Data Summaries

Prof. Wells

STA 209, 2/3/23

Outline

In this lecture, we will. . .

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- Consider a few extensions of `ggplot2`
- Discuss measurements of center and spread for quantitative data
- Use contingency tables to investigate relationships among categorical variables

Section 1

Summarizing Quantitative Data

Exam Statistics

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What summarizing information would it be helpful to know in order to assess how well the class did?

1. What was the typical score (maybe average or median)?
2. How much variation was there in scores?
3. What was the shape of the data?
4. Were there any outliers?

The Mean

The **mean** or average of a data set is one measure of *center*, obtained by adding all observed values and dividing by their number:

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

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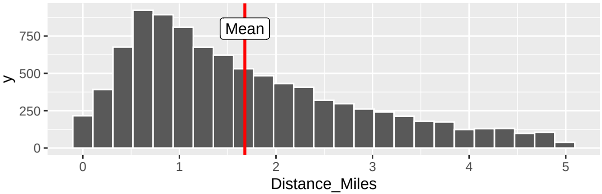

- If the histogram were made of solid material, the mean would be the point along the horizontal axis where the solid is perfectly balanced.

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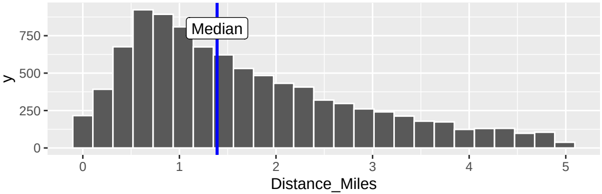

- The median corresponds to the line that divides a histogram into two equal area pieces.

Mean, Median, and Skew

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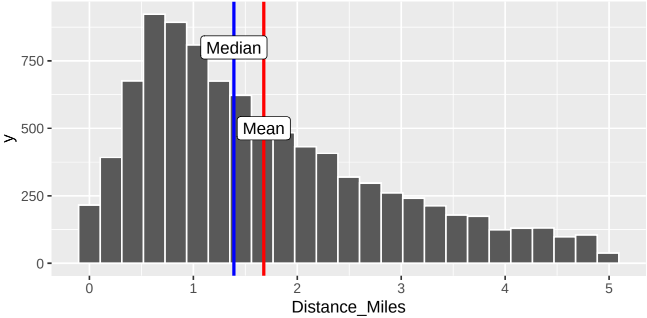

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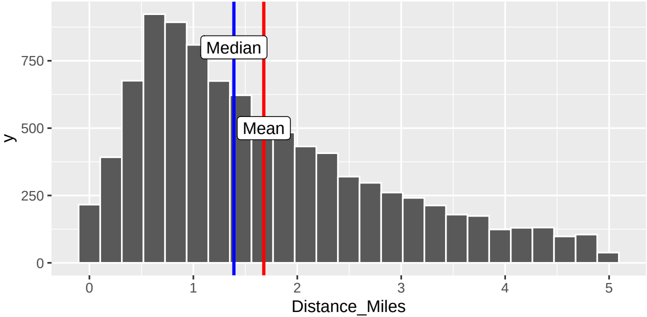

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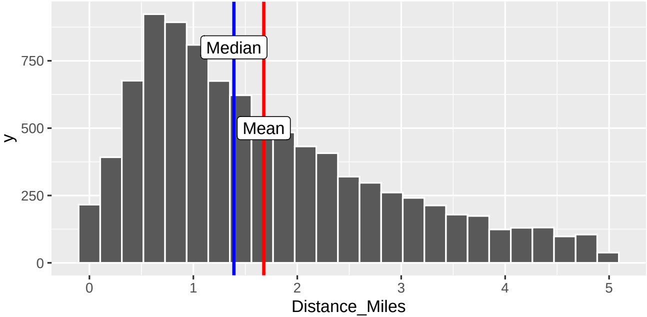

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  - Why?

Robustness

Consider two data sets, one with a large outlier and one without:

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The mean value of a dataset is very sensitive to outliers.

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mean(my_data)
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```
## [1] 5.5
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```
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## [1] 20.5
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The median, however, is not.

```
median(my_data)
```

```
## [1] 6
```

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median(my_data_with_oulier)
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Measures of Variability

We'd like to assess how variable the data set is.

