Data Visualization

Visualizing 1D categorical and continuous variables

June 8th, 2023

New dataset - 2021 MVP Shohei Ohtani's batted balls

Created dataset of batted balls by the American League MVP Shohei Ohtani in 2021 season using `baseballr`:

```r
library(tidyverse)
ohtani_batted_balls <-
  read_csv("https://shorturl.at/mnwL1")
head(ohtani_batted_balls)
```

```
## # A tibble: 6 × 7
##   pitch_type batted_ball_type  hit_x hit_y exit_velocity launch_angle outcome
##   <chr>      <chr>             <dbl> <dbl>         <dbl>        <dbl> <chr>
## 1 FC         line_drive        89.7  144.          113.            20 home_run
## 2 CH         fly_ball           3.35  83.9          83.9           55 field_out
## 3 CH         fly_ball         -65.6  126.          102.            38 field_out
## 4 CU         ground_ball       39.2   50.4          82.5            8 field_out
## 5 FC         fly_ball         -37.6  138.          101.            23 field_out
## 6 KC         popup            -51.9   41.6          84             65 field_out
```

- each row / observation is a batted ball from Ohtani's 2021 season
- **Categorical** / qualitative variables: `pitch_type`, `batted_ball_type`, `outcome`
- **Continuous** / quantitative variables: `hit_x`, `hit_y`, `exit_velocity`, `launch_angle`

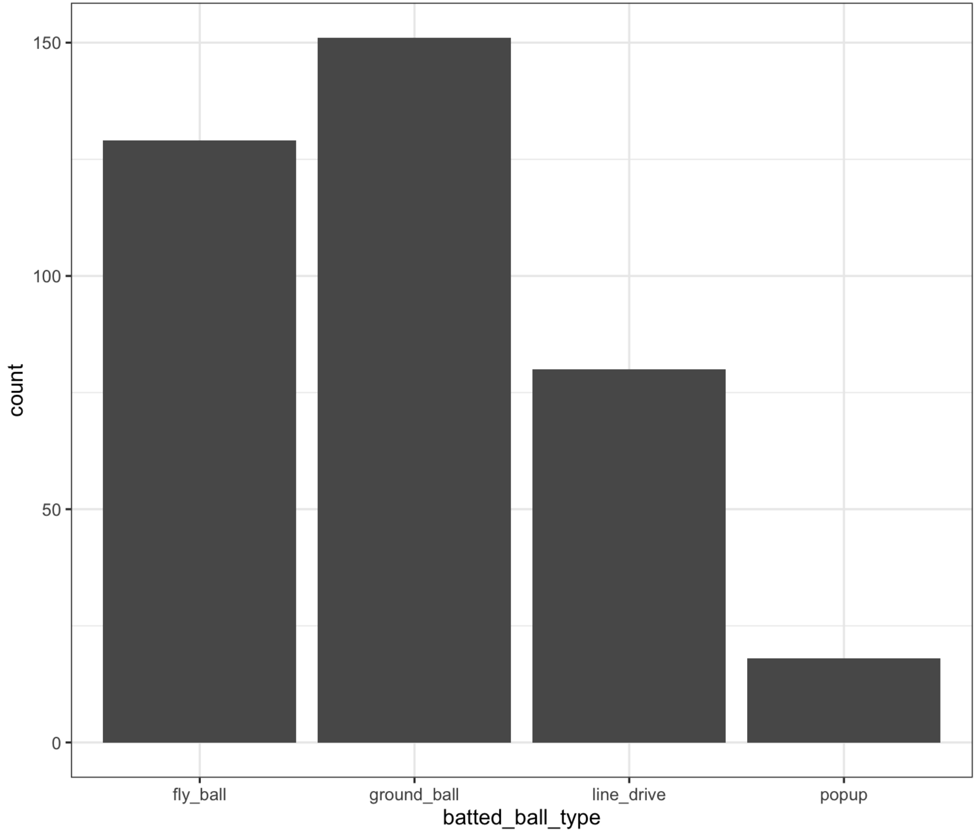
Visualizing 1D categorical data

How can we summarize `batted_ball_type` and other categorical variables?

- We make a **bar chart** with `geom_bar()`

```
ohtani_batted_balls %>%
  ggplot(aes(x = batted_ball_type)) +
  geom_bar() +
  theme_bw()
```

- Only map `batted_ball_type` to the x-axis
- Counts of each type are displayed on y-axis...



Remember statistical summaries!

1. **`geom_bar()`** begins with the **`diamonds`** data set

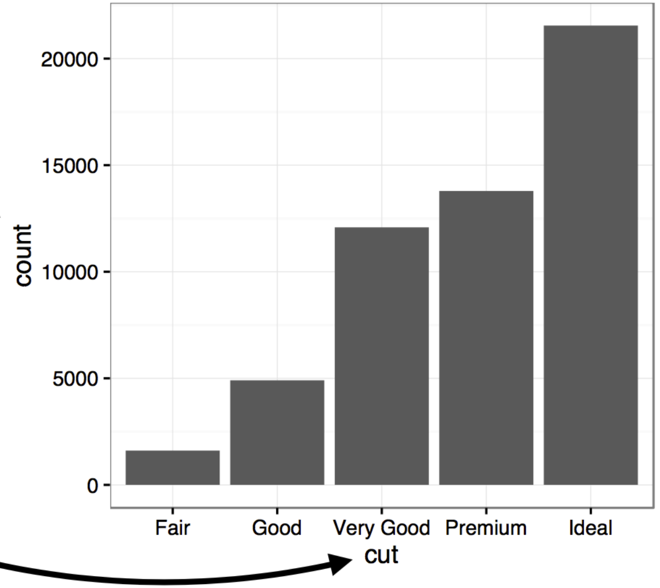
carat	cut	color	clarity	depth	table	price	x	y	z
0.23	Ideal	E	SI2	61.5	55	326	3.95	3.98	2.43
0.21	Premium	E	SI1	59.8	61	326	3.89	3.84	2.31
0.23	Good	E	VS1	56.9	65	327	4.05	4.07	2.31
0.29	Premium	I	VS2	62.4	58	334	4.20	4.23	2.63
0.31	Good	J	SI2	63.3	58	335	4.34	4.35	2.75
...	...	...	...	...	...	...	...	...	...

stat_count()

2. **`geom_bar()`** transforms the data with the "count" stat, which returns a data set of cut values and counts.

cut	count	prop
Fair	1610	1
Good	4906	1
Very Good	12082	1
Premium	13791	1
Ideal	21551	1

3. **`geom_bar()`** uses the transformed data to build the plot. cut is mapped to the x axis, count is mapped to the y axis.



