# **Chapter 25**

# **Mathematical Statistics**

## 25.1 Introduction, Random Sampling

1. No problem set in this section

### 25.2 Point Estimation of Parameters

**1.** The normal distribution with  $\mu = 0$ , is

$$f(x) = \frac{1}{\theta \sqrt{2\pi}} \exp\left[-\frac{x^2}{2\theta^2}\right]$$
 25.2.1

$$l(\theta) = \left(\frac{1}{\theta \sqrt{2\pi}}\right)^n \exp\left[-\frac{1}{2\theta^2} \sum_j x_j^2\right]$$
 25.2.2

$$\ln(l) = -n \ln(\theta \sqrt{2\pi}) - \frac{1}{2\theta^2} \sum_{i} x_j^2$$
 25.2.3

$$\frac{\mathrm{d}}{\mathrm{d}\theta}\ln(l) = -\frac{n}{\theta} + \frac{1}{\theta^3} \sum_j x_j^2 = 0$$
 25.2.4

$$\theta^* = \sqrt{\frac{\sum_j x_j^2}{n}} = \widetilde{\sigma}$$
 25.2.5

The other parameter is the sample standard deviation with a change in the pre-factor from (n-1) to (n).

**2.** Known variance is  $\sigma^2 = 16$ .

$$f(x) = \frac{1}{4\sqrt{2\pi}} \exp\left[-\frac{(x-\theta)^2}{32}\right]$$
 25.2.6

$$l(\theta) = \left(\frac{1}{4\sqrt{2\pi}}\right)^n \exp\left[-\frac{1}{32}\sum_j (x_j - \theta)^2\right]$$
 25.2.7

$$\ln(l) = -n \ln(4\sqrt{2\pi}) - \frac{1}{32} \sum_{j} (x_j - \theta)^2$$
 25.2.8

$$\frac{\mathrm{d}}{\mathrm{d}\theta} \ln(l) = \frac{1}{16} \sum_{j} (x_j - \theta) = 0$$
 25.2.9

$$\theta^* = \frac{1}{n} \sum_{j=1}^n x_j = \bar{x}$$
 25.2.10

The MLE estimator is the sample mean.

**3.** For a Poisson distribution with parameter  $\theta$ ,

$$l = \prod_{j=1}^{n} e^{-\theta} \frac{\theta^{x_j}}{x_j!} = e^{-n\theta} \frac{\theta^{x_1 + \dots + x_n}}{x_1! \ x_2! \ \dots \ x_n!}$$
 25.2.11

$$\ln(l) = -n\theta + \left[\sum_{i} x_{i}\right] \ln(\theta) - \ln(x_{1}! \ x_{2}! \ \cdots \ x_{n}!)$$
 25.2.12

$$\frac{\partial}{\partial \theta} \ln(l) = -n + \frac{1}{\theta} \sum_{i} x_{i} = 0$$
 25.2.13

$$\theta^* = \frac{1}{n} \sum_{j} x_j = \bar{x}$$
 25.2.14

The MLE estimate of the Poisson parameter is the sample mean.

**4.** For the uniform distribution with parameters a, b,

$$f(x) = \frac{1}{(b-a)} \quad \forall \quad x \in [a, b]$$
 25.2.15

$$l = (b-a)^{-n},$$
  $\ln(l) = -n \ln(b-a)$  25.2.16

$$\frac{\mathrm{d}}{\mathrm{d}a}\ln(l) = \frac{n}{(b-a)} = 0$$
 25.2.17

This has no solution for nonzero n. This means the MLE does not exist for the parameters a, b. Instead, look at the smallest and largest sample value  $x_1$ ,  $x_n$ . These are intuitively, the estimates of

the smallest and largest possible values of x in the population.

$$\widetilde{a} = \min_{j} x_{j}$$
  $\widetilde{b} = \max_{j} x_{j}$  25.2.18

As the sample size approaches the population size, it is more and more probable that  $x_1 \to a$  and  $x_n \to b$  asymptotically.

**5.** Using the MLE method for a sample of size n drawn from a Bernoulli PDF, of which x are successes,

$$l = P(X = x) = p^x q^{n-x}$$
  $\ln(l) = x \ln(p) + (n-x) \ln(q)$  25.2.19

$$\frac{\partial l}{\partial \theta} = \frac{x}{\theta} - \frac{n-x}{1-\theta} \qquad 0 = x(1-\theta) + (x-n)\theta \qquad 25.2.20$$

$$\theta^* = \frac{x}{n}$$
 25.2.21

The MLE estimator of the binomial parameter p is the fraction of successes in the sample, x/n

**6.** Extending the experiment to m times the earlier experiment,

$$l = p^{x_1 + \dots + x_m} \cdot q^{n - x_1 + n - x_2 + \dots + n - x_m}$$
 25.2.22

$$\ln(l) = \sum_{j} x_j \cdot \ln(p) + \left(nm - \sum_{j} x_j\right) \cdot \ln(q)$$
 25.2.23

$$\frac{\partial}{\partial \theta} \ln(l) = \frac{m\bar{x}}{\theta} - \frac{m(n-\bar{x})}{1-\theta} = 0$$
 25.2.24

$$\theta^* = \frac{1}{mn} \sum_{j=1}^m x_j$$
 25.2.25

7. Using the result from Problem 6,

$$\theta^* = \frac{7}{12}$$
 25.2.26

**8.** The event  $A^{\complement}$  occurs (x-1) times and then the event A occurs for a trial to have X=x,

$$P(X = x) = f(x)$$
  $f(x) = (1 - p)^{x-1} \cdot p = q^{x-1} \cdot p$  25.2.27

for some positive integer x.

For a sample of size n and with observed values  $\{x_1, \ldots, x_n\}$ ,

$$P(\{x_i\}) = q^{x_1 - 1 + x_2 - 1 + \dots + x_n - 1} \cdot p^n = l$$
25.2.28

$$\ln(l) = n \ln(p) + \left[ \sum_{j=1}^{n} x_j - n \right] \ln(1-p)$$
 25.2.29

$$\frac{\partial}{\partial \theta} \ln(l) = \frac{n}{\theta} - \frac{\left(\sum x_j - n\right)}{1 - \theta} = 0$$
 25.2.30

$$\theta^* = \frac{n}{\sum_{j} x_j} = \frac{1}{\bar{x}}$$
 25.2.31

The reciprocal of the sample mean is the MLE of the parameter.

9. Using the sum of a geometric progression,

$$\sum_{j=1}^{\infty} f(X=j) = p + qp + q^2p + \dots$$
 25.2.32

$$= p(1+q+q^2+\dots) = \frac{p}{1-q} = 1$$
 25.2.33

Thus, the normalization condition holds.

Using the MLE method on a single observed value X = x,

$$l = q^{x-1}p ln(l) = (x-1) ln(q) + ln(p) 25.2.34$$

$$\frac{\partial}{\partial \theta} \ln(l) = \frac{1-x}{1-\theta} + \frac{1}{\theta} \qquad \qquad \theta^* = \frac{1}{x}$$
 25.2.35

10. Using the result from Problem 8,

$$\theta_1 = \frac{1}{6.5} = \frac{2}{13} \tag{25.2.36}$$

**11.** Using the MLE method, for a sample of size n,

$$P(\lbrace x_j \rbrace) = l = \theta^n \ e^{-\theta} \sum_{j=1}^{n} x_j \qquad \qquad \ln(l) = n \ln(\theta) - \theta \sum_{j=1}^{n} x_j \qquad \qquad 25.2.37$$

$$\frac{\partial}{\partial \theta} \ln(l) = \frac{n}{\theta} - \sum x_j = 0 \qquad \qquad \theta^* = \frac{n}{\sum x_j} = \frac{1}{\bar{x}}$$
 25.2.38

The reciprocal of the sample mean is the MLE of the parameter.

