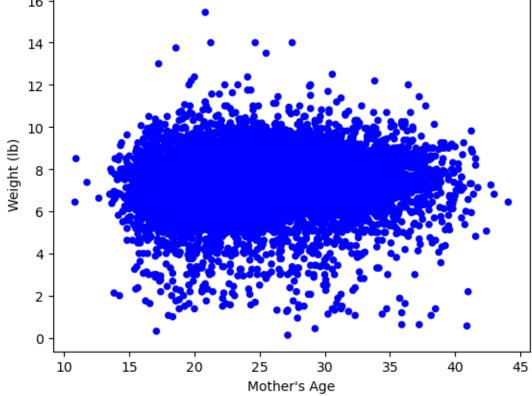
## Rodriguez Felipe DSC530 7.2Exercise

January 29, 2023

```
[70]: # Taken from book to download scripts
      from os.path import basename, exists
      def download(url):
          filename = basename(url)
          if not exists(filename):
              from urllib.request import urlretrieve
              local, _ = urlretrieve(url, filename)
              print("Downloaded " + local)
[71]: | download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/nsfg.py")
      download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/first.py")
      download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/
       ⇔thinkstats2.py")
      download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/thinkplot.
      download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/estimation.
      download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/
       ⇒2002FemPreg.dct")
      download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/
       ⇒2002FemPreg.dat.gz")
[72]: # Imports scipts used
      import nsfg
      import pandas as pd
      import thinkplot
      import thinkstats2
      import math
      import random
      import numpy as np
      from estimation import RMSE, MeanError
      import first
```

7-1 Using data from the NSFG, make a scatter plot of birth weight versus mother's age. Plot

percentiles of birth weight versus mother's age. Compute Pearson's and Spearman's correlations. How would you characterize the relationship between these variables?



```
[77]: # Displays Pearson's and Spearman's Correlation
print("Pearson's Correlation", thinkstats2.Corr(age_preg, birth_weight))
```

```
print("Spearman's Correlation", thinkstats2.SpearmanCorr(age_preg, ⊔⇔birth_weight))
```

Pearson's Correlation 0.06883397035410911 Spearman's Correlation 0.09461004109658226

The scatter plot shows a week correlation between age and weight since it is non linear. Both Pearson and Spearman correlation are low and support the weak correlation in the scatter plot.

8-1 In this chapter we used  $\bar{x}$  and median to estimate  $\mu$ , and found that  $\bar{x}$  yields lower MSE. Also, we used  $S^2$  and  $S^2_{n-1}$  to estimate , and found that  $S^2$  is biased and  $S^2_{n-1}$  unbiased. Run similar experiments to see if  $\bar{x}$  and median are biased estimates of  $\mu$ . Also check whether  $S^2$  or  $S^2_{n-1}$  yields a lower MSE.

```
[78]: # Mean Error Function
      def Mean_Error(n=7, m=100000):
          mu = 0
          sigma = 1
          # Creates mean and median lists
          means = []
          medians = []
          # Calculation of Mean Error
          for _ in range(m):
              xs = [random.gauss(mu, sigma) for i in range(n)]
              xbar = np.mean(xs)
              median = np.median(xs)
              # Adds values to list
              means.append(xbar)
              medians.append(median)
          # Displays Results
          print('MSE Results')
          print('mean error xbar', MeanError(means, mu))
          print('mean error median', MeanError(medians, mu))
```

```
[79]: # Bias Function
def Bias(n=7, m=100000):
    mu = 0
    sigma = 1

    estimates1 = []
    estimates2 = []
    for _ in range(m):
        xs = [random.gauss(mu, sigma) for i in range(n)]
        biased = np.var(xs)
        unbiased = np.var(xs, ddof=1)
        estimates1.append(biased)
```

```
estimates2.append(unbiased)

print('Biased vs Unbiased Results')
print('RMSE biased', RMSE(estimates1, sigma**2))
print('RMSE unbiased', RMSE(estimates2, sigma**2))
```

```
[80]: def main():
          Mean_Error()
          Bias()

if __name__ == '__main__':
          main()
```

```
MSE Results
mean error xbar 0.0003920250241303121
mean error median 0.0007809353008293616
Biased vs Unbiased Results
RMSE biased 0.5140058974128343
RMSE unbiased 0.5764352241123035
```

8-2 Suppose you draw a sample with size n=10 from an exponential distribution with =2. Simulate this experiment 1000 times and plot the sampling distribution of the estimate L. Compute the standard error of the estimate and the 90% confidence interval.

Repeat the experiment with a few different values of n and make a plot of standard error versus n.

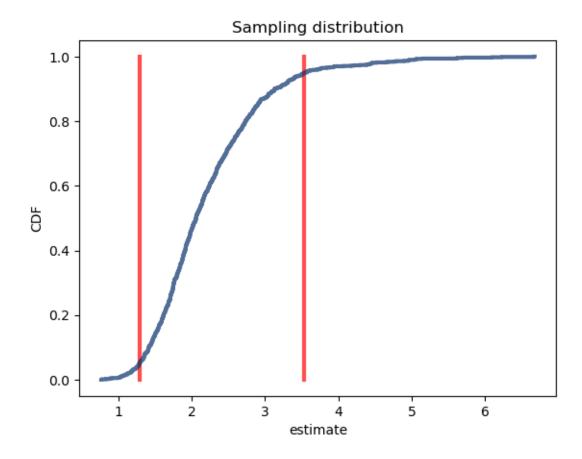
```
[81]: # Calculates RMSE grabbed from book
def RMSE(estimates, actual):
    # Calculation
    e2 = [(estimate-actual)**2 for estimate in estimates]
    mse = np.mean(e2)
    return np.sqrt(mse)
```

```
[82]: # Used from Estimation.py
def SimulateSample(lam=2, n=10, m=1000):
    # lam: parameter of an exponential distribution
    # n: sample size
    # m: number of iterations

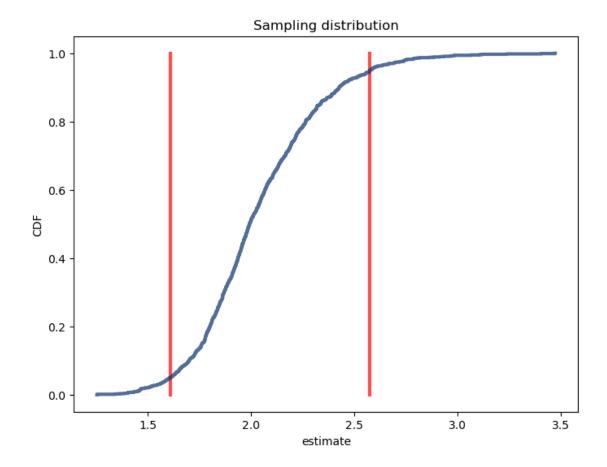
# Establishes Plots for percentiles, used later
def VertLine(x, y=1):
    thinkplot.Plot([x, x], [0, y], color='red', linewidth=3)

# Creates Estimates list
    estimates = []
    # Calculation
    for j in range(m):
        xs = np.random.exponential(1/lam, n)
```

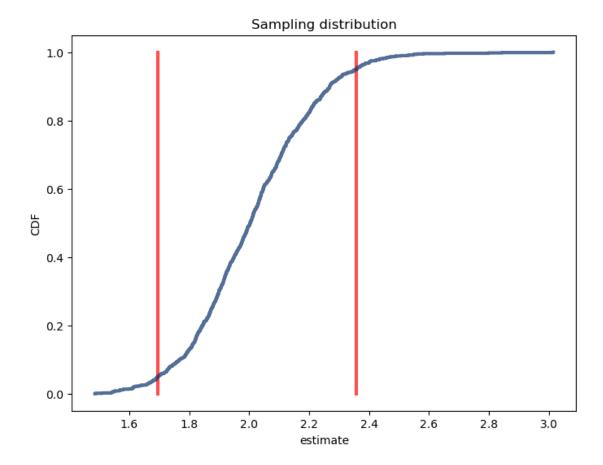
```
lamhat = 1/np.mean(xs)
              # Adds calculation to list
              estimates.append(lamhat)
          # Calculate Standard Error base on estimate list and exponential parameter
          standard_error = RMSE(estimates, lam)
          print('standard error', standard_error)
          # Creates estimates cdf
          cdf = thinkstats2.Cdf(estimates)
          # Creates confidence interval based on 90%
          confidence_interval = cdf.Percentile(5), cdf.Percentile(95)
          print('confidence interval', confidence_interval)
          # Plots lines for 5th and 95th Percentile
          VertLine(confidence_interval[0])
          VertLine(confidence_interval[1])
          # Plots the CDF
          thinkplot.Cdf(cdf)
          thinkplot.Show(root='estimation2',
                         xlabel='estimate',
                         ylabel='CDF',
                         title='Sampling distribution')
          return standard_error
[83]: def main():
          # Establishes different values for sample size
          for n in [10, 50, 100]:
              print('Sample size:', n)
              stderr = SimulateSample(n=n)
      if __name__ == '__main__':
         main()
     Sample size: 10
     standard error 0.8026281306832422
     confidence interval (1.2894786659794217, 3.534847307551774)
```



Sample size: 50 standard error 0.3013747624233301 confidence interval (1.6096525122515635, 2.575582712058378)



Sample size: 100 standard error 0.20038615457224068 confidence interval (1.6965719075499197, 2.3586207627256424)



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