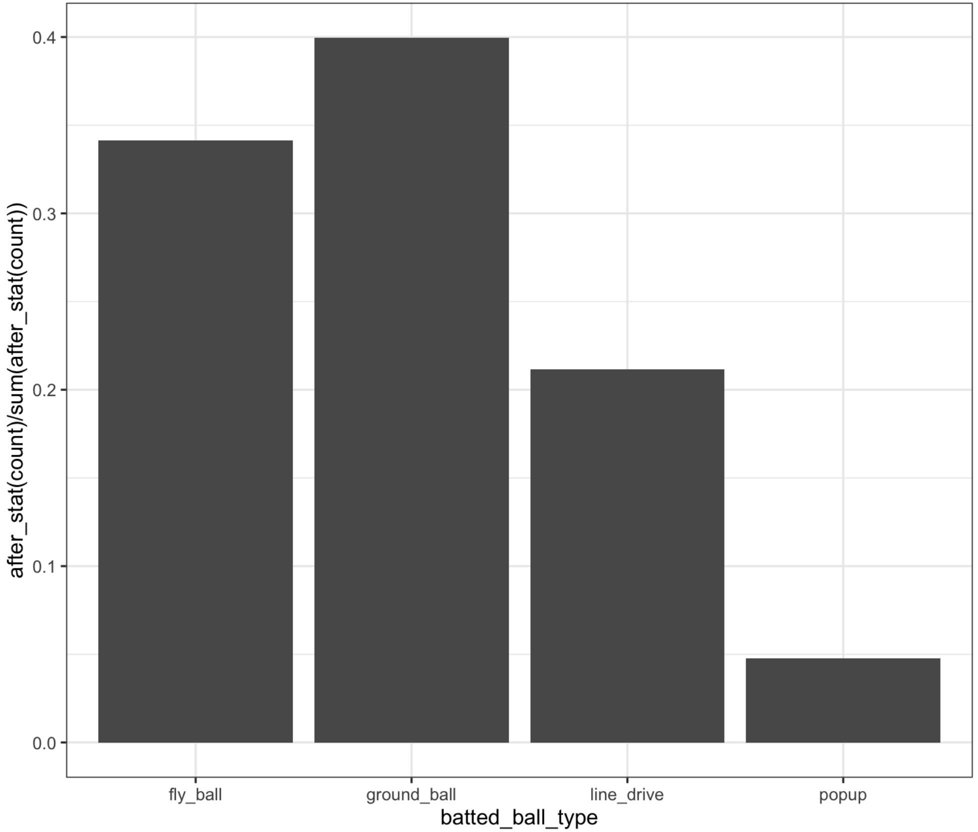
From Chapter 3 of R for Data Science

What does a bar chart show?

Marginal distribution: probability that categorical variable X (e.g., `batted_ball_type`) takes each particular value x (e.g. `fly_ball`). *So how do we display the individual probabilities?*

```
ohtani_batted_balls %>%
  ggplot(aes(x = batted_ball_type)) +
  geom_bar(aes(y = after_stat(count) / sum(af
  theme_bw()
```

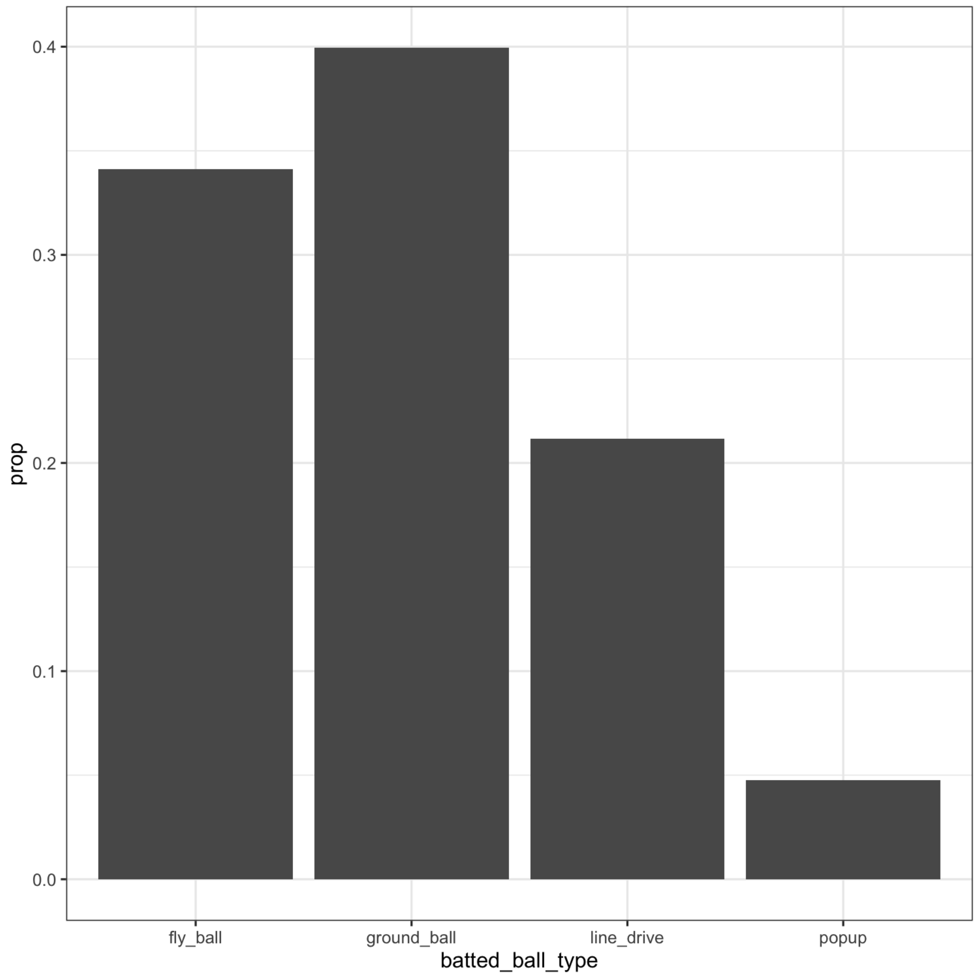
- `after_stat()` indicates the aesthetic mapping is performed after the statistical transformation
- Use `after_stat(count)` to access the `stat_count()` called by `geom_bar()`
- **We can code this in a more clear way**



Compute and display the proportions directly

```
ohtani_batted_balls %>%
  group_by(batted_ball_type) %>%
  summarize(count = n()) %>%
  ungroup() %>%
  mutate(total = sum(count),
         prop = count / total) %>%
  ggplot(aes(x = batted_ball_type)) +
  geom_bar(aes(y = prop),
           stat = "identity") +
  theme_bw()
```

- Category counts give info about sample size, but this could be labeled in the chart
- Proportions $=$ the **probability mass function** (PMF) for **discrete** variables
  - e.g. $P(\texttt{batted\_ball\_type} = \texttt{fly\_ball})$



Population versus sample...

