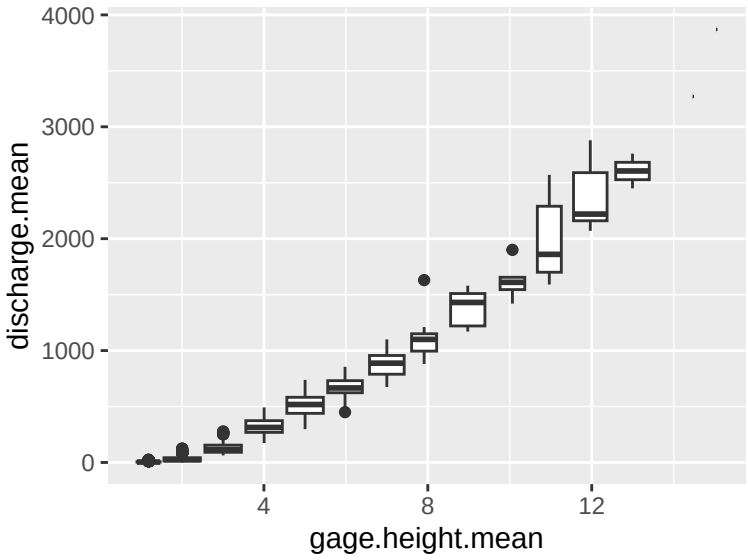
```
#
ggplot(USGS.flow.data) +
  geom_boxplot(aes(x = gage.height.mean.approval, y = gage.height.mean))
```

```
## Warning: Removed 24870 rows containing non-finite values (‘stat_boxplot()‘).
```



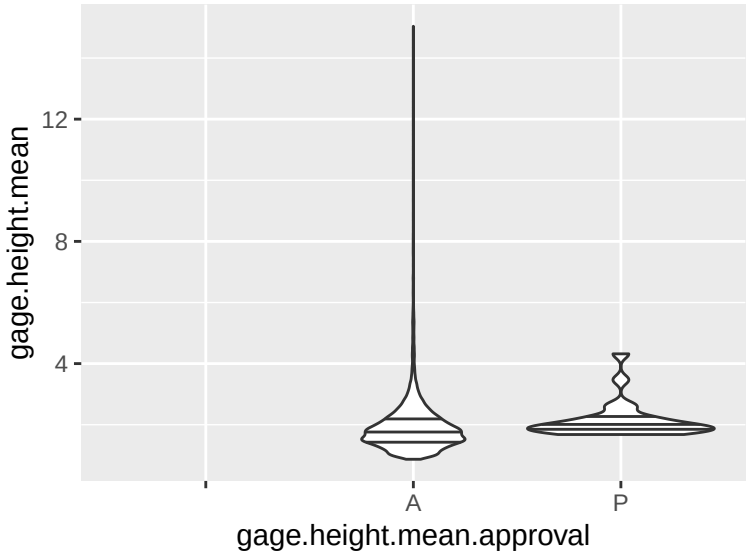

```
#
ggplot(USGS.flow.data) +
  geom_boxplot(aes(x = gage.height.mean, y = discharge.mean, group = cut_width(gage.height.mean, 1)))
```

```
## Warning: Removed 24870 rows containing missing values (‘stat_boxplot()‘).
```




```
#
ggplot(USGS.flow.data) +
  geom_violin(aes(x = gage.height.mean.approval, y = gage.height.mean),
              draw_quantiles = c(0.25, 0.5, 0.75))
```

```
## Warning: Removed 24870 rows containing non-finite values (‘stat_ydensity()‘).
```

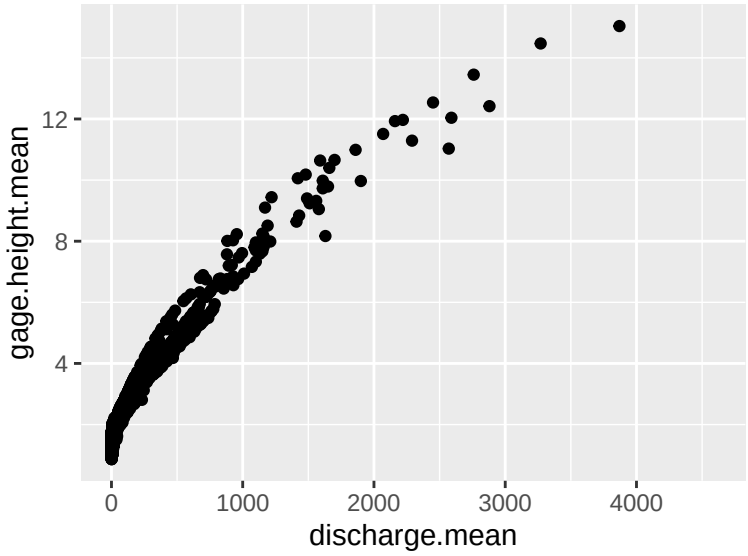


Scatterplot (function: geom_point)

Visualize relationships between continuous numerical variables.

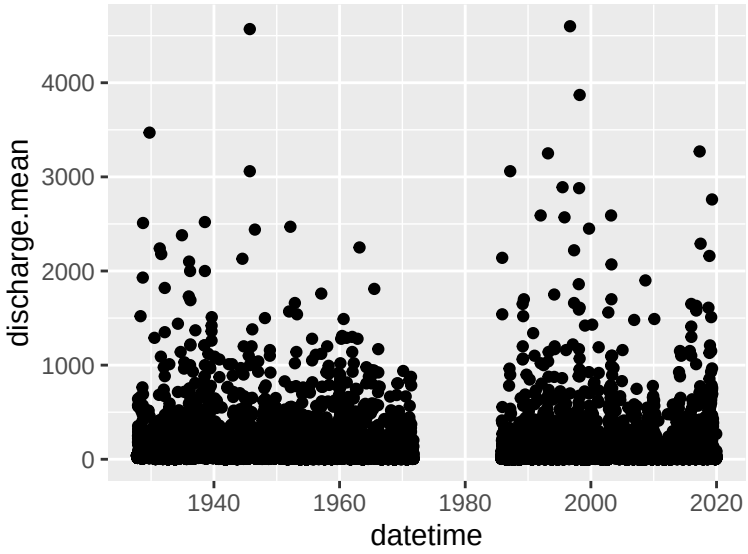
```
ggplot(USGS.flow.data) +
  geom_point(aes(x = discharge.mean, y = gage.height.mean))
```

```
## Warning: Removed 24870 rows containing missing values (`geom_point()`).
```




```
ggplot(USGS.flow.data) +
  geom_point(aes(x = datetime, y = discharge.mean))
```

```
## Warning: Removed 5108 rows containing missing values (`geom_point()`).
```



Question: under what circumstances would it be beneficial to use each of these graph types (bar plot, histogram, frequency polygon, box-and whisker, violin, scatterplot)?

Answer:

Ending discussion

What did you learn about the USGS discharge dataset today? What separate insights did the different graph types offer? > Answer:

How can multiple options for data exploration inform our understanding of our data?

Answer:

Do you see any patterns in the USGS data for the Eno River? What might be responsible for those patterns and/or relationships?

Answer: