Ramani530Week7

January 29, 2023

1 Week 7 - Assignment 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?
```

[21]:
```
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)
```

[210]:
```
import thinkstats2
import thinkplot
import numpy as np
import pandas as pd
import math

download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/CDBRFS08.
↪ASC.gz")
download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/nsfg.py")
download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/
↪2002FemPreg.dct")
download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/
↪2002FemPreg.dat.gz")
download("https://github.com/AllenDowney/ThinkStats2/raw/master/code/brfss.py")
```

[86]:
```
df_nsfg = nsfg.ReadFemPreg()
#df_nsfg = df_nsfg.dropna(subset=['agepreg', 'totalwgt_lb'])
# per the solution, dataset is filtered to live born
```

```
not_live = df_nsfg[df_nsfg.outcome != 1]
live = df_nsfg[df_nsfg.outcome == 1]
live_first_born = live[live.birthord ==1]
live_subs = live.dropna(subset=['agepreg', 'totalwgt_lb'])
len(df_nsfg), len(live), len(live_subs),  len(not_live), len(live_first_born)
```

[86]: (13593, 9148, 9038, 4445, 4413)

[58]:
```
# SpearmanCorrelation
def SpearmanCorr(xdf, ydf):
    x_ranks = pd.Series(xdf).rank()
    y_ranks = pd.Series(ydf).rank()
    return Corr(x_ranks, y_ranks)
```

[57]:
```
def Cov(xdf, ydf, mean_x=None, mean_y=None):
     #-- Commenting the below since np.asarray is already done in the calling␣
 ↪function.
    #xdf = np.asarray(xdf)
    #ydf = np.asarray(ydf)

    if mean_x is None:
        mean_x = np.mean(xdf)
    if mean_y is None:
        mean_y = np.mean(ydf)

    cov = np.dot(xdf-mean_x, ydf-mean_y) / len(xdf)
    return cov
```

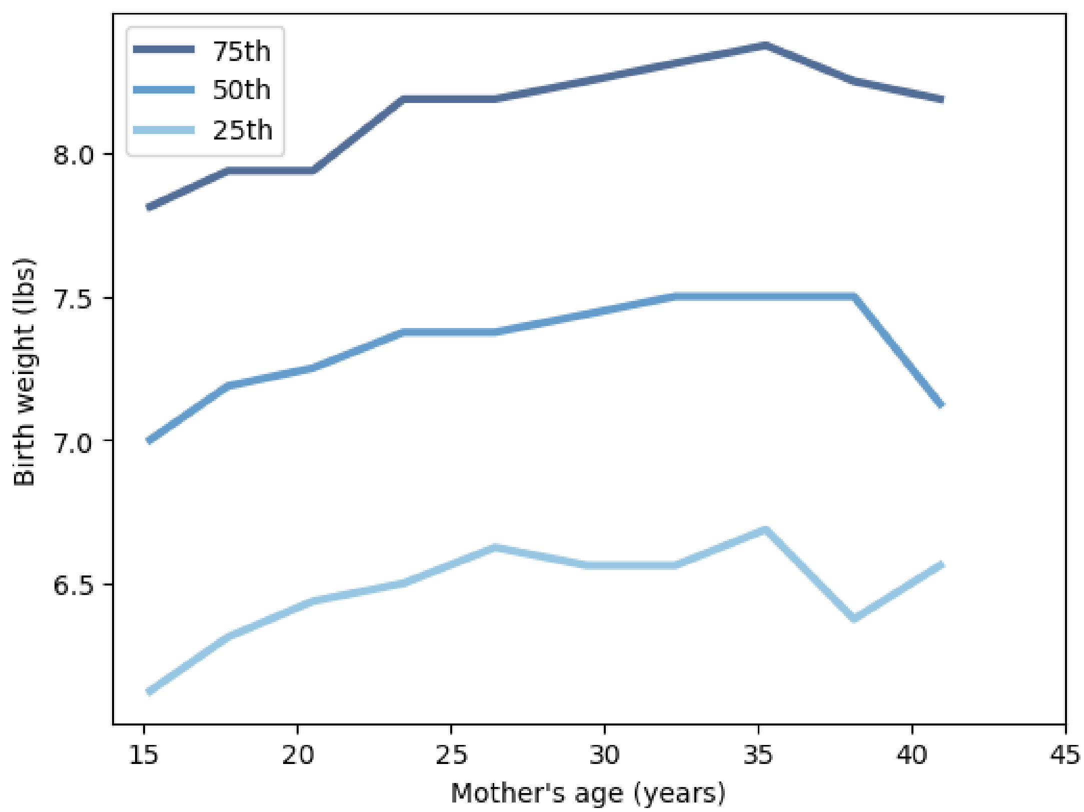
[59]:
```
def Corr(xdf, ydf):
    xs = np.asarray(xdf)
    ys = np.asarray(ydf)