We have the **population** of Ohtani's batted balls in the 2021 season$\Rightarrow$ **we know the true probabilities**:

- $P(\texttt{batted\_ball\_type} = \texttt{fly\_ball})$
- $P(\texttt{batted\_ball\_type} = \texttt{ground\_ball})$
- $P(\texttt{batted\_ball\_type} = \texttt{line\_drive})$
- $P(\texttt{batted\_ball\_type} = \texttt{popup})$

What if we pretend this is a sample from all hypothetical Ohtani 2021 seasons?

Empirical distribution: We **estimate** the **true marginal** distribution with **observed (sample) data**

$\Rightarrow$ Estimate P (`batted_ball_type` = C_j) with $\hat{p}_j$ for each category C_j (e.g. $\hat{p}_{\texttt{fly\_ball}}$)

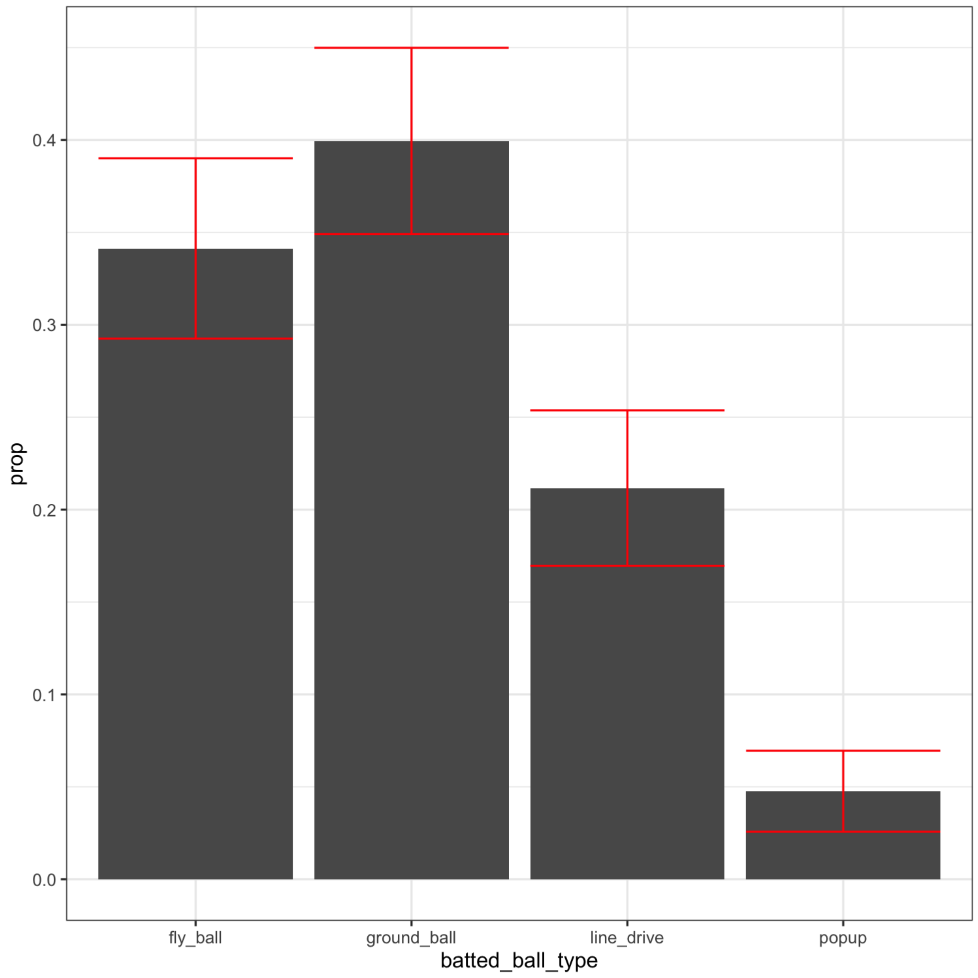
Compute **standard error** for each $\hat{p}_j$:

$$SE(\hat{p}_j) = \sqrt{\frac{\hat{p}_j(1 - \hat{p}_j)}{n}}$$

For large $n \Rightarrow \approx 95\%$ **confidence interval (CI)**: $\hat{p}_j + / - 2 \cdot SE(\hat{p}_j)$

Add confidence intervals to bar chart

```
ohtani_batted_balls %>%
  group_by(batted_ball_type) %>%
  summarize(count = n()) %>%
  ungroup() %>%
  mutate(total = sum(count),
         prop = count / total,
         se = sqrt(prop * (1 - prop) / total),
         lower = prop - 2 * se,
         upper = prop + 2 * se) %>%
  ggplot(aes(x = batted_ball_type)) +
  geom_bar(aes(y = prop),
           stat = "identity") +
  geom_errorbar(aes(ymin = lower,
                    ymax = upper),
                color = "red") +
  theme_bw()
```