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Guess 1: Compute the average difference

$$\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})$$

Distance_Miles	Mean	Deviations
1.57	1.2	0.37
2.09	1.2	0.89
0.38	1.2	-0.82
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Avg_Deviations
0

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Pop_Variance
0.3454

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$$\text{Standard Deviation} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Visualizing Standard Deviation

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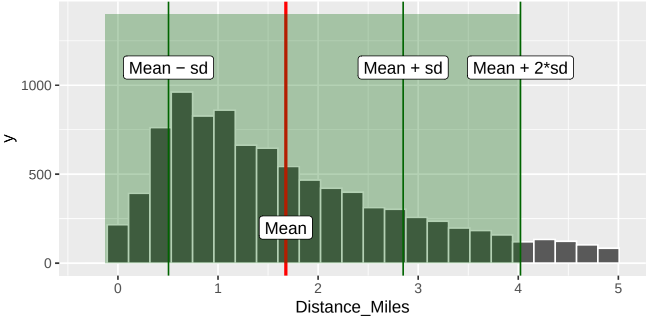

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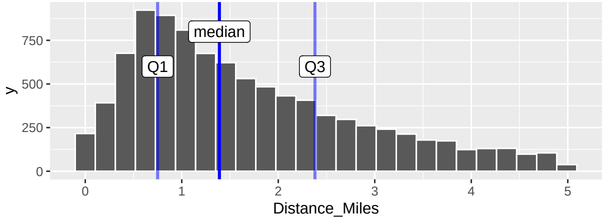

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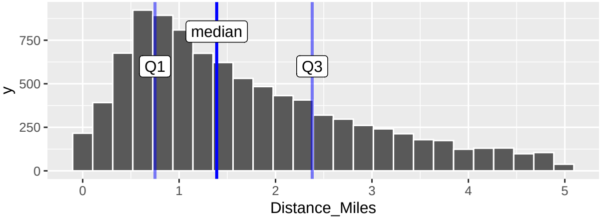

- The *IQR* is the distance between the 1st and 3rd quartile: $\mathrm{IQR} = Q3 - Q1$
- Comparing $\mathrm{Median} - Q1$ and $Q3 - \mathrm{Median}$ can show shape of distribution.

Section 2

Summarizing Categorical Data

The Distribution of a Categorical Variable

Distributions of categorical variables can be presented in tables and summarized in bar charts:

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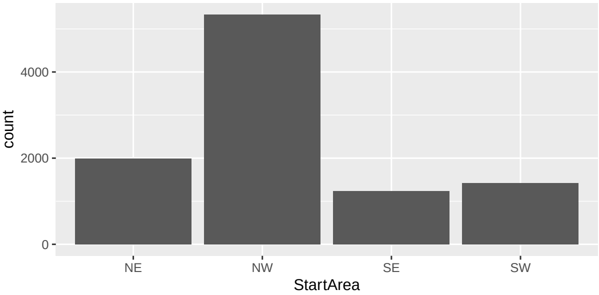
n	1989	5334	1240	1424



Contingency Tables

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- Contingency tables can be created by applying the `table()` function to 2 colums of a data frame:

```
table(biketown$StartArea, biketown$PaymentPlan)
```

Marginal Counts

- Suppose we want to recover the individual distribution of each variable in a table.

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my_table<-table(biketown$StartArea, biketown$PaymentPlan)
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```
margin.table(my_table, 1)
```

```
##
##   NE   NW   SE   SW
## 1989 5334 1240 1424
```

```
margin.table(my_table,2)
```

```
##
##      Casual Subscriber
##        5354       4633
```

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```
my_table
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```
prop.table(my_table)
```

	Casual	Subscriber
NE	0.1142485	0.0849104
NW	0.2589366	0.2751577
SE	0.0762992	0.0478622
SW	0.0866126	0.0559728