    mean_x, var_x = thinkstats2.MeanVar(xdf)
    mean_y, var_y = thinkstats2.MeanVar(ydf)

    corr = Cov(xs, ys, mean_x, mean_y) / np.sqrt(var_x * var_y)
    return corr
```

[82]:
```
mothers_age = live_subs.agepreg
birth_weight = live_subs.totalwgt_lb
print('Corr', Corr(mothers_age, birth_weight))
print('SpearmanCorr', SpearmanCorr(mothers_age, birth_weight))
```

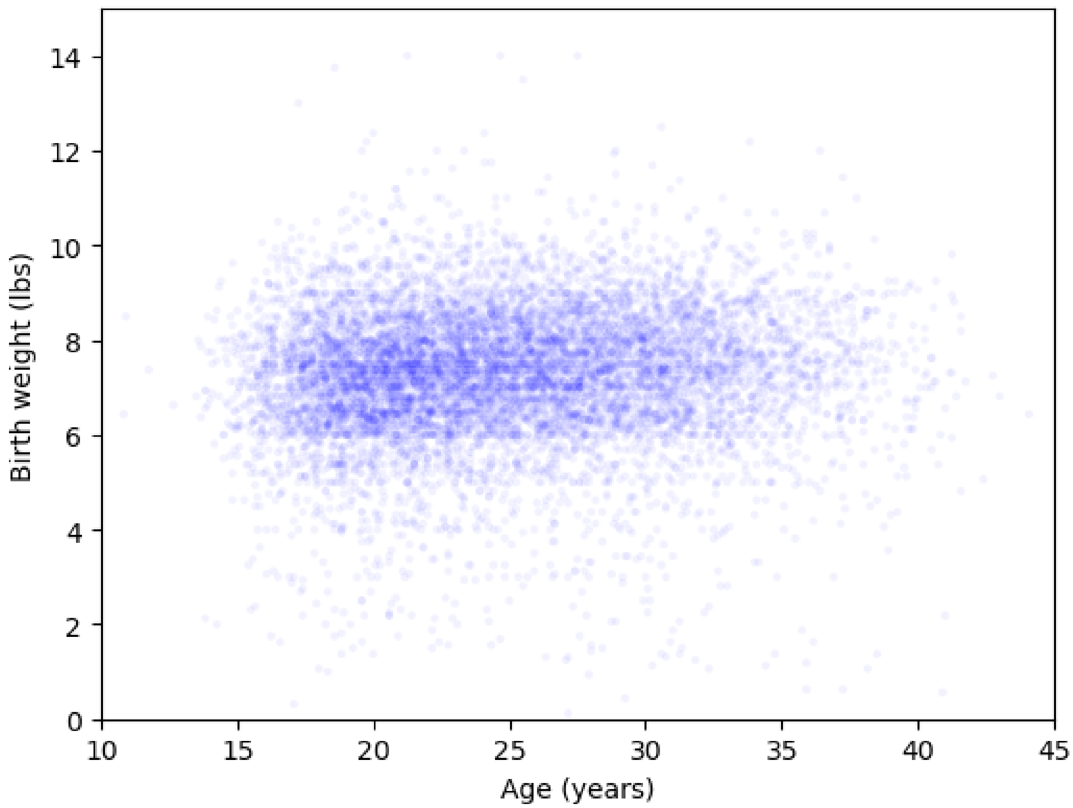
```
Corr 0.06883397035410908
SpearmanCorr 0.09461004109658226
```

[100]:

```
def BinnedPercentiles(df):
    """Bin the data by age and plot percentiles of weight for each bin.