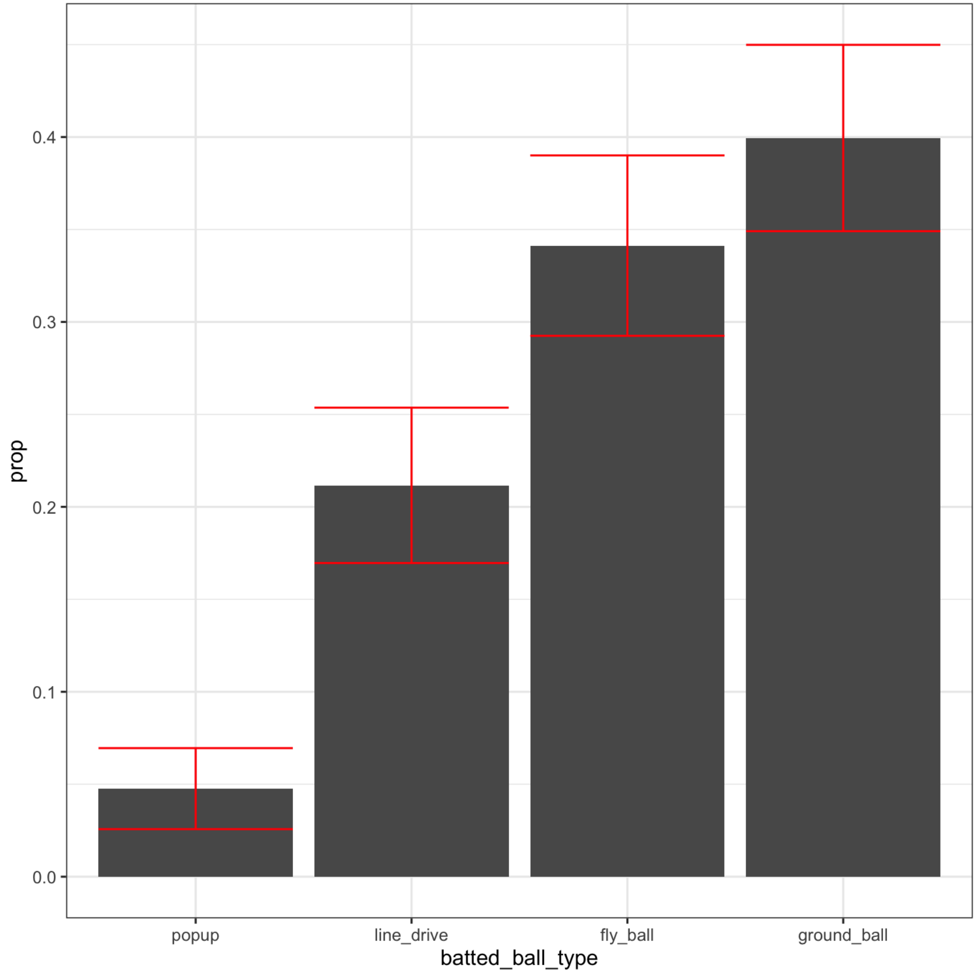


Be careful about your interpration of CIs...

You should remember to label your charts!

Fun with factors using `forcats`

```
ohtani_batted_balls %>%
  group_by(batted_ball_type) %>%
  summarize(count = n()) %>%
  ungroup() %>%
  mutate(total = sum(count),
         prop = count / total,
         se = sqrt(prop * (1 - prop) / total),
         lower = prop - 2 * se,
         upper = prop + 2 * se,
         batted_ball_type =
           fct_reorder(batted_ball_type,
                       prop)) %>%
  ggplot(aes(x = batted_ball_type)) +
  geom_bar(aes(y = prop),
           stat = "identity") +
  geom_errorbar(aes(ymin = lower,
                    ymax = upper),
                color = "red") +
  theme_bw()
```



Did you say pie chart?

This is the only pie chart I will show you all summer

(Note: These slides originally come from Professor Yurko, a known hater of pie charts)

Describing 1D continuous data

How can we summarize `exit_velocity` and other continuous variables?

- **Center**: mean, median, number and location of modes
- **Spread**: range (max - min), quantiles, variance (standard deviation), etc.
- **Shape**: skew vs symmetry, outliers, heavy vs light tails, etc.
- Compute basic summary statistics

```
summary(ohtani_batted_balls$exit_velocity)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   27.50   83.75   96.00   93.26  105.55  119.00      27
```

```
sd(ohtani_batted_balls$exit_velocity)
```

```
## [1] NA
```

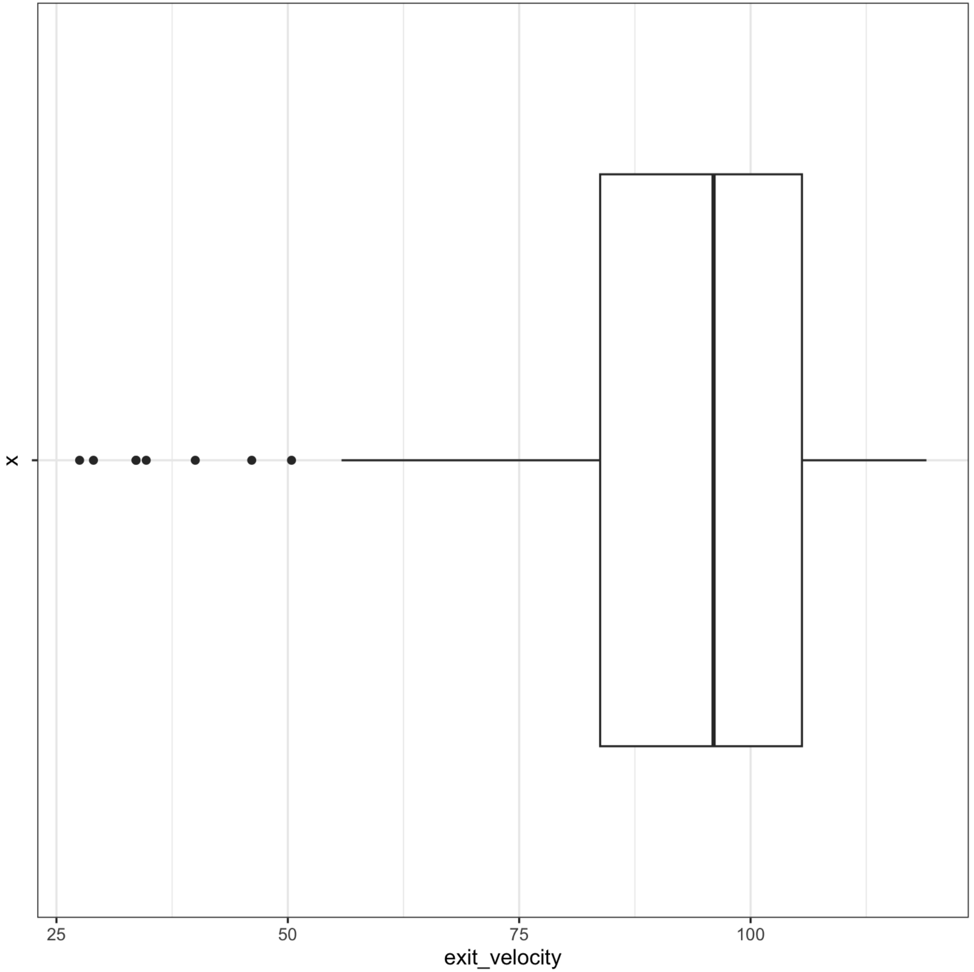
Box plots visualize summary statistics

- We make a **box plot** with `geom_boxplot()`

```
ohtani_batted_balls %>%
  ggplot(aes(y = exit_velocity)) +
  geom_boxplot(aes(x = "")) +
  theme_bw() +
  coord_flip()
```

- **Pros**:
  - Displays outliers, percentiles, spread, skew
  - Useful for side-by-side comparison (tomorrow)
- **Cons**:
  - Does not display the full distribution shape!
  - Does not display modes

Why use `aes(x = "")` inside `geom_boxplot()`?