### **12.** Finding the mean directly,

$$\mathbb{E}[X] = \int_0^\infty x\theta \ e^{-\theta x} \ dx \qquad = \left[ -(x+1/\theta) \ e^{-\theta x} \right]_0^\infty$$
 25.2.39

$$=\frac{1}{\theta}$$
 25.2.40

Substituting into the original PDF,

$$f(x) = \frac{e^{-x/\mu}}{\mu} \quad \forall \quad x \ge 0$$
 25.2.41

Using the same procedure as in Problem 11,

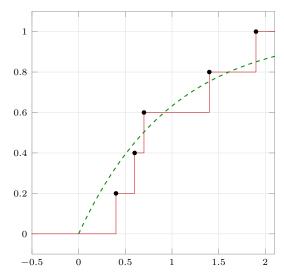
$$\hat{\mu} = \bar{x} \qquad \qquad \hat{\theta} = \frac{1}{\bar{x}}$$
 25.2.42

### 13. Computing the sample statistic,

$$\hat{\theta} = \frac{1}{\bar{x}} = \frac{5}{1.9 + 0.4 + 0.7 + 0.6 + 1.4} = 1$$
 25.2.43

$$F(x) = \int_0^x e^{-x} dx = 1 - e^{-x}$$
 25.2.44

#### Discrete vs Continuous CDF



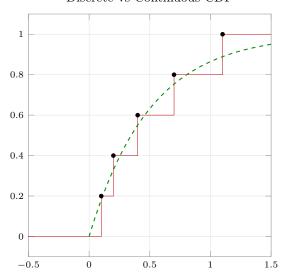
Even this small sample is a good approximation of the underlying CDF,

14. Computing the sample statistic,

$$\hat{\theta} = \frac{1}{\bar{x}} = \frac{5}{0.4 + 0.7 + 0.2 + 1.1 + 0.1} = 2$$
 25.2.45

$$F(x) = \int_0^x 2e^{-2x} dx = 1 - e^{-2x}$$
 25.2.46

Discrete vs Continuous CDF



15. Looking at the sample mean and variance as a function of the size of each sample, keeping the number of samples m fixed.

Sample Mean		Sample Variance	
Mean	Variance	Mean	Variance
0.005	0.096	0.881	0.166
0.00234	0.0100	0.9873	0.0210
0.00138	0.0009297	1.0005	0.002
-0.000197	0.0000103	0.9997	0.0002
	Mean 0.005 0.00234 0.00138	Mean         Variance           0.005         0.096           0.00234         0.0100           0.00138         0.0009297	Mean         Variance         Mean           0.005         0.096         0.881           0.00234         0.0100         0.9873           0.00138         0.0009297         1.0005

As the sample size increases, the MLE estimators of the population mean and variance become better point estimates, as evidenced by each of these point estimates getting more tightly distributed about their true values.

### 25.3 Confidence Intervals

- 1. Point estimates offer no indication of their relation to the true value, which confidence intervals are able to provide through their confidence value  $\gamma$ .
- 2. The known variance is  $\sigma^2 = 16$ . When increasing the confidence value to 0.99, the interval is 1.3 times larger.

Quantity	Value	Quantity	Value
$\bar{x}$	49.67	$\bar{x}$	49.67
$\gamma$	0.95	$\gamma$	0.99
c	1.96	c	2.58
k	3.20	k	4.21
Lower limit	46.47	Lower limit	45.46
Upper limit	52.87	Upper limit	53.87

**3.** Using the relation,

$$k \propto \frac{1}{\sqrt{n}}$$
  $n \to 2n \implies k \to \frac{k}{\sqrt{2}}$  25.3.1

**4.** The known variance is  $\sigma^2 = 16$ .

Quantity	Value
$\bar{x}$	74.81
$\gamma$	0.95
c	1.96
k	0.55
Lower limit	74.26
Upper limit	75.36

5. Using the formula for the confidence interval length,

$$k = \frac{c\sigma}{\sqrt{n}} = \sigma \qquad \qquad n = c^2 = 1.96^2$$
 25.3.2

$$n_1 = 4$$
 25.3.3

$$k = \frac{c\sigma}{\sqrt{n}} = \frac{\sigma}{2}$$
  $n = c^2 = 4 \cdot 1.96^2$  25.3.4

$$n_2 = 16$$
 25.3.5

**6.** By direct calculation,

$$k = \frac{c\sigma}{\sqrt{n}} \qquad 1 = \frac{2.576 \cdot 5}{\sqrt{n}} \qquad 25.3.6$$

$$n = 165.89$$
  $n^* = 166$  25.3.7

From the figure, this number should lie in the range 150 - 170, which matches the true value of  $n^*$ .

### 7. Since this is a binomial distribution, with

$$\bar{p} = \frac{126}{800} \qquad \qquad \bar{x} = n\bar{p}$$
 25.3.8

$$s = \sqrt{n\bar{p}(1-\bar{p})}$$
 25.3.9

Quantity	Value
$\bar{p}$	0.1575
$\gamma$	0.95
c	1.9629
k	0.71504
Lower limit $p$	15.66~%
Upper limit $p$	15.84~%

### 8. Since this is a binomial distribution, with

$$\bar{p} = \frac{12012}{24000} \qquad \qquad \bar{x} = n\bar{p} \qquad \qquad 25.3.10$$

$$s = \sqrt{n\bar{p}(1-\bar{p})}$$
 25.3.11

Quantity	Value
$ar{p}$	0.5005
$\gamma$	0.99
c	2.576
k	1.288
Lower limit $p$	50.045~%
Upper limit $p$	50.055~%

- $\bf 9.$  Using the student's t distribution since the variance is unknown,
- 10. Using the student's t distribution since the variance is unknown,

Quantity	Value	Quantity	Value
$\bar{x}$	65.0000	$ar{x}$	661.2000
$\gamma$	0.9900	$\gamma$	0.9900
c	3.2498	c	4.6041
k	1.2818	k	9.8101
Lower limit	63.7182	Lower limit	651.3899
Upper limit	66.2818	Upper limit	671.0101

11. Using the student's t distribution since the variance is unknown,

Quantity	Value
$\bar{x}$	9533.3333
$\gamma$	0.9900
c	4.0321
k	366.8536
Lower limit	9166.4797
Upper limit	9900.1870

- 12. Using the student's  $\chi^2$  distribution for the variance,
- 13. Using the student's  $\chi^2$  distribution for the variance,

Quantity	Value	Quantity	Value
$\gamma$	0.9500	$\overline{\gamma}$	0.9500
$c_1$	8.9065	$c_1$	1.6899
$c_2$	32.8523	$c_2$	16.0128
Lower limit	0.0231	Lower limit	0.0461
s	0.0400	s	0.1055
Upper limit	0.0853	Upper limit	0.4372

- 14. Using the student's  $\chi^2$  distribution for the variance,
- 15. Using the student's  $\chi^2$  distribution for the variance, textbook uses n-1=100 instead of n=100.