    df: DataFrame
    """
    bins = np.arange(10, 48, 3)
    indices = np.digitize(df.agepreg, bins)
    groups = df.groupby(indices)

    mothers_ages = [group.agepreg.mean() for i, group in groups][1:-1]
    cdfs = [thinkstats2.Cdf(group.totalwgt_lb) for i, group in groups][1:-1]

    thinkplot.PrePlot(3)
    for percent in [75, 50, 25]:
        birth_weights = [cdf.Percentile(percent) for cdf in cdfs]
        label = '%dth' % percent
        thinkplot.Plot(mothers_ages, birth_weights, label=label)

    thinkplot.Config(xlabel="Mother's age (years)",
                     ylabel='Birth weight (lbs)',
                     xlim=[14, 45], legend=True)

BinnedPercentiles(live_subs)
```



[219]:
```
# Solution

thinkplot.Scatter(mothers_age, birth_weight, alpha=0.05, s=10)
thinkplot.Config(xlabel='Age (years)',
                 ylabel='Birth weight (lbs)',
                 xlim=[10, 45],
                 ylim=[0, 15],
                 legend=False)
```



The Pearson is around 0.07 and Spearman's is around 0.095. Pearson is lower than Spearman, the difference between them suggests some effects of outliers or a non-linear relationship.

Mother's Age vs Birth Weight plot is non-linear. Babies Birth weight shows a quick pace increase for young mothers between 15 and 26. We can see the plot gradually dips for mothers over 35 years age. This dip is not consistent. A perfect correlation as per Pearson is 1 or -1. Had the correlation been over 0.5, it would have been a strong correlation.

Scatterplot shows a weak relationship between the variables as it is unclear and scattered.

2 Week 7 - Assignment 8.1

[ ]:
```
#In this chapter we used x¯ and median to estimate  , and found that x¯yields␣
↪lower MSE.
#Also, we used S^2 and Sn-1^2 to estimate  , and found that S^2 is biased and␣
↪Sn-1^2 is unbiased.

#Also check whether S2 or Sn-12 yields a lower MSE.
```

[197]:
```
def MSE(estimates, actual):
    """Computes the mean error of a sequence of estimates.

    estimate: sequence of numbers
    actual: actual value

    returns: float mean error
    """
    errors = [estimate-actual for estimate in estimates]
    return np.mean(errors)
```

[198]:
```
def EstimateMSE(n=7, m=1000):
    """Evaluates RMSE of sample mean and median as estimators.

    n: sample size
    m: number of iterations
    """
    mu = 0
    sigma = 1

    means = []
    medians = []
    for _ in range(m):
        xs = [random.gauss(mu, sigma) for _ in range(n)]
        xbar = np.mean(xs)
        median = np.median(xs)
        means.append(xbar)
        medians.append(median)

    print('Experiment 1')
    print('rmse xbar', MSE(means, mu))
    print('rmse median', MSE(medians, mu))
```

[206]:
```
EstimateMSE(n=15, m=1000)
print('-------------------------')
EstimateMSE(n=15, m=1500)
print('-------------------------')
EstimateMSE(n=10, m=1000)
```

```python
print('-------------------------')
EstimateMSE(n=10, m=1500)
print('-------------------------')
EstimateMSE(n=5, m=1000)
print('-------------------------')
EstimateMSE(n=5, m=1500)
print('-------------------------')
```

```
Experiment 1
rmse xbar 0.006248563944306441
rmse median 0.008458400325090919
-------------------------
Experiment 1
rmse xbar 0.0047810274432309235
rmse median -0.0004625011617971911
-------------------------
Experiment 1
rmse xbar 0.0007238211952469658
rmse median 0.002291835532500987
-------------------------
Experiment 1
rmse xbar -0.01141939372772157
rmse median -0.015035748710329757
-------------------------
Experiment 1
rmse xbar 0.006632931536930217
rmse median 0.0007875324002945128
-------------------------
Experiment 1
rmse xbar -0.005526647578646661
rmse median 0.0045892673319455485
-------------------------
```

[213]:
```python
def RMSE(estimates, actual):
    """Computes the root mean squared error of a sequence of estimates.

    estimate: sequence of numbers
    actual: actual value

    returns: float RMSE
    """
    e2 = [(estimate-actual)**2 for estimate in estimates]
    mse = np.mean(e2)
    return np.sqrt(mse)
```

[214]:
```python
def EstimateRMSE(n=7, iters=100000):
    """RMSE for biased and unbiased estimators of population variance.
```

