

# Stats384 - Homework 1

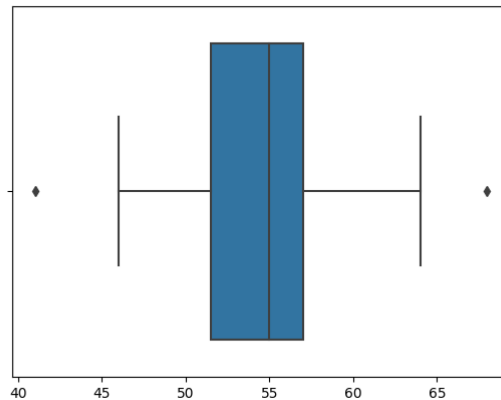
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## 1 7.16

**1.1 Construct a boxplot of the data and comment on interesting features.**

Data: [62 50 53 57 41 53 55 61 59 64 50 53 64 62 50 68 54 55 57 50 55 50 56 55 46 55 53 54 52 47 47 55 57 48 63 57 57 55 53 59 53 52 50 55 60 50 56 58]



Box and Whisker Plot

- Data has a relatively symmetric distribution with a small difference between q1 and q3 although this difference alone does not seem to be an accurate depiction of the data

**1.2 Calculate and interpret a 95% CI for true average breakdown voltage  $\mu$ . Does it appear that  $\mu$  has been precisely estimated? Explain.**

$$ConfidenceInterval = \bar{x} \pm \left( \frac{t \cdot s}{\sqrt{n}} \right)$$

Where  $\bar{x} \approx 54.70833333333336$ ,  $t = .95$ ,  $s \approx 5.175899009404604$ ,  $n = 48$ ,  
 $\sqrt{48} \approx 6.92820323028 = \sqrt{n}$   
 95% CI = (53.244, 56.173)

**1.3 Suppose the investigator believes that virtually all values of breakdown voltage are between 40 and 70. What sample size would be appropriate for the 95CI to have a width of 2 kV (so that  $\mu$  is estimated to within 1 kV with 95% confidence)?**

$$n = \left( \frac{Z \cdot \sigma}{E} \right)^2$$

where  $z = 1.96$  for the given 95% confidence interval,  $\sigma \approx 5.175899009404604$ ,  
 and  $E$  is given to be 1  
 $n \approx 102.91619722222221 \approx 103$

Thus, a sample size of 103 would be needed to answer the question

```

1 import seaborn as sns
2 import matplotlib.pyplot as plt
3 import pandas as pd
4 import numpy as np
5 import math
6
7 #array of given data
8 nums = [
9     62, 50, 53, 57, 41, 53, 55, 61, 59, 64,
10    50, 53, 64, 62, 50, 68, 54, 55, 57, 50,
11    55, 50, 56, 55, 46, 55, 53, 54, 52, 47,
12    47, 55, 57, 48, 63, 57, 57, 55, 53, 59,
13    53, 52, 50, 55, 60, 50, 56, 58
14 ]
15
16 #make box and whisker plot
17 sns.boxplot(x = nums, orient = 'h')
18 plt.show()
19
20 confidenceLevel = 0.95
21 marginOfError = 1
22 zScore = 1.96
23 sdev=np.std(nums)
24 sampleSize = ((zScore*sdev)/marginOfError) ** 2
25

```

```

26 #calculate and print out desired values
27 mean = sum(nums)/len(nums)
28 print("Mean: ", mean)
29 print("Standard Deviation: ", sdev)
30 print("Number of datapoints:", len(nums))
31 print("Confidence Interval Lower: ", (mean- (.95*sdev))/(math
    .sqrt(48)))
32 print("Confidence Interval Upper: ", (mean+(.95*sdev))/(math
    .sqrt(48)))
33 print("Necessary sample size for 95\% CI with 2 kV width",
    sampleSize)