Quantity	Value	Quantity	Value
$\gamma$	0.9500	 $\gamma$	0.9500
$c_1$	1.6899	$c_1$	73.3611
$c_2$	16.0128	$c_2$	128.4220
Lower limit	0.0461	Lower limit	7.1693
s	0.1055	s	9.3000
Upper limit	0.4372	Upper limit	12.5503

- **16.** Using the student's  $\chi^2$  distribution for the variance,
- 17. Using the student's  $\chi^2$  distribution for the variance, with data from Problem 9,

Quantity	Value	Quantity	Value
$\gamma$	0.9500	$\gamma$	0.9500
$c_1$	2.7004	$c_1$	2.7004
$c_2$	19.0228	$c_2$	19.0228
Lower limit	2.8650	Lower limit	0.7360
s	6.0556	s	1.5556
Upper limit	20.1823	Upper limit	5.1844

18. The difference of two normal RVs is,

$$Y = 3X_1 - X_2 \qquad \qquad \mu_Y = 3^2 \mu_1 - \mu_2 = 34 \qquad 25.3.12$$

$$\sigma_y^2 = 3^2 \sigma_1^2 + \sigma_2^2 = 23 \tag{25.3.13}$$

19. Using the sum of normal RVs,

$$\mu = 100 + 5 = 105$$

$$\sigma = \sqrt{1^2 + 0.5^2} = \frac{\sqrt{5}}{2}$$
25.3.14

$$P(104 < Y < 106) = P\left(\frac{-2}{\sqrt{5}} < Z < \frac{2}{\sqrt{5}}\right)$$
 = 0.6289

**20.** Using the sum of normal RVs, Y = nX,

$$\mu = 40n \qquad \qquad \sigma = \sqrt{4n} \qquad \qquad \text{25.3.16}$$

$$P(Y > 2000) = P\left(Z > \frac{2000 - 40n}{2\sqrt{n}}\right)$$
 = 0.05

$$\frac{1000}{\sqrt{n}} - 20\sqrt{n} = 1.64485 \qquad n = (7.03)^2 = 49.421 \qquad 25.3.18$$

$$n^* \ge 50$$
 25.3.19

# 25.4 Testing of Hypotheses. Decisions

1. Examples, for the two sided test, the right sided and left sided tests,

null: 
$$\theta = a$$
 alternative:  $\theta \neq a$  25.4.1

null: 
$$\theta \le b$$
 alternative:  $\theta > b$  25.4.2

null: 
$$\theta \ge c$$
 alternative:  $\theta < c$  25.4.3

- 2. The tests are,
  - Mean of a normal RV with known variance. Uses the standard normal PDF
  - Mean of a normal RV with unknown variance. Uses Student's t-RV
  - Variance of a normal RV. Uses the  $\chi^2$  RV
  - Comparison of the means of two normal RVs with paired datasets, using the standard normal RV
  - Comparison of the means of two normal RVs, using a t-RV and the pooled sample variance.
  - Comparison of the variances of two normal RVs, using the F-distribution

3. Using numpy to do the right-sided test, the null hypothesis is accepted.

Quantity	Value
$\alpha$	0.0500
$ar{x}$	0.2857
s	4.3095
n	7
Statistic	0.1754
Limit	1.9432

4. Using numpy to do the two-sided test, the null hypothesis is accepted.

Quantity	Value
$\alpha$	0.0500
$ar{x}$	0.5069
s	0.5000
n	4040
Statistic	0.0139
Lower Limit	-1.9600
Upper Limit	1.9600

**5.** Using numpy to do the two-sided test, the null hypothesis is accepted.

Quantity	Value
$\alpha$	0.0500
$ar{x}$	0.5016
s	0.5000
n	12000
Statistic	0.0032
Lower Limit	-1.9600
Upper Limit	1.9600

**6.** Using numpy to do the left-sided test, the null hypothesis is rejected.

Quantity	Value
$\alpha$	0.0500
$ar{x}$	58.5000
$\sigma^2$	9.0000
n	20.0000
Statistic	-2.2361
Limit	-1.6449

**7.** Using numpy to do the left-sided test, the null hypothesis is accepted.

Quantity	Value
$\alpha$	0.0500
$ar{x}$	58.5000
$\sigma^2$	9.0000
n	5.0000
Statistic	-1.1180
Limit	-1.6449

#### **8.** The value of c is

$$c = \Phi(0.05) \cdot \frac{\sigma}{\sqrt{n}} + \mu_0 \qquad = 58.8966$$
 25.4.4

$$P(X > c)_{\mu = \mu_1} = 1 - \Phi\left(\frac{c - \mu_1}{\sigma/\sqrt{n}}\right)$$
  $\beta = 0.00235$  25.4.5

$$\eta = 1 - \beta = 99.76 \%$$
 25.4.6

#### 9. The upper and lower limits are,

$$l_1 = \Phi^{-1}(0.025) \cdot \frac{\sigma}{\sqrt{n}} + \mu_0 = 58.685$$
 25.4.7

$$l_2 = \Phi^{-1}(0.975) \cdot \frac{\sigma}{\sqrt{n}} + \mu_0 = 61.315$$
 25.4.8

Where  $\Phi^{-1}$  is the inverse of the standard normal distribution, also called the percent point function PPF.

**10.** Using the right sided test for m samples each of size n = 10, at  $\alpha = 0.1$ ,

m	Fraction Accepted
100	0.91
1000	0.907
10000	0.9022
100000	0.89894

Performing a similar test for the variance,

m	Fraction Accepted
100	0.93
1000	0.897
10000	0.9033
100000	0.90124

The fraction of random samples that fail the test asymptotically converges to the false negative rate  $\alpha = 0.1$ .

11. Performing the two sided t— test using numpy, the hypothesis is rejected.

Quantity	Value
$\alpha$	0.9500
$ar{x}$	4990
s	20
n	50
Statistic	-3.5355
Lower Limit	-2.0096
Upper Limit	2.0096

12. Performing the two sided t— test using numpy, the hypothesis is accepted.

Quantity	Value
$\alpha$	0.9500
$ar{x}$	37000
s	5000
n	25
Statistic	2.0000
Limit	1.7109

13. Performing the two sided t- test using numpy, the hypothesis is accepted.

Quantity	Value
$\alpha$	0.9500
$ar{x}$	0.5500
s	0.7387
n	8
Statistic	2.1058
Lower Limit	-2.3646
Upper Limit	2.3646

14. Performing the two sided z- test using numpy, the hypothesis is accepted.

Quantity	Value
$\alpha$	0.05
$ar{x}$	0.7750
$\sigma$	75
n	400
Statistic	0.0577
Lower Limit	-1.9600
Upper Limit	1.9600

15. Performing the right-sided  $\chi^2-$  test using numpy, the hypothesis is accepted.

Quantity	Value
$\alpha$	0.0500
$\sigma$	0.8000
s	1.0000
n	20
Statistic	29.6875
Limit	30.1435

16. Performing the right-sided  $\chi^2-$  test using numpy, the hypothesis is accepted.

Quantity	Value
$\alpha$	0.0500
$\sigma$	5.0000
s	3.5000
n	28
Statistic	13.2300
$\operatorname{Limit}$	40.1133

17. Performing the right-sided two-sample paired t- test using numpy, the hypothesis that the mileage of B is significantly greater is accepted.