```
    n: sample size
    iters: number of iterations
    """
    mu = 0
    sigma = 1

    estimates1 = []
    estimates2 = []
    for _ in range(iters):
        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('Experiment 2')
    print('RMSE biased', RMSE(estimates1, sigma**2))
    print('RMSE unbiased', RMSE(estimates2, sigma**2))
```

[218]:
```
EstimateRMSE(n=15, iters=1000)
print('-------------------------')
EstimateRMSE(n=15, iters=1500)
print('-------------------------')
EstimateRMSE(n=10, iters=1000)
print('-------------------------')
EstimateRMSE(n=10, iters=1500)
print('-------------------------')
EstimateRMSE(n=5, iters=1000)
print('-------------------------')
EstimateRMSE(n=5, iters=1500)
print('-------------------------')

EstimateRMSE(n=10, iters=1000)
EstimateRMSE(n=10, iters=1500)
EstimateRMSE(n=10, iters=2000)
```

```
Experiment 2
RMSE biased 0.3474649583064034
RMSE unbiased 0.36543609377324854
-------------------------
Experiment 2
RMSE biased 0.3473808486462186
RMSE unbiased 0.36598273200844733
-------------------------
Experiment 2
RMSE biased 0.4520098899296252
RMSE unbiased 0.487878615093879
-------------------------
```

```
Experiment 2
RMSE biased 0.4294891262066729
RMSE unbiased 0.46564154598339325
-------------------------
Experiment 2
RMSE biased 0.6157945545201466
RMSE unbiased 0.7428291547640287
-------------------------
Experiment 2
RMSE biased 0.5964431150132299
RMSE unbiased 0.6948797286511459
-------------------------
Experiment 2
RMSE biased 0.4623498230903493
RMSE unbiased 0.5031354138991077
Experiment 2
RMSE biased 0.4317358560590925
RMSE unbiased 0.4692932980499777
Experiment 2
RMSE biased 0.4493357952353522
RMSE unbiased 0.48830806549601163
```

1) xbar and median yield lower mean error as m increases, so neither one is obviously biased.
2) The biased estimator of variance yields lower RMSE than the unbiased estimator. And the difference holds up as m increases.

3 Week 7 - Assignment 8.2

[ ]:
```
#Suppose that 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.
```

[190]:
```
def SimulateSample(lam=2, n=1000, iters=1000):
    """Sampling distribution of L as an estimator of exponential parameter.

    lam: parameter of an exponential distribution
    n: sample size
    iters: number of iterations
    """
    def VertLine(x, y=1):
```

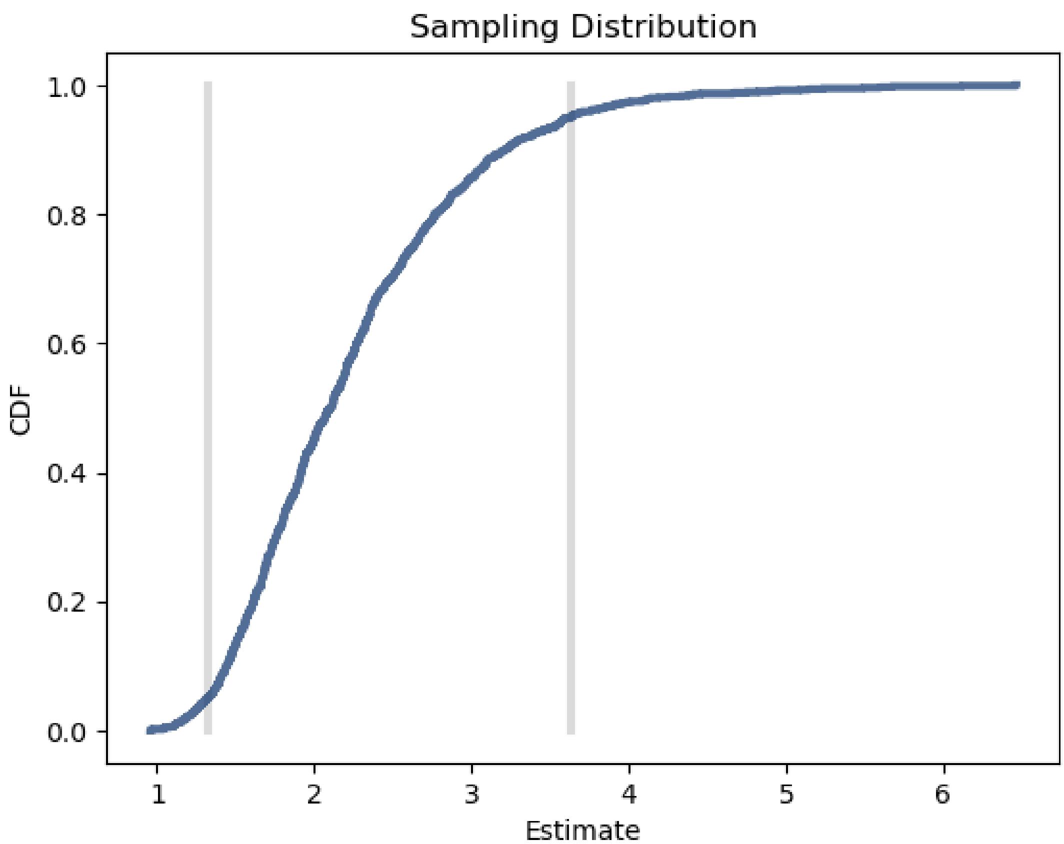
```
        thinkplot.Plot([x, x], [0, y], color='0.8', linewidth=3)