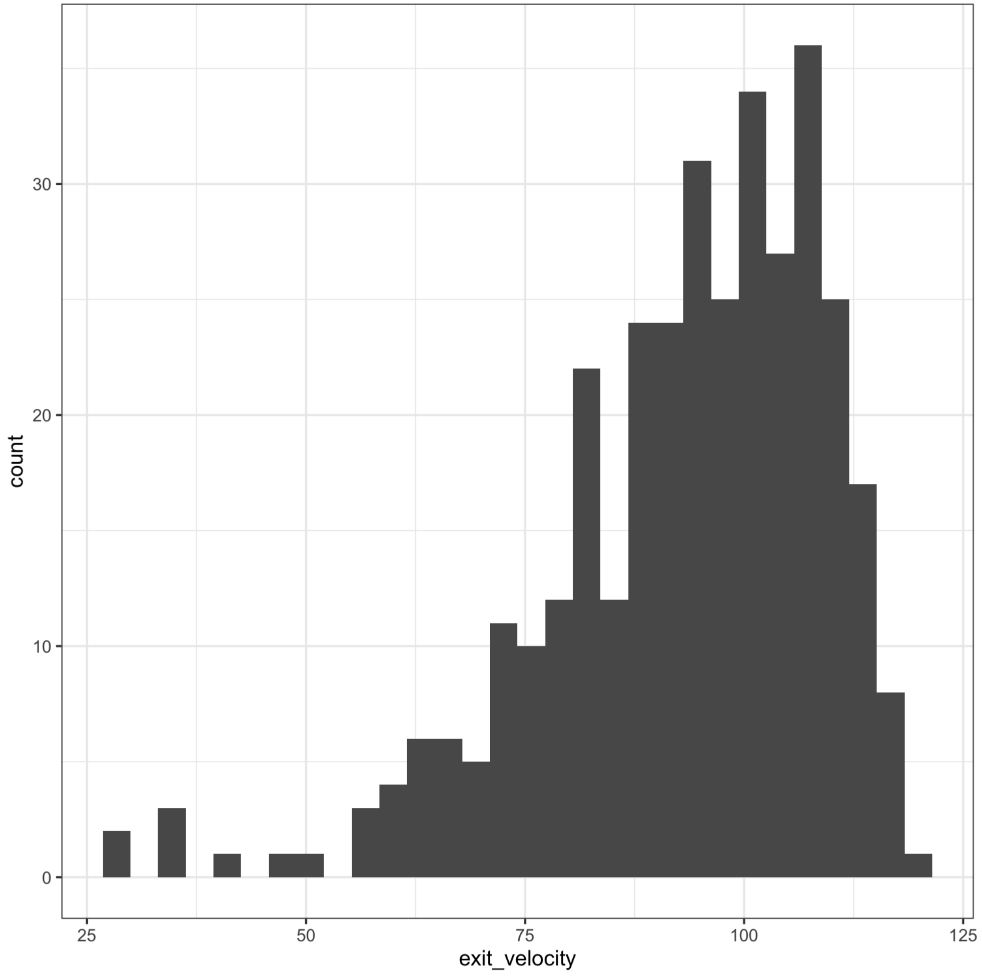
Histograms display 1D continuous distributions

- We make **histograms** with `geom_histogram()`

```
ohtani_batted_balls %>%
  ggplot(aes(x = exit_velocity)) +
  geom_histogram() +
  theme_bw()
```

$$\#\text{ total obs.} = \sum_{j=1}^{k} \#\text{ obs. in bin } j$$

- **Pros**:
  - Displays full shape of distribution
  - Easy to interpret
- **Cons**:
  - Have to choose number of bins and bin locations (will revisit later)



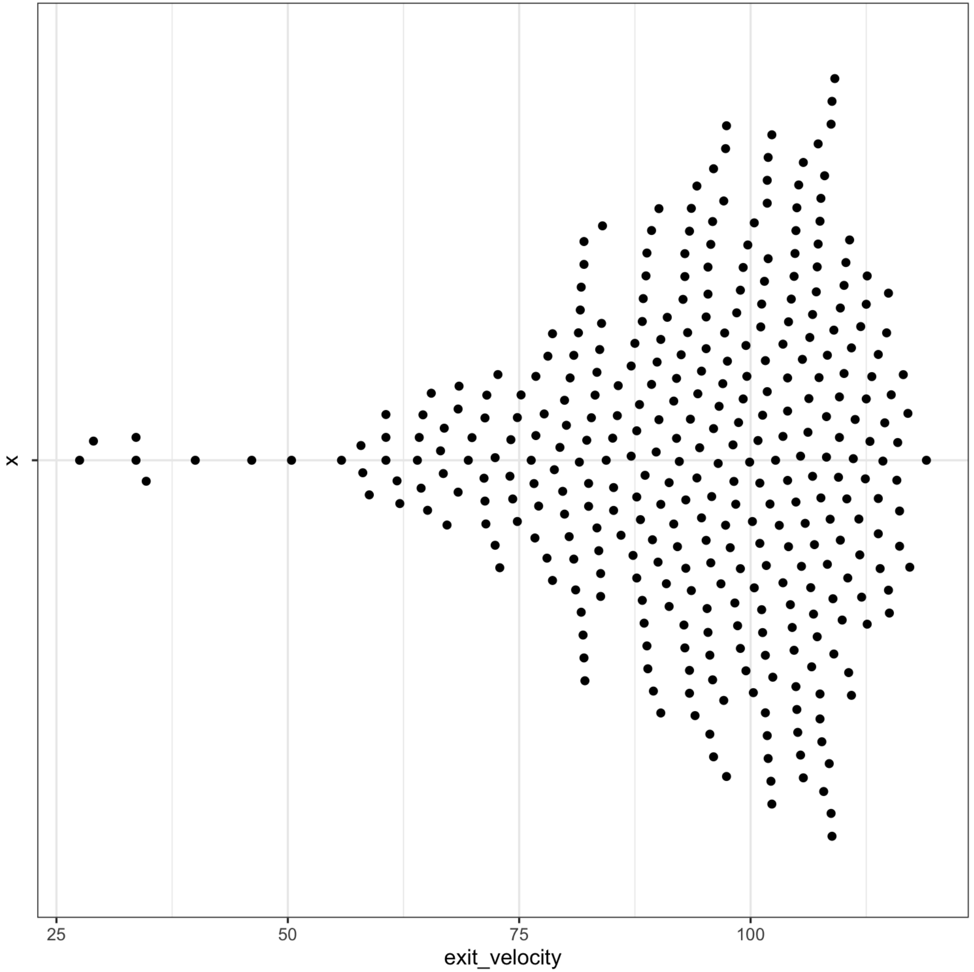
Display the data points directly with beeswarm plots

- We make a **beeswarm plot** using the `ggbeeswarm` package

```
library(ggbeeswarm)
ohtani_batted_balls %>%
  ggplot(aes(y = exit_velocity)) +
  geom_beeswarm(aes(x = ""),
                cex = 3) +
  theme_bw() +
  coord_flip()
```

- **Pros**:
  - Displays each data point
  - Easy to view full shape of distribution
- **Cons**:
  - Can be overbearing with large datasets
  - Which algorithm for arranging points?