Value	Quantity
0.05	$\alpha$
-0.6	$ar{x}$
0.4	$s_x$
0.6	$s_y$
16	$n_1$
16	$n_2$
-3.3282	Statistic
1.6973	Limit

18. Performing the right-sided two-sample paired F- test using numpy, the hypothesis that the variance of the first sample is smaller is rejected.

Quantity	Value
$\alpha$	0.0500
$s_x$	18.7083
$s_y$	7.8680
$n_1$	6
$n_2$	7
Statistic	5.6538
Limit	4.3874

**19.** Let c be some limit dependent on the confidence value  $\gamma$ . For Type I errors, with  $\mu_1 > \mu_0$ ,

$$\alpha = P\left(\frac{z - \mu_0}{\sigma/\sqrt{n}} > c\right) \tag{25.4.9}$$

This quantity goes up with increasing n, which means  $\alpha$  goes down with increasing n keeping all other elements fixed.

For Type II errors, once again with  $\mu_1 > \mu_0$ 

$$\beta = P\left(z + \frac{\mu_1 - \mu_0}{\sigma/\sqrt{n}} > c\right)$$
 25.4.10

This value can also be made arbitrarily small by increasing n.

The fact that normal distributions span the entire real line means that these values can never be zero. By a similar procedure, the case  $\mu_1 < \mu_0$  can also be proved.

**20.** Performing the right-sided two-sample generalized t- test using numpy, the hypothesis that the means of the two samples are equal is rejected.

Quantity	Value
$\alpha$	0.0500
$\bar{x} - \bar{y}$	-4
$s_x$	3
$s_y$	3
$n_1$	12
$n_2$	18
Statistic	-0.2520
Lower Limit	-2.0484
Upper Limit	2.0484

# 25.5 Quality Control

1. The control limits for the mean are,

Quantity	Value
LCL (1%)	0.9485
$\mathtt{UCL}\ (1\%)$	1.0515

**2.** For integer multiples of  $\sigma$ , with the pre-factors  $k_1$  and  $k_2$  attached to the terms  $\sigma/\sqrt{n}$  to cross check,

Quantity	Value
LCL $(0.3\%)$	0.9703
$k_1$	2.97
$\mathtt{UCL}\ (0.3\%)$	1.0297
$k_2$	-2.97

**3.** Using the formula for the range,

$$Y = \text{UCL} - \text{LCL}$$
 
$$Y = 2 \cdot \frac{2.58\sigma}{\sqrt{n}}$$
 25.5.1

$$n = \left(\frac{2 \cdot 2.58 \cdot 0.02}{0.02}\right)^2 = 26.6256 \qquad n \ge 27$$
 25.5.2

**4.**  $n \to 2n$  makes the ctrol limit span go from  $Y \to Y/\sqrt{2}$ 

$$\alpha = 1\%$$
  $k_1 = 2.58$  25.5.3

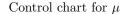
$$\alpha = 5\%$$
  $k_1 = 1.96$  25.5.4

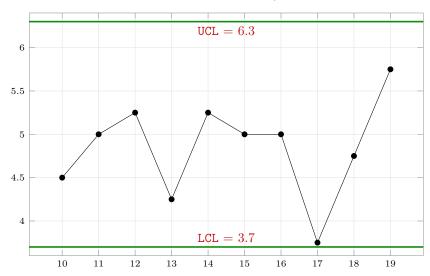
$$k_1 \rightarrow k_2$$
  $Y \rightarrow 1.316 Y$  25.5.5

**5.** Using the relation,

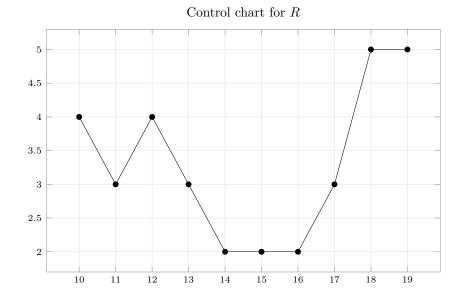
$$Y = \frac{2k_{\alpha} \cdot \sigma}{\sqrt{n}} \qquad Y \to \frac{Y}{2} \implies n \to 4n$$
 25.5.6

**6.** The control chart for the mean is,

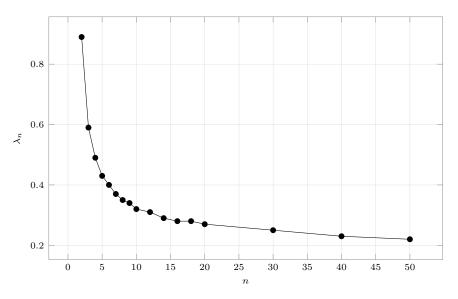




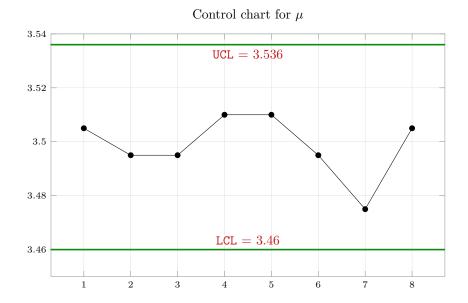
7. The control chart for the ranges is,



**8.** The function is a monotone decreasing function, since an increase in sample size leads to a decrease in standard error in the mean and therefore in the interval.

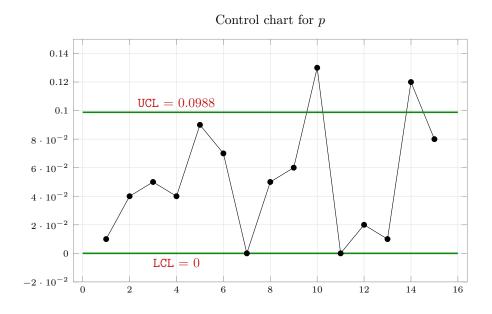


**9.** The control chart for the mean is,



10. The control chart for the fraction defective is,

$$p = 0.04 \sigma^2 = pq = 0.0384 25.5.7$$



11. The control chart for the fraction defective is,

$$UCL = p + \frac{3\sigma}{\sqrt{n}}$$
 
$$LCL = p - \frac{3\sigma}{\sqrt{n}}$$
 25.5.9

$$CL = p 25.5.10$$

Now, for the number defective per sample,

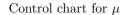
$$UCL = p + 3\sqrt{n} \sigma \qquad LCL = p - 3\sqrt{n} \sigma \qquad 25.5.11$$

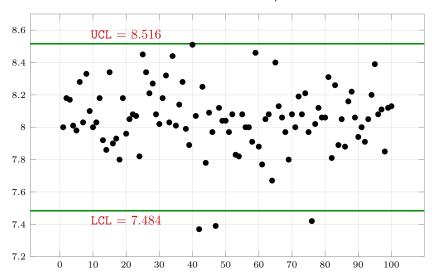
$$CL = \mu = np \qquad \qquad \sigma = \sqrt{p(1-p)}$$
 25.5.12

#### 12. Control charts

- (a) Random numbers generated in numpy
- (b) The control charts for the mean,

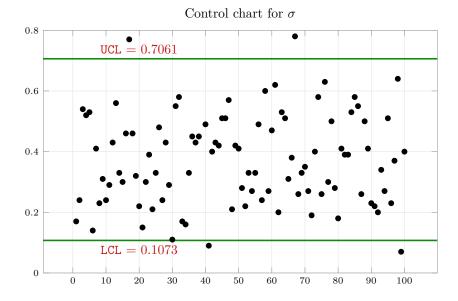
LCL = 
$$\mu_0 - 2.58 \frac{\sigma}{\sqrt{n}} = 7.484$$
 UCL =  $\mu_0 + 2.58 \frac{\sigma}{\sqrt{n}} = 8.516$  25.5.13