```

Listing 1: Computations for 7.16 in Python

```

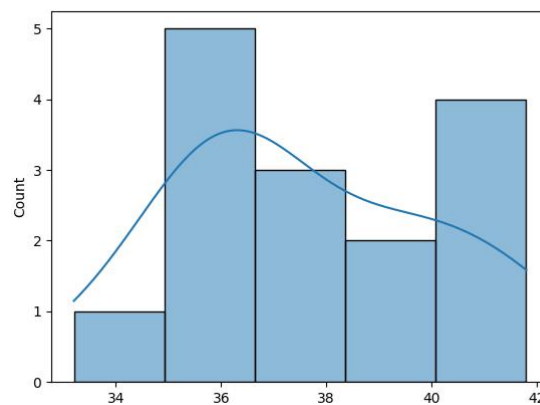
#Compilation, Output of Listing 1 Code
Prat:Stats384 pratyush$ python3 7_16_0927.py
Mean: 54.708333333333336
Standard Deviation: 5.175899009404604
Number of datapoints: 48
Confidence Interval Lower: 53.998610495318545
Confidence Interval Upper: 55.41805617134813
Necessary sample size for 95% CI: with 2 kV width w/ 95% CI 102.91619722222221
Prat:Stats384 pratyush$

```

## 2 7.46

### 2.1 Is it plausible that this sample was selected from a normal population distribution?

Data: [33.2 41.8 37.3 40.2 36.7 39.1 36.2 41.8 36.0 35.2 36.7 38.9 35.8 35.2 40.1]



## Univariate Histogram of the Data

- It is plausible that this sample was selected from a normal population distribution. The data visualized as a histogram vaguely resembles a normal distribution curve, although the test statistic following the Shapiro-Wilk test is very close to 1, at 0.9442427754402161

### 2.2 Calculate an upper confidence bound with confidence level 95% for the population standard deviation of maximum pressure.

$$\sqrt{\frac{(n-1) \cdot s^2}{\chi^2_{\alpha/2, n-1}}},$$

where  $n = 15$ ,  $s \approx 3.26$ , Confidence level is known to be .95, so  $\alpha = .05$ .

We'll use Python's SciPy library to compute  $\chi^2$  and the result.

```
1 import numpy as np
2 import seaborn as sns
3 import matplotlib.pyplot as plt
4 from scipy import stats
5 from scipy.stats import chi2
6
7
8 data = np.array([33.2, 41.8, 37.3, 40.2, 36.7, 39.1, 36.2,
9                 41.8, 36.0, 35.2, 36.7, 38.9, 35.8, 35.2,
10                40.1])
11
12 mean = np.mean(data)
13 sampleSize = len(data)
14 s = (data-mean)**2
15 root_s=np.sum(s)
16 sdev = np.std(data, ddof = 1)
17 confidenceLevel = 0.95
18 alpha = 1 - confidenceLevel
19 degreesOfFreedom = sampleSize-1
20 chiSquareCritical = chi2.ppf((1-alpha)/2, df=
21     degreesOfFreedom)
22 ucl = np.sqrt(((degreesOfFreedom * sdev**2) /
23     chiSquareCritical))
24
25
26 sns.histplot(data=data, kde=True)
27 plt.show()
28
29 res = stats.shapiro(data)
30 res.statistic
31 print(res)
32 print("Upper Confidence Bound: ", ucl)
33 print("n: ", sampleSize)
34 print("sdev: ", sdev)
```

```
31 | print("Chi Square Crit: ", chiSquareCritical)
```

Listing 2: Computations for 7.46 in Python

```
#Compilation, Output of Listing 2 Code
Prat:Stats384 pratyush$ python3 7_46_0927.py
ShapiroResult(statistic=0.9442427754402161, pvalue=0.43871933221817017)
Upper Confidence Bound: 2.6665981083563
n: 15
sdev: 2.5715105807028404
Chi Square Crit: 13.01935693022946
Prat:Stats384 pratyush$
```

As such, the Upper Confidence Bound at 95% Confidence is calculated at roughly 2.6665981083563 standard deviations.