    estimates = []
    for _ in range(iters):
        xs = np.random.exponential(1.0/lam, n)
        lamhat = 1.0 / np.mean(xs)
        estimates.append(lamhat)

    stderr = RMSE(estimates, lam)
    print('Standard Error', stderr)

    cdf = thinkstats2.Cdf(estimates)
    ci = cdf.Percentile(5), cdf.Percentile(95)
    print('Confidence Interval', ci)
    VertLine(ci[0])
    VertLine(ci[1])

    # plot the CDF
    thinkplot.Cdf(cdf)
    thinkplot.Config(xlabel='Estimate',
                     ylabel='CDF',
                     title='Sampling Distribution')

    return stderr
```

[220]:

```
SimulateSample(n=10,lam=2, iters=1000)
```

```
Standard Error 0.7930313140624027
Confidence Interval (1.322626410885211, 3.6307690569999864)
```

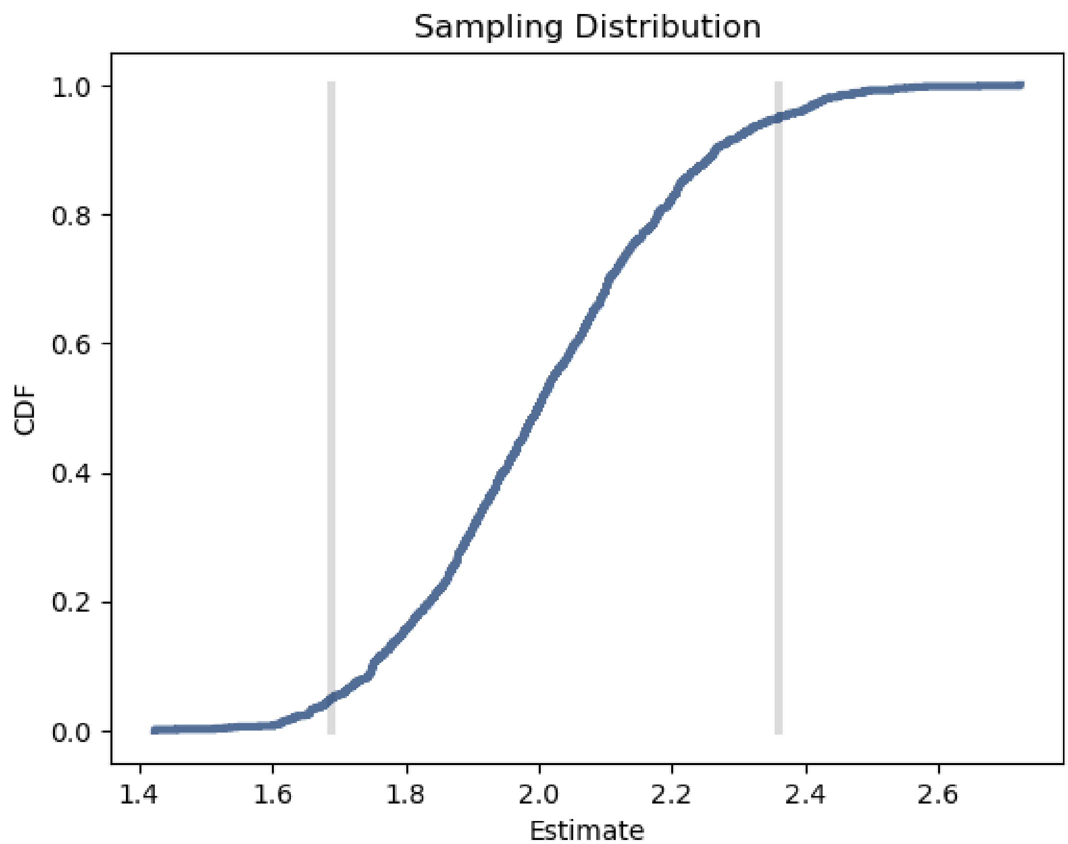
[220]: 0.7930313140624027



[221]:
```
SimulateSample(n=100,lam=2, iters=1000)
```