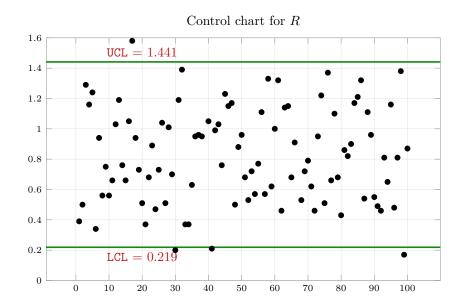
(c) The control charts for the standard deviation,

$$LCL = \sqrt{\frac{\sigma^2}{(n-1)} c_1} = 0.1073$$
  $UCL = \sqrt{\frac{\sigma^2}{(n-1)} c_2} = 0.7061$  25.5.14



(d) The control charts for the range,

$$LCL = \frac{\sigma_L}{\lambda_4} = 0.219$$
  $UCL = \frac{\sigma_U}{\lambda_4} = 1.441$  25.5.15



- (e) In correspondence with  $\alpha=5\%$ , a small fraction of the samples are outside control limits in each of the three control charts.
- 13. The fraction of all data points lying outside  $\mu \pm k\sigma$  for a normal RV is,

$$1 - P(\mu - \sigma < X < \mu + \sigma) = 31.73\%$$
 25.5.16

$$1 - P(\mu - 2\sigma < X < \mu + 2\sigma) = 4.55\%$$
 25.5.17

$$1 - P(\mu - 3\sigma < X < \mu + 3\sigma) = 0.27\%$$
 25.5.18

14. The new control limits are,

$$\bar{x} \to \sum_j x_j$$
  $\mu \to n\mu$  25.5.19

$$\sigma \to n\sigma$$
 LCL/UCL =  $n\mu \pm k_{\alpha} \sigma \sqrt{n}$  25.5.20

The mean and variance are both multiplied by a factor n. Here, k is a function of the confidence level

**15.** For a Poisson process with parameter  $\lambda$ ,

$$LCL = \mu - 3\sigma = \lambda - 3\sqrt{\lambda}$$
 25.5.21

$$UCL = \mu + 3\sigma = \lambda + 3\sqrt{\lambda}$$
 25.5.22

For the specific case of  $\lambda = 3.6$ ,

$$LCL = 3.6 - 3\sqrt{3.6} = -2.09$$
  $LCL = 3.6 + 3\sqrt{3.6} = 9.29$  25.5.23

$$CL = \lambda = 3.6$$

Since a Poisson process has to be non-negative, the LCL is set to zero whenever the formula yields a negative lower limit.

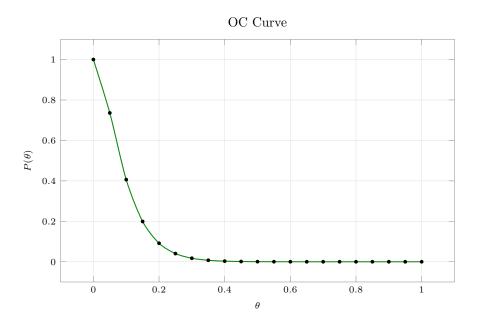
# 25.6 Acceptance Sampling

1. The specific values are,

$$\theta = 0.01$$
  $P(A; \theta) = 0.9825$  25.6.1

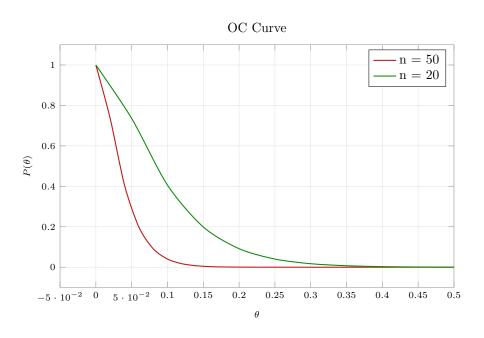
$$\theta = 0.02$$
  $P(A; \theta) = 0.9384$  25.6.2

$$\theta = 0.1$$
  $P(A; \theta) = 0.4060$  25.6.3



## **2.** Changing the sample size to n = 50,

$\theta = 0.01$	$P(A; \theta) = 0.9098$	25.6.4
$\theta = 0.02$	$P(A ; \theta) = 0.7357$	25.6.5
$\theta = 0.1$	$P(A: \theta) = 0.0404$	25.6.6

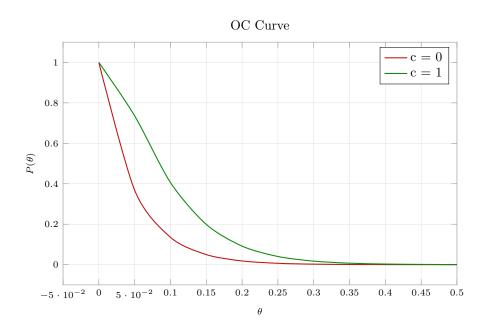


The effect is to make the OC curve decay to zero much faster. This is reasonable, since it is much more probable that a sample contains a defective item, with larger n, keeping  $\theta$  constant.

**3.** Changing the acceptance limit to c = 0,

$$\theta = 0.01$$
  $P(A ; \theta) = 0.8187$  25.6.7  $\theta = 0.02$   $P(A ; \theta) = 0.6703$  25.6.8

$$\theta = 0.1$$
  $P(A; \theta) = 0.1353$  25.6.9



The effect is to make the OC curve decay to zero much faster. This is reasonable, since it is much more probable that a sample contains one defective item than zero, keeping  $\theta$  constant.

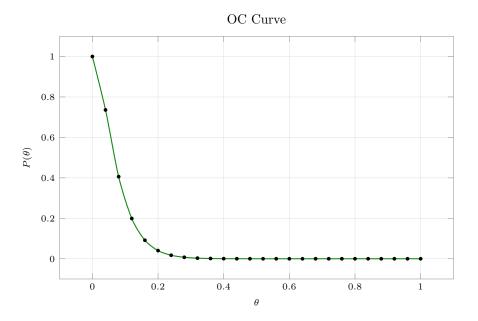
4. From the definition of AQL and RQL, the given defective fractions are  $\theta_0$  and  $\theta_1$  respectively.

$$Risk_p = 1 - P(A; \theta_0) = 0.0616$$
 25.6.10

$$Risk_c = P(A; \theta_1) = 0.1991$$
 25.6.11

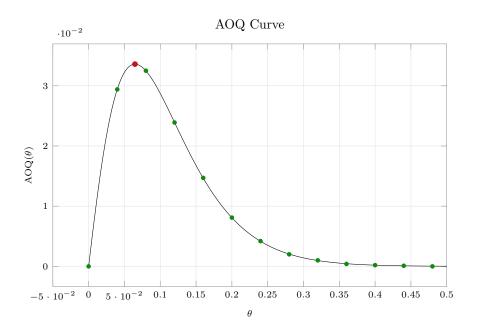
**5.** Given n = 25 and c = 1,

$${\rm Risk}_p = 1 - P(A \; ; \; {\rm AQL}) \qquad \qquad = 0.055 \qquad \qquad \mbox{25.6.12}$$



