Density Estimation: Lecture Notes

06-12-2023

This file will be my first attempt to take notes via an .Rmd file. Today's morning lecture for SURE 2023 is about density estimation.

Building Intuition about Density Estimation

Bold idea: mass of objects can be measured

BUT many comparisons are not "like with like" because volumes vary

Density = mass/volume to the rescue!

Probability's bold idea: probability of events can be measured

How do we measure probability?

For continuous variables: probability density function

Rules:

- P(event) is between 0,1 (inclusive)
- Area under PDF integrates to 1 (like fixing the volume in density, directly comparable)

The Idea on Estimation

The notion of inference:

Samples are snapshots into population but we care about population-level questions

So, we must make assumptions and estimations...

- Must assume the event space follows some distribution
- Must assume the specific distribution that generates the data
- Must estimate the parameters for specific distribution

This estimation comes from statistical techniques

The Data

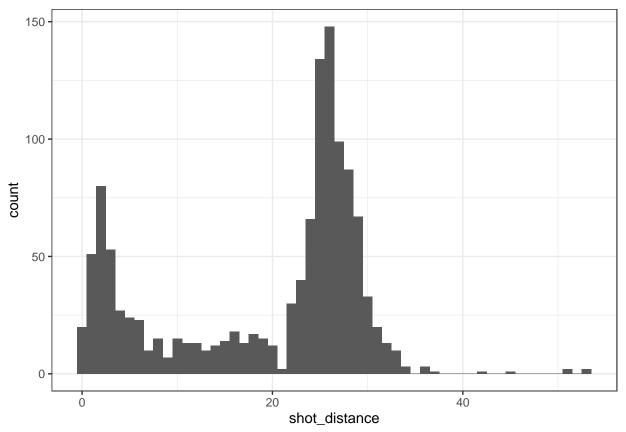
The data for today is about Steph Curry's shots.

curry_shots <- read_csv("https://shorturl.at/xFI18")
head(curry_shots)</pre>

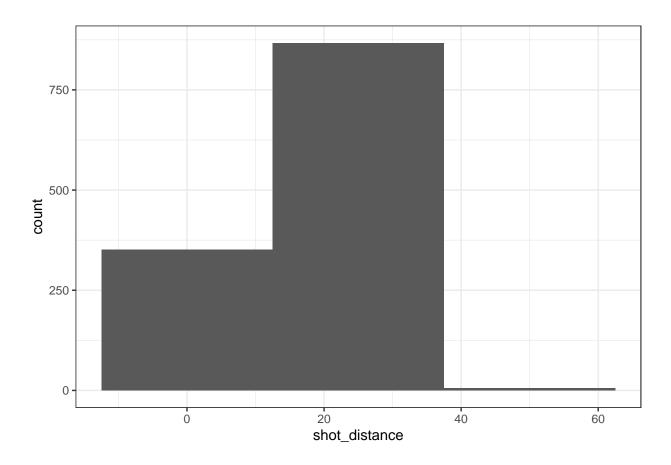
```
## # A tibble: 6 x 8
     shot_x shot_y shot_distance is_shot_made period fg_type
                                                                shot_zone shot_type
                           <dbl> <lgl>
##
      <dbl> <dbl>
                                               <dbl> <chr>
                                                                <chr>
                                                                          <chr>
## 1
      -109
               260
                              28 FALSE
                                                   1 3PT Field~ Above th~ Pullup J~
                              26 FALSE
## 2
        48
               257
                                                   1 3PT Field~ Above th~ Running ~
## 3
      -165
              189
                              25 TRUE
                                                   1 3PT Field~ Above th~ Jump Shot
## 4
                              1 FALSE
                                                   1 2PT Field~ Restrict~ Driving ~
       -13
              12
## 5
        -15
                22
                               2 FALSE
                                                   1 2PT Field~ Restrict~ Layup Sh~
## 6
        18
               16
                               2 FALSE
                                                   1 2PT Field~ Restrict~ Driving ~
```

Histograms

```
curry_shots %>%
ggplot(aes(x = shot_distance)) +
geom_histogram(binwidth = 1) +
theme_bw()
```



```
curry_shots %>%
ggplot(aes(x = shot_distance)) +
geom_histogram(binwidth = 25) +
theme_bw()
```