```
Standard Error 0.20101648315814405
Confidence Interval (1.689853723183377, 2.3617003114738115)
```

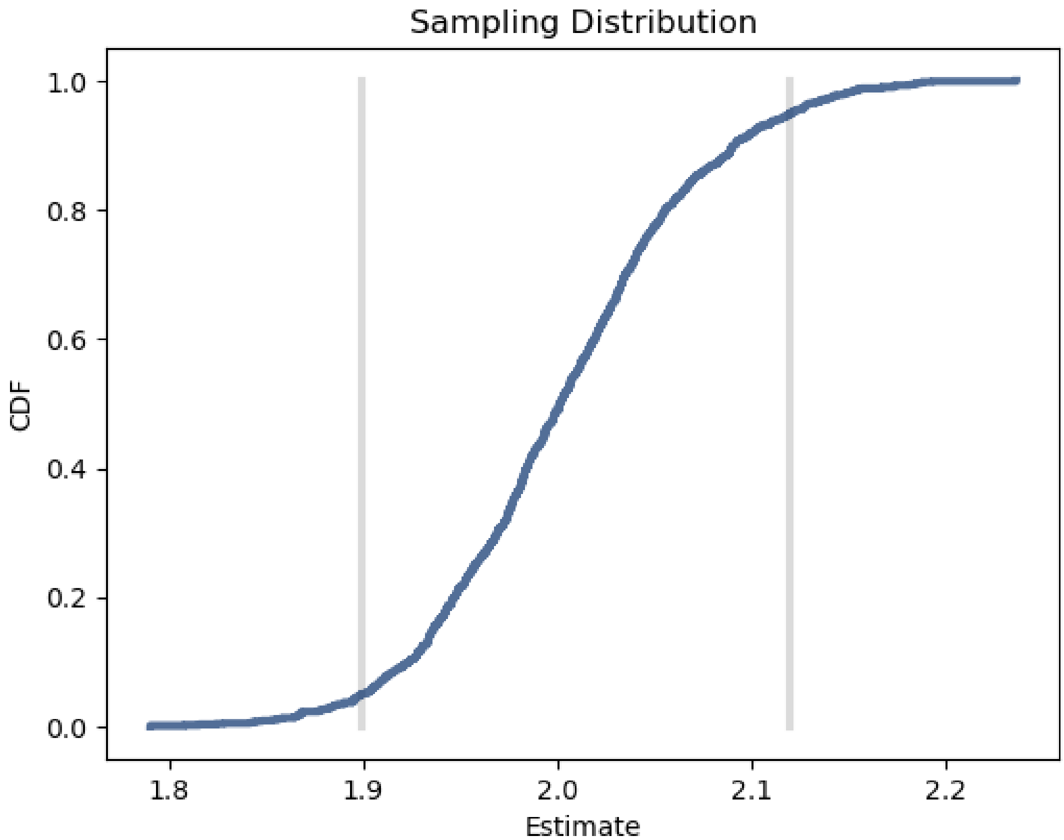
[221]:
```
0.20101648315814405
```



[222]:
```
SimulateSample(n=1000,lam=2, iters=1000)
```

```
Standard Error 0.06647870608780343
Confidence Interval (1.8993870573283615, 2.119912089553423)
```

[222]:
```
0.06647870608780343
```



As the sample size increases, the standard error and CI decrease.

n=10:

Standard Error 0.7930313140624027

Confidence Interval (1.322626410885211, 3.6307690569999864)

n=100:

Standard Error 0.20101648315814405

Confidence Interval (1.689853723183377, 2.3617003114738115)

n=1000:

Standard Error 0.06647870608780343

Confidence Interval (1.8993870573283615, 2.119912089553423)