What does `cex = 3` do?

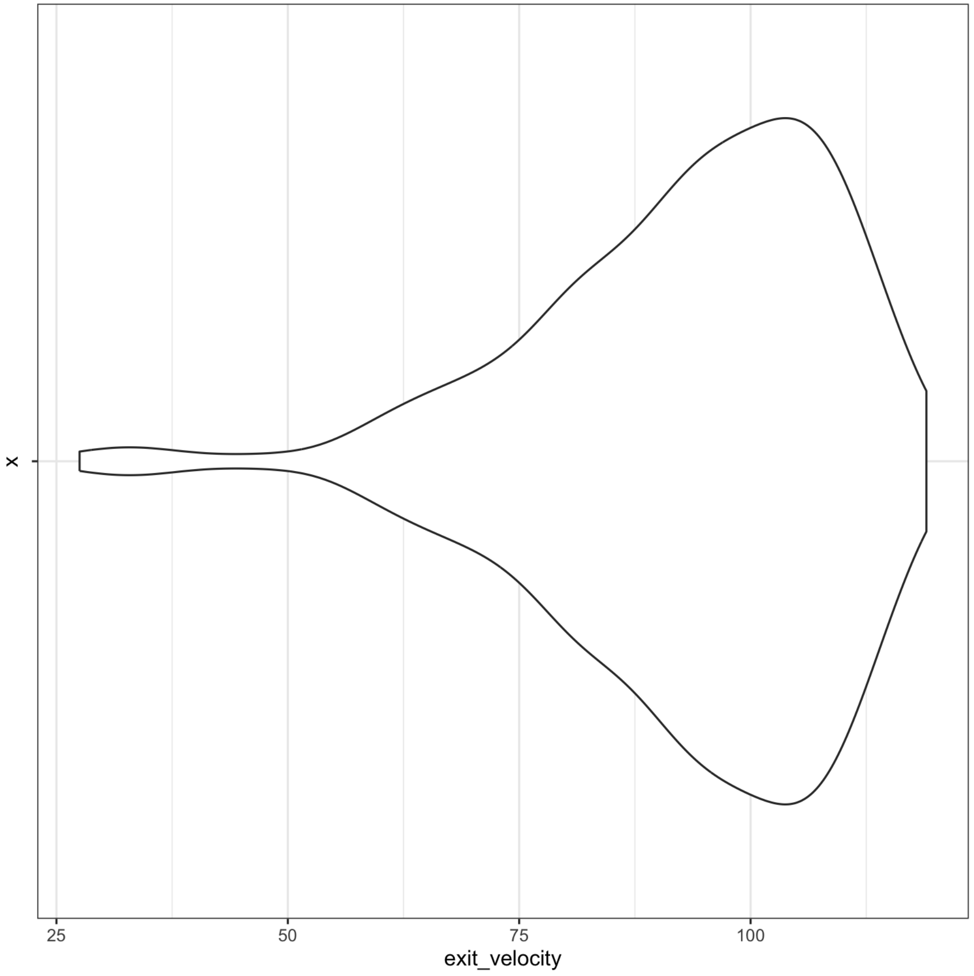


Smooth summary with violin plots

- We make **violin plots** with `geom_violin()`

```
ohtani_batted_balls %>%
  ggplot(aes(y = exit_velocity)) +
  geom_violin(aes(x = "")) +
  theme_bw() +
  coord_flip()
```

- **Pros**:
    - Displays full shape of distribution
    - Can easily layer...

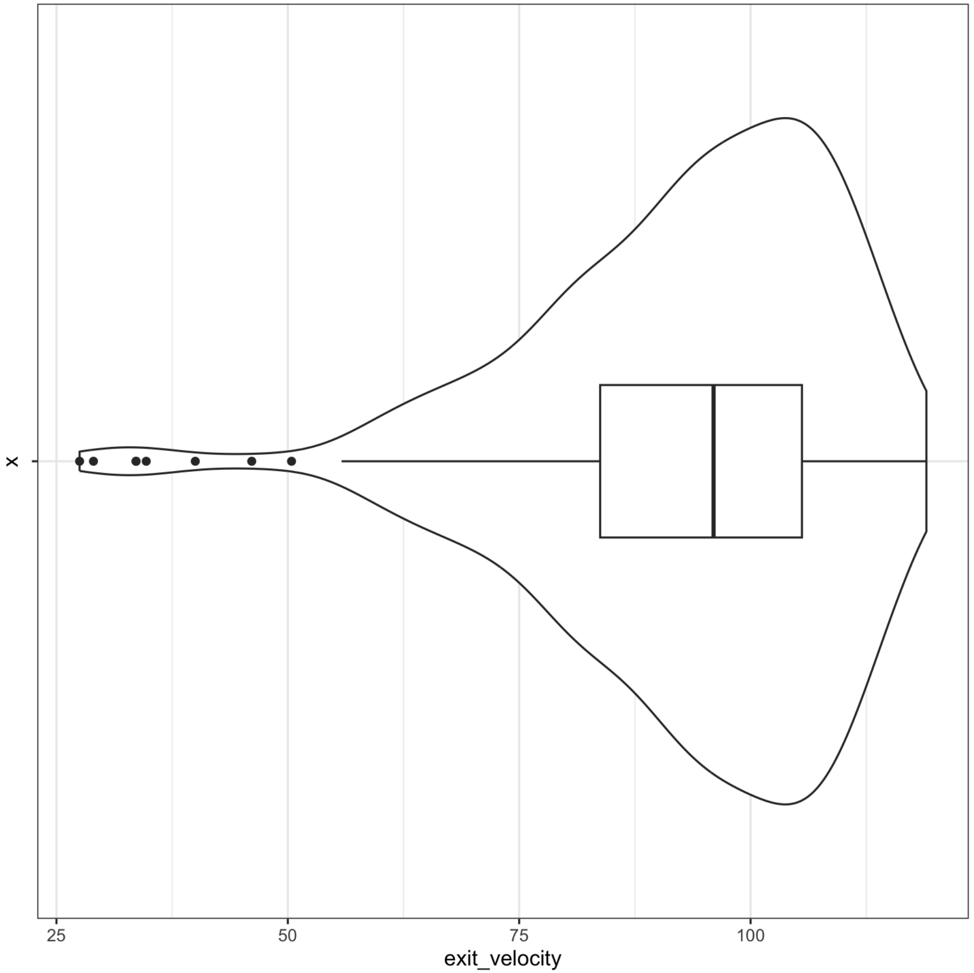


Smooth summary with violin plots + box plots

- We make **violin plots** with `geom_violin()`

```
ohtani_batted_balls %>%
  ggplot(aes(y = exit_velocity,
             x = "")) +
  geom_violin() +
  geom_boxplot(width = .2) +
  theme_bw() +
  coord_flip()
```