**6.** Given n = 25 and c = 1,

$${
m Risk}_p = 1 - P(A \; ; \; {
m AQL}) = 0.055$$



Since c is small, the analytical maximum can be found using differentiation

$$f(x) = (25x) \cdot e^{-25x} (1 + 25x)$$
 25.6.14

$$x^* = 0.0647$$
  $f_{\text{max}} = \text{AOQL} = 0.0336$  25.6.15

7. From the definition of AQL and RQL, the given defective fractions are  $\theta_0$  and  $\theta_1$  respectively.

$$\operatorname{Risk}_p = 1 - P(A \; ; \; \mathsf{AQL}) = 1 - \frac{\binom{2}{0} \, \binom{18}{2}}{\binom{20}{2}} = 0.1947 \tag{25.6.16}$$

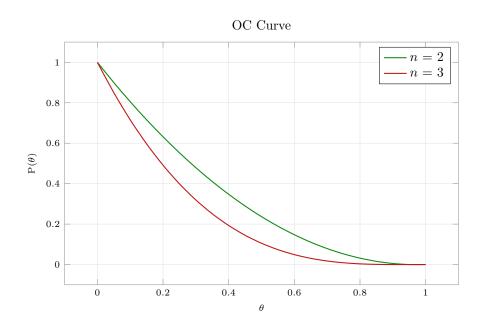
$$\operatorname{Risk}_{c} = P(A \; ; \; \text{RQL}) = \frac{\binom{12}{0} \binom{8}{2}}{\binom{20}{2}} = 0.1474$$
 25.6.17

**8.** Comparing c=3 and c=2, the probabilties go down as the number of objects being sampled goes up, for the same  $\theta$ .

$$\theta$$
 $c=2$ 
 $c=3$ 

 0.1
 0.8053
 0.7158

 0.2
 0.6316
 0.4912

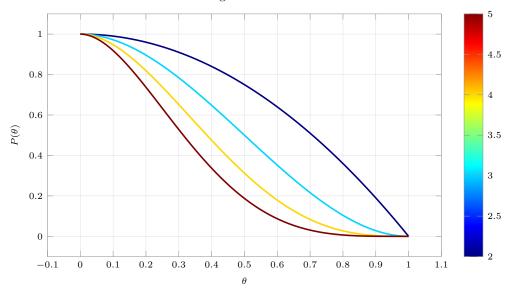


**9.** Using the binomial distribution with the defective probability being  $\theta$ ,

$$P(A; \theta) = \sum_{x=0}^{1} \binom{n}{x} (1-\theta)^{n-x} \cdot \theta^{x}$$
 25.6.18

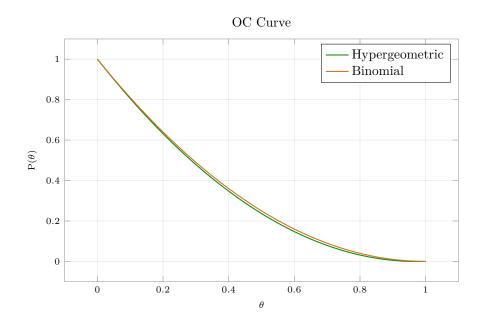
$$= (1 - \theta)^n + n\theta (1 - \theta)^{n-1}$$
 25.6.19

### OC curve using binomial distribution



**10.** Using the formula in Problem 9, with n=2

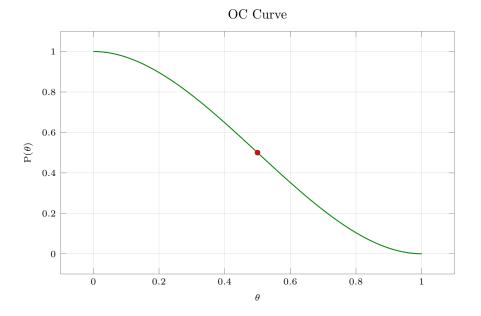
$$P(A; \theta) = \sum_{x=0}^{0} \binom{n}{x} (1-\theta)^{n-x} \cdot \theta^{x}$$
 =  $(1-\theta)^{2}$  25.6.20



The approximation is very close to the accurate values from the hypergeometric PDF.

11. Given c = 1, n = 3 and using the binomial distribution,

$$P(A; 0.5) = {3 \choose 0} \cdot (1 - 0.5)^3 \cdot 0.5^0 + {3 \choose 1} \cdot (1 - 0.5)^2 \cdot 0.5^1 = \frac{1}{2}$$
 25.6.21



**12.** Using the binomial distribution, with n = 100, p = 0.05

$$\operatorname{Risk}_{p} = 1 - P(A; AQL) = 1 - \sum_{x=0}^{c} \binom{n}{x} q^{n-x} p^{x}$$
 25.6.22

$$1 - 0.02 = \sum_{x=0}^{c} {100 \choose x} (0.95)^{100-x} (0.05)^{x} = 0.98$$
 25.6.23

Using the normal approximation to the binomial distribution,

$$Z \sim \frac{X - np}{\sqrt{npq}}$$
 25.6.24

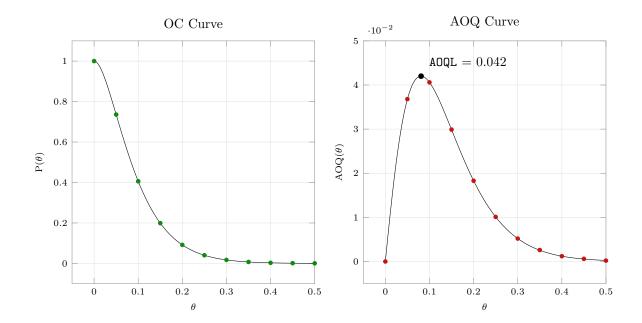
Since the producer's risk has to be 2% or larger, the smallest possible value of c is 9

13. The consumer's risk formula for the data in Problem 12 with RQL = 0.12 is,

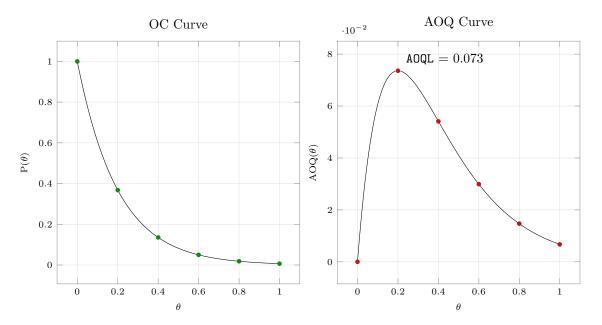
$$\operatorname{Risk}_c = P(A \; ; \; \text{RQL}) = \sum_{x=0}^{9} \binom{100}{x} (0.12)^x \; (0.88)^{100-x}$$
 25.6.25

$$=0.2256$$
 25.6.26

**14.** Given c = 1, n = 20 and using the Poisson distribution,



**15.** Given c = 0, n = 5 and using the Poisson distribution,



# 25.7 Goodness of Fit, Chi-squared Test

1. Performing the  $\chi^2$  goodness of fit test, the sample being normally distributed is accepted.

Quantity	Value
$\alpha$	0.05
K	10
$\widetilde{\mu}$	364.7
$\widetilde{\sigma}$	26.7
Statistic	2.81
Limit	14.07

2. Using the binomial distribution, the sample having a binomial distribution with p = 0.25 is accepted.

$$\chi^2 = \frac{(27 - 0.25 \cdot 80)^2}{0.25 \cdot 80} + \frac{(53 - 0.75 \cdot 80)^2}{0.75 \cdot 80} = 3.27$$
 25.7.1

$$limit = \chi_1^2(0.05) = 3.8414$$
 25.7.2

**3.** The sample having a binomial distribution with p = 0.5 is rejected.

$$\chi^2 = \frac{(40 - 0.5 \cdot 100)^2}{0.5 \cdot 100} + \frac{(60 - 0.5 \cdot 100)^2}{0.5 \cdot 100} = 4$$
 25.7.3

$$limit = \chi_1^2(0.05) = 3.8414$$
 25.7.4

**4.** The sample having a uniform distribution with K=2 is accepted.

$$\chi^2 = \frac{(4 - 0.5 \cdot 10)^2}{0.5 \cdot 10} + \frac{(6 - 0.5 \cdot 10)^2}{0.5 \cdot 10} = 0.4$$
 25.7.5

$$limit = \chi_1^2(0.05) = 3.8414$$
 25.7.6

This is a much less egregious result under the assumption of fairness, and the hypothesis is much less likely to be rejected.