Row and Column Proportions

How do we create a table version of the segmented bar chart?

```
ggplot(biketown, aes(x =StartArea, fill =PaymentPlan))+geom_bar(position ="fill")
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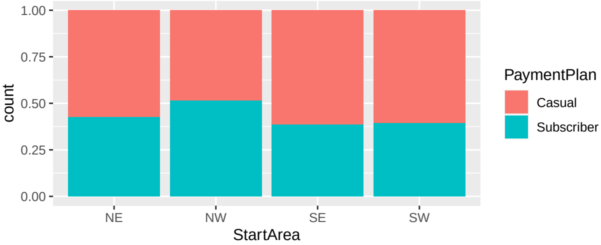

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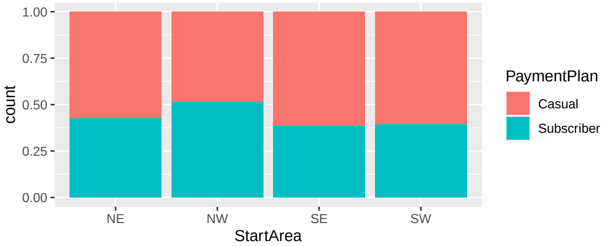


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prop.table(my_table, 1)
```

```
##
##         Casual Subscriber
##   NE 0.5736551  0.4263449
##   NW 0.4848144  0.5151856
##   SE 0.6145161  0.3854839
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```

- Each row gives breakdown of `PaymentPlan` by levels of `StartArea`

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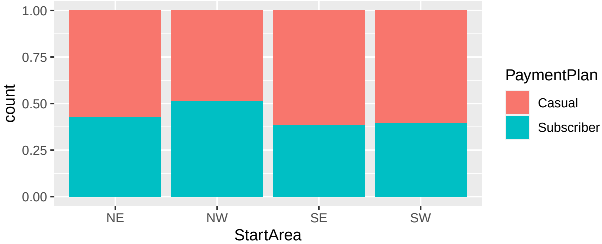


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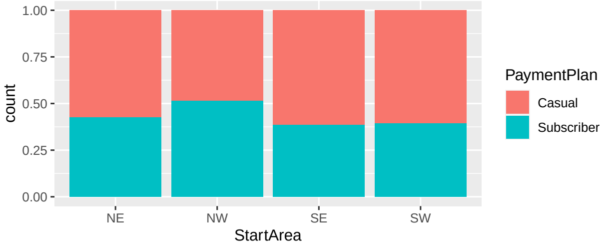


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- Do column proportions?

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```
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##   NW 0.4830034  0.5931362
##   SE 0.1423235  0.1031729
##   SW 0.1615614  0.1206562
```

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And compare to the total proportion table:

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```
##
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##    NE 0.11424852 0.08491038
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##    SW 0.08661260 0.05597276
```

Section 3

Extending ggplot2

Adding additional variables?

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1. 3D Scatterplots; possible, but challenging to code and interpret (still limited to 2d display)
2. Map variables to additional aesthetics (beyond just `x` and `y`)
3. Show several 2D plots side-by-side.

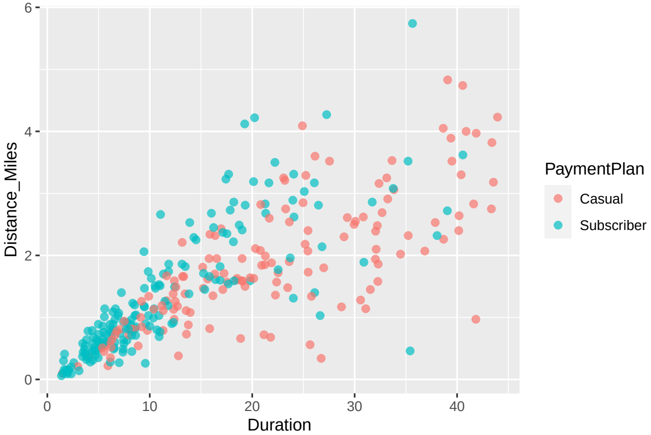
Multiple Variables on 2d Plots

Does ride speeds depend on payment plan?

Multiple Variables on 2d Plots

Does ride speeds depend on payment plan?