### 3 7.48

**3.1 Calculate a confidence interval with confidence level 98% for the true average compressive strength under these circumstances**

$$\text{Confidence Interval} = \bar{x} \pm \left( \frac{t \cdot s}{\sqrt{n}} \right),$$

Where  $\bar{x} = 64.41, t = 2.224, s = 10.32, n = 18, n = 48$ .

The CI is computed to be (59.00018526375335, 69.81981473624664).

**3.2 Calculate a 98% lower prediction bound for the compressive strength of a single future specimen tested under the given circumstances.**

Using the previously constructed CI, it can be said that the 98% lower prediction bound is  $\approx 59$

## 4 7.54

**4.1** It is important that face masks used by firefighters be able to withstand high temperatures because firefighters commonly work in temperatures of 200–500°F. In a test of one type of mask, 11 of 55 masks had lenses pop out at 250°. Construct a 90% upper confidence bound for the true proportion of masks of this type whose lenses would pop out at 250°.

The formula for the upper confidence bound for a proportion is

$$\hat{p} + Z_{\alpha/2} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}, \text{ where } \hat{p} = 11/55, z_{\alpha/2} = 1.645, \text{ and } n = 55.$$

This computes to  $\approx .3002$ . Contextualized, this means it is with 90% confidence we can say that the true proportion of popped masks is  $\leq 30.02\%$ .

## 5 7.56

**5.1** Estimate the true average crack initiation depth with a 99% CI and interpret the resulting interval.

Data: [4.7, 5.1, 5.2, 5.3, 5.6, 5.8, 6.3, 6.7, 7.2, 7.4, 7.7, 8.5, 8.9, 9.3, 10.1, 11.2]

Using SciPy's statistics library, it is computed that the 99% confidence interval for the data is (5.791, 8.584).

Contextualized, it is with 99% confidence that the true average of the data lies between 5.791 and 8.584.

```
1 import numpy as np
2 import scipy.stats as stats
3
4 data = [4.7, 5.1, 5.2, 5.3, 5.6, 5.8, 6.3, 6.7, 7.2, 7.4,
5         7.7, 8.5, 8.9, 9.3, 10.1, 11.2]
6 mean = np.mean(data)
7 std_dev = np.std(data)
8
9 ci = stats.t.interval(0.99, len(data) - 1, loc=mean,
10                      scale=std_dev / (len(data)**0.5))
11 ci_lower, ci_upper = ci
12
13 print(f"The 99% confidence interval is ({ci_lower:.3f}, {ci_upper:.3f})")
```

Listing 3: Computation for 7.56 Confidence Interval

#Compilation, output for 7.56 computation

```
Prat:Stats384 pratyush$ python3 7_56_0927.py
The 99% confidence interval is (5.791, 8.584)
Prat:Stats384 pratyush$
```

## 6 8.3.35a

**6.1 Is there compelling evidence for concluding that true average repair time exceeds 200 min? Carry out a test of hypotheses using a significance level of .05.**

Data: [120, 480, 149, 270, 547, 340, 43, 228, 202, 240, 218]

In addition, we are given  $\bar{x} = 249.7$ ,  $s = 145.1$ , and  $\alpha = 0.05$  and  $n = 11$ .

So,  $H_0 : \mu \leq 200$  and  $H_a : \mu > 200$

$$t = (\bar{x} - \mu) / (s / \sqrt{n}),$$

where  $t$  is computed to be  $\approx 2.331$  Using SciPy's statistics library, the critical value for  $\alpha = .05$  and  $df = 10$  is  $\approx 1.812$ .