- **Pros**:
  - Displays full shape of distribution
  - Can easily layer... with box plots on top
- **Cons**:
  - Summary of data via **density estimate**
  - Mirror image is duplicate information



What do visualizations of continuous distributions display?

Probability that continuous variable X takes a particular value is 0

e.g. $P(\texttt{exit\_velocity} = 100) = 0, why?$

Instead we use the **probability density function (PDF)** to provide a **relative likelihood**

- Density estimation is the focus of lecture next Monday

For continuous variables we can use the **cumulative distribution function (CDF)**,

$$F(x) = P(X \leq x)$$

For n observations we can easily compute the **Empirical CDF (ECDF)**:

$$\hat{F}_n(x) = \frac{\text{\# obs. with variable} \leq x}{n} = \frac{1}{n} \sum_{i=1}^{n} 1(x_i \leq x)$$

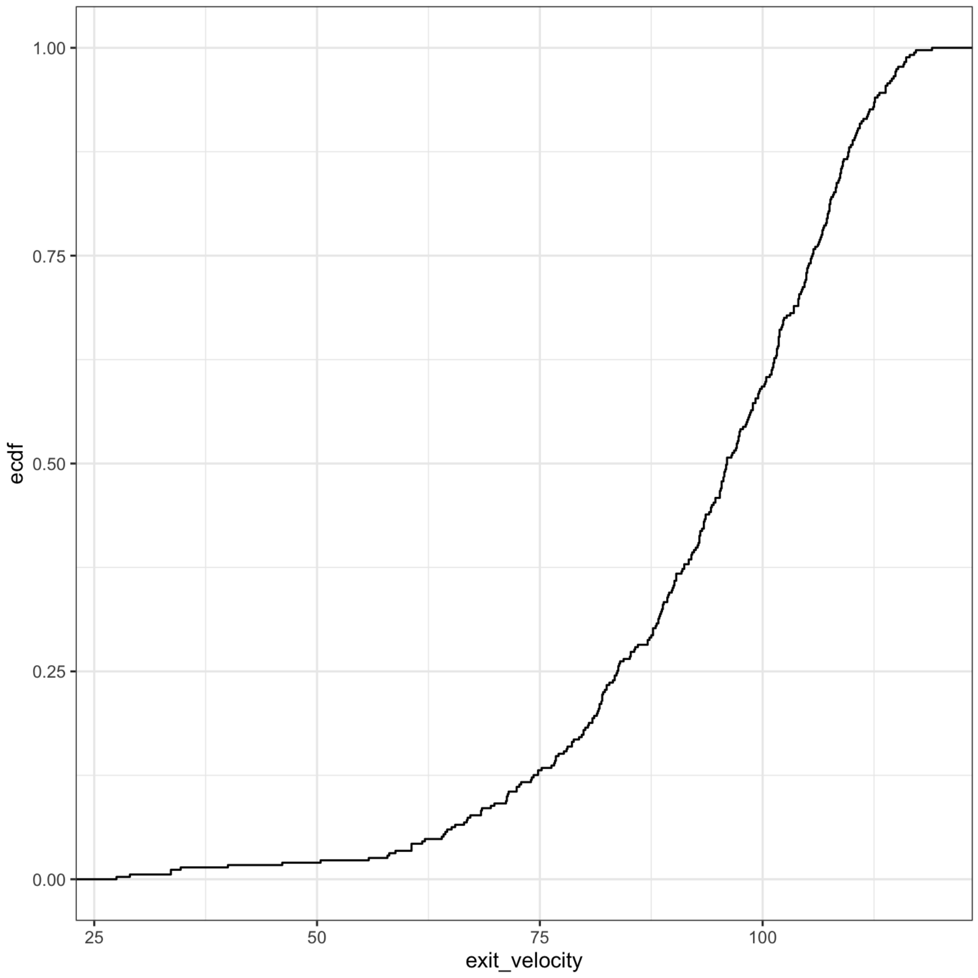
- where $1()$ is the indicator function, i.e. `ifelse(x_i <= x, 1, 0)`

Display full distribution with ECDF plot

- We make **ECDF plots** with `stat_ecdf()`

```
ohtani_batted_balls %>%
  ggplot(aes(x = exit_velocity)) +
  stat_ecdf() +
  theme_bw()
```

- **Pros**:
  - ECDF displays all information in data (except for order)
  - As $n \rightarrow \infty$, our ECDF $\hat{F}_n(x)$ converges to the true CDF $F(x)$
  - Easy to interpret...
- **Cons**:
  - ... and yet it's not as popular!