```
ggplot(data = biketown_sample,
       mapping = aes(x=Duration, y=Distance_Miles, color=PaymentPlan))+
  geom_point(alpha = .7, size = 2)
```



Facets

- Faceting is used to split one graphic into many smaller ones, based on the values of a categorical variable.

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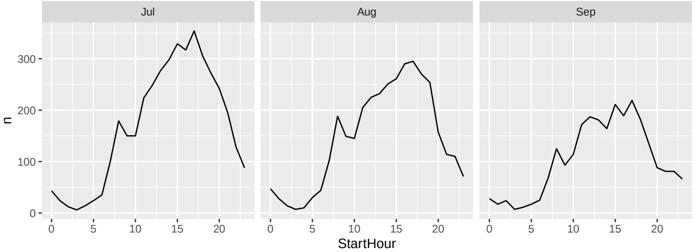
```
ggplot(data = biketown2, mapping = aes(x = StartHour, y = n)) +
  geom_line() +
  facet_wrap(~Month, ncol = 3)
```



Adding Context

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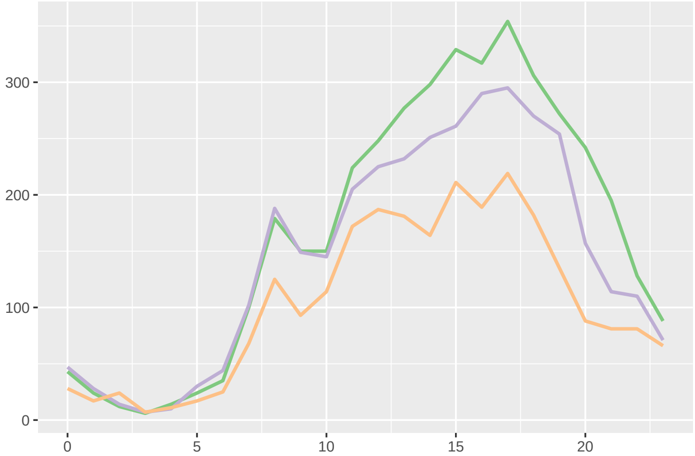

Adding Context

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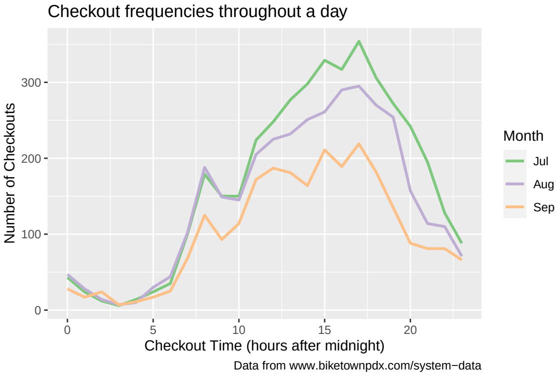
```
ggplot(data = biketown2, mapping = aes(x = StartHour, y = n, color = Month)) +
  geom_line( ) +
  labs(x = "Checkout Time (hours after midnight)", y = "Number of Checkouts",
       title  = "Checkout frequencies throughout a day",
       caption = "Data from www.biketownpdx.com/system-data")
```



Change Graphic Colors

By default, R uses `Teal` and `Salmon` colors when plotting cat. variables with 2 levels

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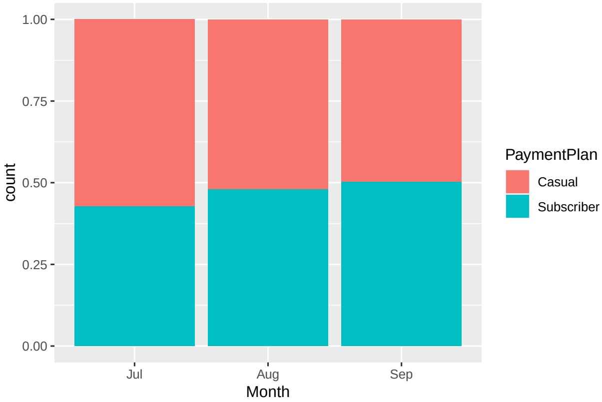
```
ggplot(data = biketown, mapping = aes(x = Month, fill = PaymentPlan)) +
  geom_bar(position = "fill")
```



Change Graphic Colors

But it's possible to alter this by manually specifying colors.

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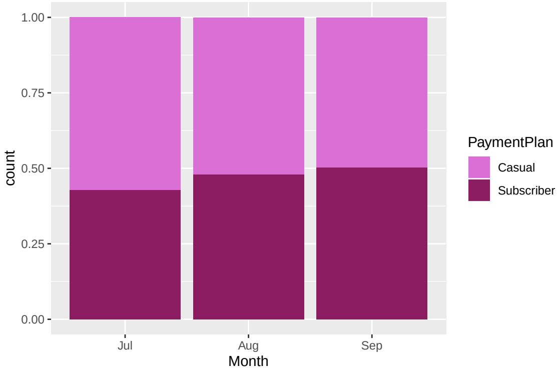
```
ggplot(data = biketown, mapping = aes(x = Month, fill = PaymentPlan)) +
  geom_bar(position = "fill")+
  scale_fill_manual(values = c("orchid", "maroon4"))