$t = 2.331 > 1.812$ , so  $H_0$  can be rejected. Contextualized, this means that there is compelling evidence to conclude that the true average repair time is over 200 minutes when  $\alpha = 0.05$ .

```
1 import scipy.stats as st
2
3 alpha = .05
4 df = 10
5 critVal = st.t.ppf(1-alpha, df)
6
7 print(critVal)
```

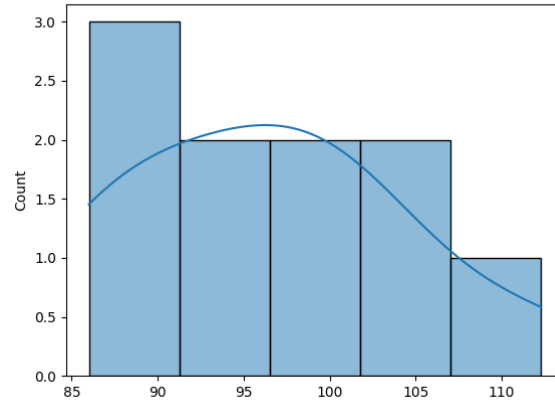
Listing 4: Critical Value 8.3.35a

```
#Compilation, output for critical value needed for 8.3.35a
Prat:Stats384 pratyush$ python3 8_335_0927.py
1.8124611228107335
Prat:Stats384 pratyush$
```

## 7 8.3.37

**7.1 Is it plausible that the compressive strength for this type of concrete is normally distributed?**

Data: [112.3, 97.0, 92.7, 86.0, 102.0, 99.2, 95.8, 103.5, 89.0, 86.7]



Univariate Histogram of the Data

- It is plausible that this sample was selected from a normal population distribution. The data visualized as a histogram largely resembles a normal distribution curve, and the test statistic following the Shapiro-Wilk test is very close to 1, at 0.9578684568405151

**7.2 Suppose the concrete will be used for a particular application unless there is strong evidence that true average strength is less than 100 MPa. Should the concrete be used? Carry out a test of appropriate hypotheses.**

$$H_0: \mu \geq 100 \text{ MPa}$$

$$H_a: \mu < 100 \text{ MPa}$$

It is calculated that  $\bar{x} = 96.42$ ,  $n = 10$ , and  $s \approx 7.83477$ .

$\alpha$  will be set to 0.05 to adhere to common standards.

$t = (\bar{x} - \mu)/(s/\sqrt{n})$ , where  $t$  is computed to be  $\approx -1.445$  using the calculated values.

Using SciPy's statistics library, the critical value is computed to be  $\approx 1.833$ .

Since  $-1.445 \leq 1.833$ , we fail to reject the null hypothesis.

Contextualized, this means that there is insufficient evidence to conclude that the average strength is less than 100 MPa.

```

1 import seaborn as sns
2 import numpy as np
3 from scipy import stats
4 import math
5 import matplotlib.pyplot as plt
6
7

```



```

8 data = np.array([112.3, 97.0, 92.7, 86.0, 102.0, 99.2, 95.8,
9               103.5, 89.0, 86.7])
10 sns.histplot(data=data, kde=True)
11 plt.show()
12
13 mean = np.mean(data)
14 sampSize = len(data)
15 sdev = np.std(data)
16 t = (mean-100)/(sdev/(math.sqrt(sampSize)))
17 alpha = .05
18 df = sampSize-1
19 critVal = stats.t.ppf(1-alpha, df)
20
21 res=stats.shapiro(data)
22 res.statistic
23 print(res)
24
25 print("Mean", mean)
26 print("n: ", sampSize)
27 print("S: ", sdev)
28 print("t: ", t)
29 print("Critical T Value: ", critVal)

```

Listing 5: Computations for 8.3.37

```

#Compilation, output for previously listed code
Prat:Stats384 pratyush$ python3 8_337_0927.py
ShapiroResult(statistic=0.9578684568405151, pvalue=0.7613213062286377)
Mean 96.42
n: 10
S: 7.834768662825979
t: -1.4449634074223394
Critical T Value: 1.8331129326536335
Prat:Stats384 pratyush$

```