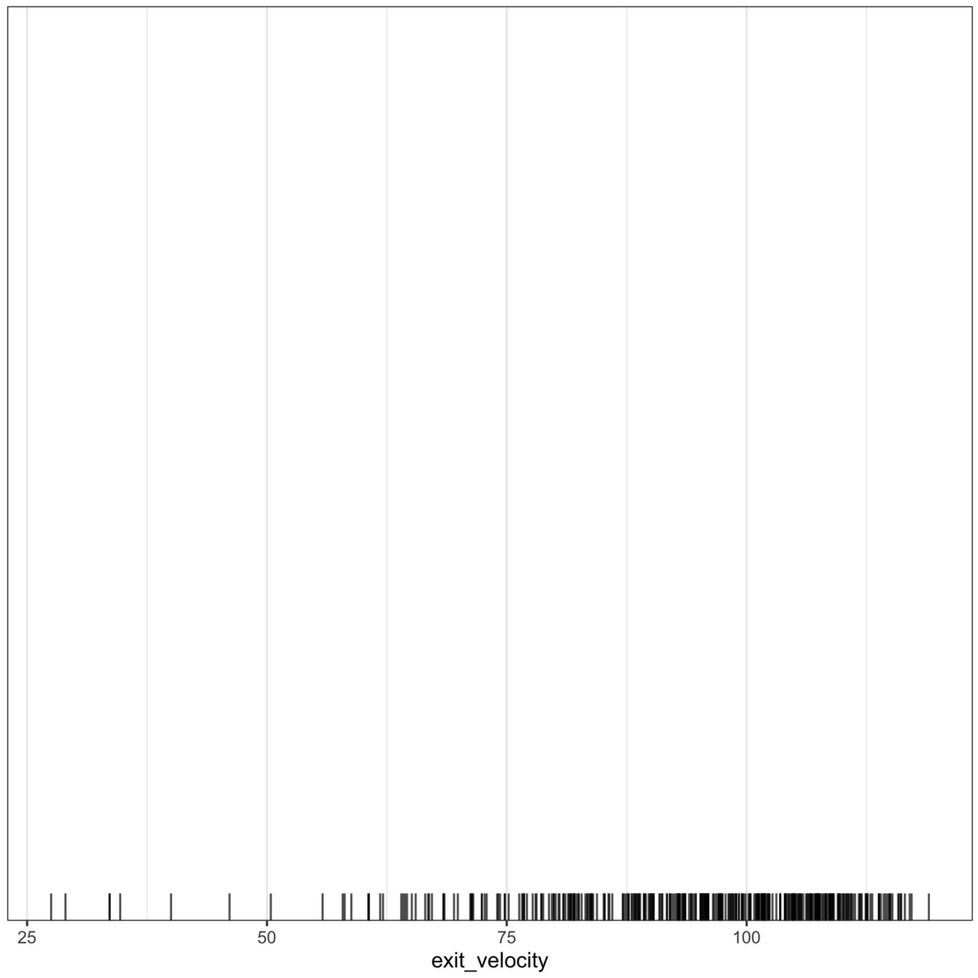


Rug plots display raw data

- We make a **rug plot** with `geom_rug()`

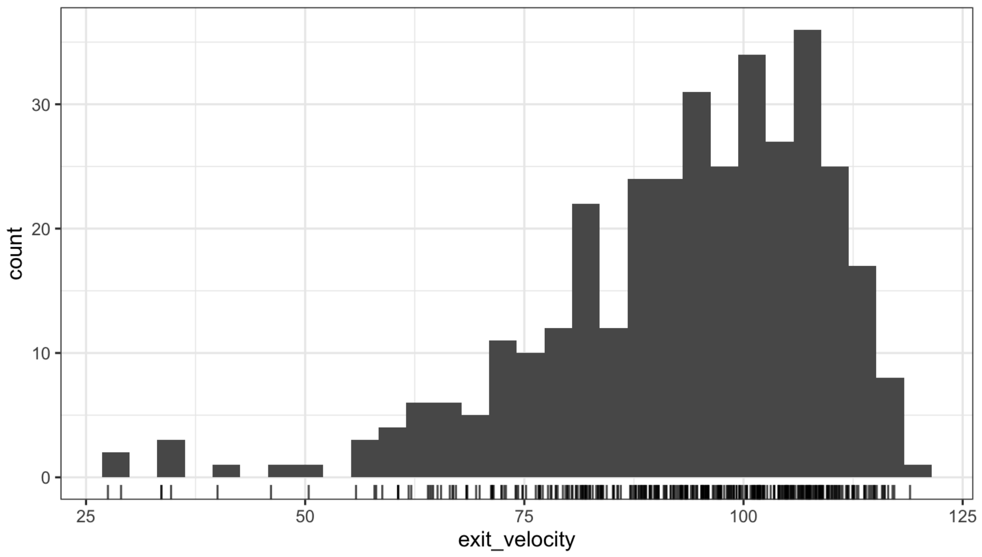
```
ohtani_batted_balls %>%
  ggplot(aes(x = exit_velocity)) +
  geom_rug(alpha = 0.7) +
  theme_bw()
```

- **Pros**:
    - Displays raw data points
    - Useful supplement for summaries and 2D plots...
- **Cons**:
    - Can be overbearing for larger datasets

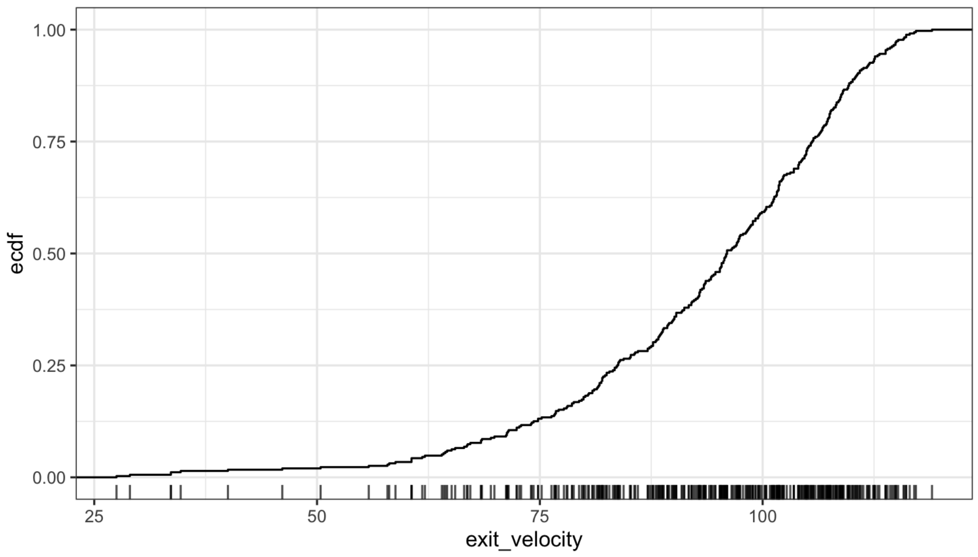


Rug plots supplement other displays

```r
ohtani_batted_balls %>%
  ggplot(aes(x = exit_velocity)) +
  geom_rug(alpha = 0.7) +
  geom_histogram() +
  theme_bw()
```




```r
ohtani_batted_balls %>%
  ggplot(aes(x = exit_velocity)) +
  geom_rug(alpha = 0.7) +
  stat_ecdf() +
  theme_bw()
```



Scatterplots for 2D continuous data

- We make a **scatterplot** with `geom_point()`

```
ohtani_batted_balls %>%
  ggplot(aes(x = exit_velocity,
             y = launch_angle)) +
  geom_point() +
  geom_rug(alpha = 0.4) +
  theme_bw()
```

Easy to supplement with rug plots

Look at the plot: what question would you want to ask, assuming you know something about baseball?

To be continued...