```



Change Graphic Colors

But it's possible to alter this by manually specifying colors.

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ggplot(data = biketown, mapping = aes(x = Month, fill = PaymentPlan)) +
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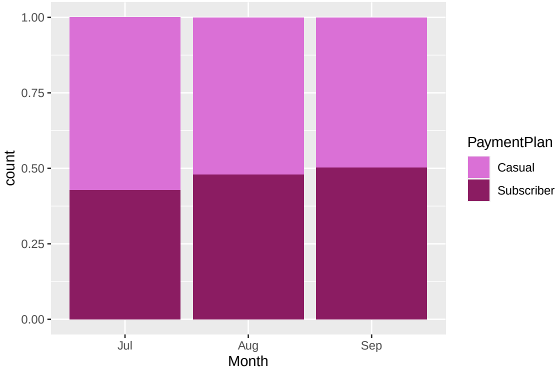

- To access a list of available colors in R, use the `colors()` function.

Using Palettes

We can also choose colors from a list of predefined color palettes:

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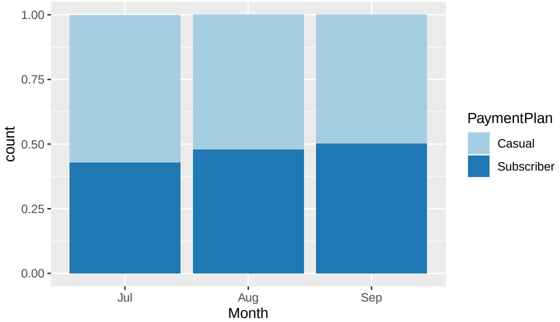
```
ggplot(data = biketown, mapping = aes(x = Month, fill = PaymentPlan)) +
  geom_bar(position = "fill")+
  scale_fill_brewer(type = "qual", palette = 3)
```



Using Palettes

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ggplot(data = biketown, mapping = aes(x = Month, fill = PaymentPlan)) +
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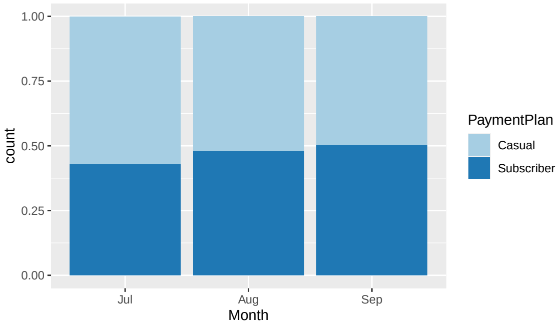

- Type can be `seq` (for sequential), `div` (for diverging), or `qual` (for qualitative)
- Each type has around 8-10 different palettes (numbered 1, 2, 3,. . .)

Change Theme

We can also control the styling of other plot elements via `theme`

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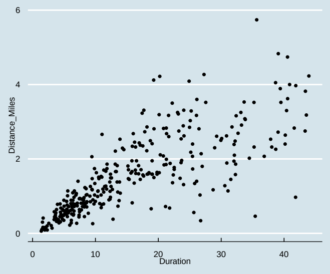
We can also control the styling of other plot elements via `theme`

```
ggplot(data = biketown_sample,
       mapping = aes(x = Duration,
                     y = Distance_Miles)
  geom_point()+
  theme_economist()
```




```
ggplot(data = biketown_sample,
       mapping = aes(x = Duration,
                     y = Distance_Miles))
  geom_point()+
  theme_bw()
```