**5.** The sample having a uniform distribution with K=6 is accepted.

$$\chi^2 = \frac{(10-10)^2}{10} + \frac{(13-10)^2}{10} + \frac{(9-10)^2}{10}$$
 25.7.7

$$+\frac{(11-10)^2}{10} + \frac{(9-10)^2}{10} + \frac{(8-10)^2}{10} = 1.6$$
 25.7.8

limit = 
$$\chi_5^2(0.05) = 11.07$$
 25.7.9

**6.** The sample having a uniform distribution with K=6 is accepted.

$$\chi^2 = \frac{(33-30)^2}{30} + \frac{(27-30)^2}{30} + \frac{(29-30)^2}{30}$$
 25.7.10

$$+\frac{(35-30)^2}{30} + \frac{(25-30)^2}{30} + \frac{(31-30)^2}{30} = \frac{7}{3}$$
 25.7.11

$$limit = \chi_5^2(0.05) = 11.07$$
 25.7.12

**7.** The sample having a uniform distribution with K=6 is accepted.

$$\widetilde{x} = \frac{60 + 49 + 56 + 46 + 68 + 39}{6} = 53$$

$$\chi^2 = \frac{(60 - 53)^2}{53} + \frac{(49 - 53)^2}{53} + \frac{(56 - 53)^2}{53}$$
 25.7.14

$$+\frac{(46-53)^2}{53} + \frac{(68-53)^2}{53} + \frac{(39-53)^2}{53} = 10.26$$

$$\lim_{t \to \infty} 11.07 \qquad 25.7.16$$

**8.** The sample having a binomial distribution with p = 0.025 is rejected.

$$\chi^2 = \frac{(17 - 0.025 \cdot 400)^2}{0.025 \cdot 400} + \frac{(383 - 0.975 \cdot 400)^2}{0.975 \cdot 400} = 5.026$$

$$limit = \chi_1^2(0.05) = 3.8414$$
 25.7.18

**9.** The sample having a uniform distribution with K=2 is accepted.

$$\chi^2 = \frac{(42 - 0.5 \cdot 90)^2}{0.5 \cdot 90} + \frac{(48 - 0.5 \cdot 90)^2}{0.5 \cdot 90} = 0.4$$
 25.7.19

limit = 
$$\chi_1^2(0.05) = 3.8414$$
 25.7.20

- 10. Choosing random numbers
  - (a) The sample having a uniform distribution with K=20 is accepted.

$$\chi^2 = \sum_{j=1}^{20} \frac{(x_j - 11.55)^2}{11.55} = 24.32$$
 25.7.21

limit = 
$$\chi_{19}^2(0.05) = 30.14$$
 25.7.22

(b) The sample having a uniform distribution with K=2 is rejected.

$$\chi^2 = \frac{(143 - 115.5)^2}{115.5} + \frac{(88 - 115.5)^2}{115.5} = 13.1$$
 25.7.23

$$limit = \chi_1^2(0.05) = 3.84$$
 25.7.24

(c) The sample having a binomial distribution with K=2 and p=0.3 is rejected.

$$\chi^2 = \frac{(96 - 0.3 * 231)^2}{0.3 * 231} + \frac{(135 - 0.7 * 231)^2}{0.7 * 231} = 14.69$$
 25.7.25

$$limit = \chi_1^2(0.05) = 3.84$$
 25.7.26

11. Running n experiments with a die rolled 300 times and checking for fairness using the  $\chi^2$  goodness of fit test on the uniform distribution,

n	Number rejected at $\alpha = 0.05$
10	1
100	7
1000	45
10000	465
100000	4931

Similar tests TBC.

12. Performing the  $\chi^2$  goodness of fit test, the sample being normally distributed is accepted.

Quantity	Value
$\alpha$	0.01
K	4.00
$\widetilde{\mu}$	59.87
$\widetilde{\sigma}$	1.50
Statistic	3.31
Limit	6.63

This uses 5 bins by combining the first 2 and last 3 bins together. The resulting limit is  $\chi^2_2(0.01)$ 

13. Using the binomial distribution, the sample having a binomial distribution with p = 0.25 is accepted.

$$\chi^2 = \frac{(123 - 0.25 \cdot 478)^2}{0.25 \cdot 478} + \frac{(355 - 0.75 \cdot 478)^2}{0.75 \cdot 478} = 0.1367$$
 25.7.27

$$limit = \chi_1^2(0.05) = 3.8414$$
 25.7.28

**14.** The values of  $e_j$  are computed first, using  $\tilde{x} = 23/50 = 0.46$ 

$$\{e_0, e_1, e_2\} = \{0.6313, 0.2904, 0.06679\}$$
 25.7.29

$$\chi^2 = \frac{(33 - 31.56)^2}{31.56} + \frac{(11 - 14.52)^2}{14.52} + \frac{(6 - 3.34)^2}{3.34}$$
 25.7.30

$$=3.037$$
 25.7.31

$$limit = \chi_1^2(0.95) = 3.84$$
 25.7.32

The sample having a Poisson distribution with is accepted.

Since only K=3 bins are used, the d.o.f. of the  $\chi^2$  distribution is 1.

15. Performing the  $\chi^2$  goodness of fit test, the sample being Poisson distributed is accepted.

# 25.8 Nonparametric Tests

**1.** For n = 6, the binomial distribution gives,

$$P(X=5) = \binom{6}{5} \cdot (0.5)^5 \cdot (0.5)^1 = 0.09375 \\ P(X=4) = \binom{6}{4} \cdot (0.5)^4 \cdot (0.5)^2 = 0.234375$$
 25.8.1

Using  $\alpha = 0.05$ , the hypothesis would be rejected with less than 6 positive values.

**2.** For n = 6, the binomial distribution gives,

$$P(X=4) = {6 \choose 4} \cdot (0.5)^4 \cdot (0.5)^2 = 0.234375$$
 25.8.2

Using  $\alpha = 0.05$ , the hypothesis would be rejected.

**3.** For n = 8, the binomial distribution gives,

$$P(X=7) = {8 \choose 7} \cdot (0.5)^7 \cdot (0.5)^1 = 0.03125$$
 25.8.3

Using  $\alpha = 0.05$ , the hypothesis would be accepted.