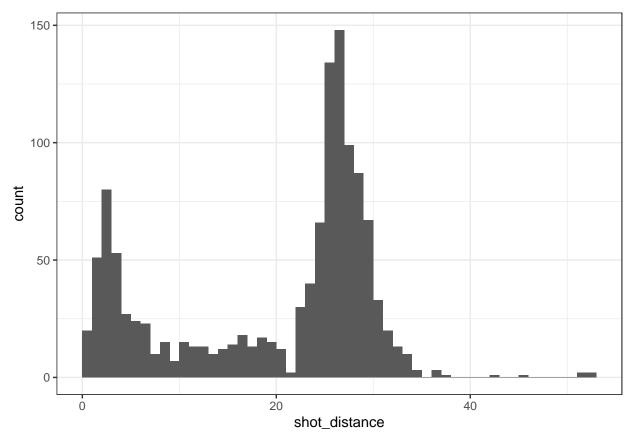


Subtle Point about Histogram Code

By default:

- ullet left-closed, right-open intervals
- centered on the integers (e.g. starting at 0.5 and going to 1.5)

```
curry_shots %>%
ggplot(aes(x = shot_distance)) +
geom_histogram(binwidth = 1, center = 0.5,
closed = "left") +
theme_bw()
```



NOTE: Freedman-Diaconis Rule for bin width

Kernel Density Estimation

GOAL: estimate the PDF f(x) for all possible values (assuming it is continuous/smooth) Formula:

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

Kernel is a "continuous weighting of f" that satisfies:

- (1) non-negative
- (2) symmetric about 0
- (3) goes to 0 as x goes to infinity or negative infinity

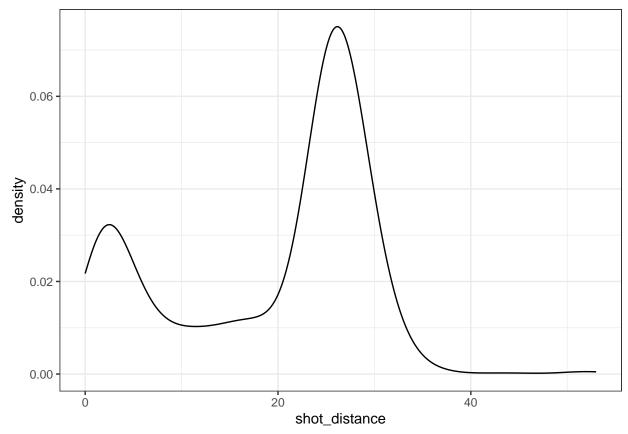
Other Notes:

- n = sample size, x = new point estimate f(x) [does not have to be in the dataset!]
- h = bandwidth analogous to histogram bin width, ensures $\hat{f}(x)$ integrates to 1
- $x_i = i$ th observation in the data set
- $K_h(x-x_i)$ is the **Kernel** function, creates **weight** given distance of ith observation from new point
- As bandwidth (h) increases, weights are more evenly spread out (and as h decreases, more concentrated around x)

- typically use Gaussian/Normal kernel [can look up online]
- $K_h(x-x_i)$ is large when x_i is close to x

Histogram is basically a step-function version of Kernel Density Estimation

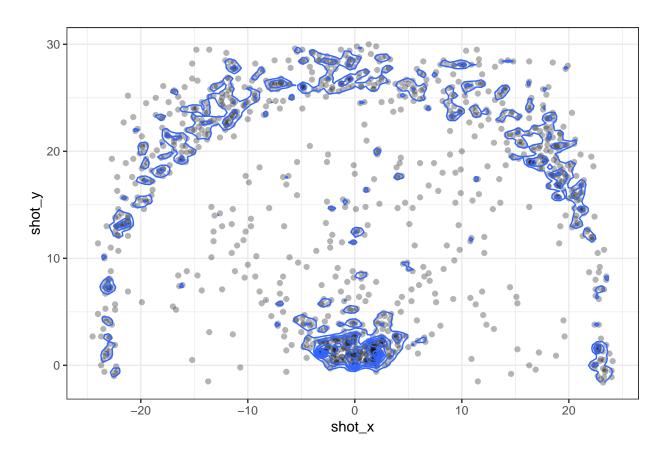
```
curry_shots %>%
ggplot(aes(x = shot_distance)) +
geom_density() +
theme_bw()
```



What about for 2D? (two continuous variables)

Contours

```
curry_shots %>% # Modify the shot coordinates
  mutate(shot_x = -shot_x / 10, shot_y = shot_y / 10) %>%
  filter(shot_y <= 30) %>%
  ggplot(aes(x = shot_x, y = shot_y)) +
  geom_point(alpha = 0.3) +
  geom_density2d(adjust = 0.1) + #adds blue level sets for contours
  coord_fixed() +
  theme_bw()
```



Heatmaps