**4.** For n = 18, and the normal approximation to the binomial distribution,

$$p = 0.5$$
  $\mu = np = 9$  25.8.4

$$\sigma = \sqrt{np(1-p)} = \frac{3}{\sqrt{2}}$$
 25.8.5

$$P(X \ge 15) = 1 - P(X \le 15)$$
 =  $1 - P\left(Z \le \frac{15 - 9 + 0.5}{3/\sqrt{2}}\right)$  25.8.6

$$= 1.09 \%$$
 25.8.7

Using  $\alpha = 0.05$ , the hypothesis would be rejected.

**5.** Repeating Problem 4 using the binomial distribution directly,

$$P(X=15) = \sum_{x=15}^{18} {18 \choose x} \cdot (0.5)^x \cdot (0.5)^{18-x} = 0.377 \%$$
 25.8.8

Using  $\alpha = 0.05$ , the hypothesis would be rejected.

**6.** The set of differences in scores (B - A) are,

$$\Delta s = \{5, 15, 5, -5, 20, 25, 30, 15, -5, 5, 10, 15, 10, -15, 15\}$$
 25.8.9

For n = 15, the binomial distribution gives,

$$P(X = 12) = {15 \choose 12} \cdot (0.5)^{1} \cdot 2 \cdot (0.5)^{3} = 0.0139$$
 25.8.10

Using  $\alpha = 0.05$ , the hypothesis would be rejected.

7. Using a test for the mean of a normal distribution (hypothesized to be zero) with unknown variance, the hypothesis would be rejected

Quantity	Value
$\alpha$	0.05
$ar{x}$	9.6667
s	11.8723
n	15
Statistic	3.1535
Limit	1.7613

**8.** Using the non-parametric sign test, with n=9

$$P(X=9) = \binom{9}{9} \cdot (0.5)^9 \cdot (0.5)^0 = 0.002$$
 25.8.12

Using  $\alpha = 0.05$ , the hypothesis would be rejected.

**9.** Using a test for the mean of a normal distribution (hypothesized to be zero) with unknown variance, the hypothesis would be **rejected** and the effect on sleeping time is positive.

Quantity	Value
$\alpha$	0.05
$ar{x}$	1.58
s	1.23
n	10
Statistic	4.0621
Limit	1.8331

**10.** Using the non-parametric sign test, with n=9

$$P(X \ge 8) = \binom{9}{8} \cdot (0.5)^8 \cdot (0.5)^1 + \binom{9}{9} \cdot (0.5)^9 \cdot (0.5)^0 = 0.02$$
 25.8.13

Using  $\alpha = 0.05$ , the hypothesis would be rejected, and the thermostat setting is too low.

- 11. Instead of checking whether the numbers are positive or negative, check if they are larger or smaller than  $\mu_0$
- **12.** Using n = 5 and T = 3,

$$P(T \le 3) = 0.242 \tag{25.8.14}$$

Using  $\alpha = 0.05$ , the hypothesis would be rejected, and the trend is increasing.

**13.** Using n = 8 and T = 4,

$$P(T \le 4) = 0.007 \tag{25.8.15}$$

Using  $\alpha = 0.05$ , the hypothesis would be rejected, and the trend is increasing.

**14.** After sorting by x, and using n = 10 and T = 10,

$$\begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} = \begin{bmatrix} 91 & 92 & 95 & 100 & 102 & 112 & 120 & 121 & 123 & 140 \\ 418 & 301 & 352 & 395 & 375 & 388 & 465 & 521 & 455 & 490 \end{bmatrix}$$
 25.8.16

$$P(T \le 10) = 0.014 \tag{25.8.17}$$

Using  $\alpha = 0.05$ , the hypothesis would be rejected, and the trend is increasing.

**15.** Using n = 6 and T = 2,

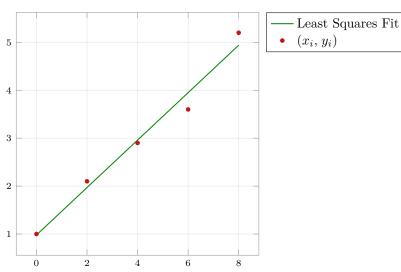
$$P(T \le 2) = 0.028 \tag{25.8.18}$$

Using  $\alpha = 0.05$ , the hypothesis would be rejected, and the trend is increasing.

# 25.9 Regression. Fitting Straight Lines. Correlation

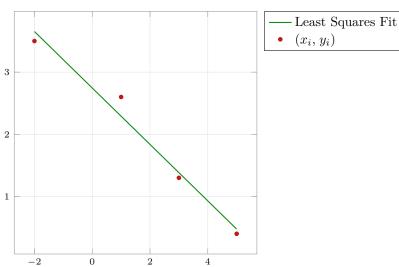
1. Graphing the regression line,

$$k_0 = 0.98, \quad k_1 = 0.495$$

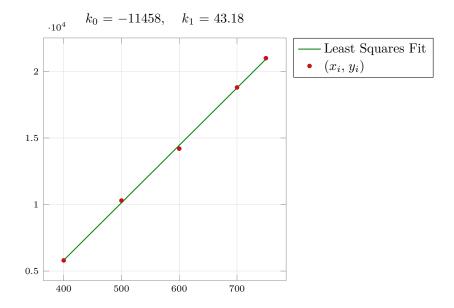


2. Graphing the regression line,

$$k_0 = 2.745, \quad k_1 = -0.454$$



**3.** Graphing the regression line,



**4.** Graphing the regression line,

$$k_0 = 75.72, \quad k_1 = -1.32$$

The least Squares Fit (x<sub>i</sub>, y<sub>i</sub>)

 $k_0 = 75.72, \quad k_1 = -1.32$ 

Least Squares Fit (x<sub>i</sub>, y<sub>i</sub>)

**5.** Graphing the regression line,

$$k_0 = -10, \quad k_1 = 0.55$$

Least Squares Fit

 $(x_i, y_i)$ 

**6.** Graphing the regression line,

$$k_0 = -9.632, \quad k_1 = 34.45$$

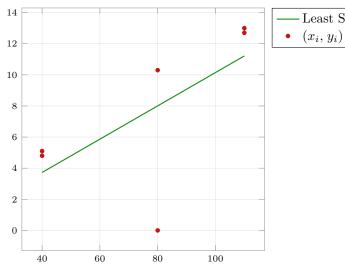
Least Squares Fit

 $(x_i, y_i)$ 

7. Graphing the regression line, and all 6 points, instead of just 3 of the points as used in the textbook solutions.  $R=1/k_1=9.34~\Omega$ 

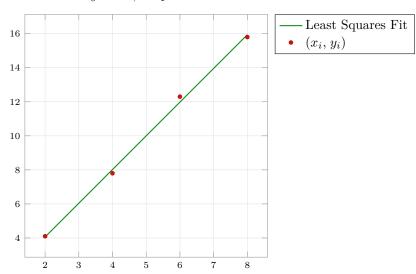
$$k_0 = -0.555, \quad k_1 = 0.107$$

- Least Squares Fit



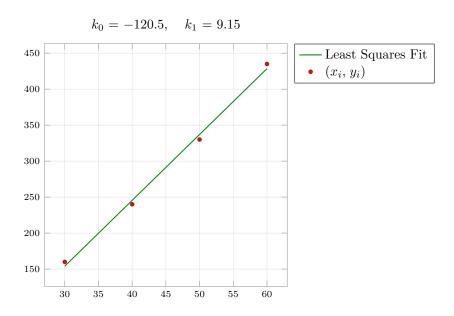
**8.** The spring modulus is  $M = 1/k_1 = 0.505$ 

$$k_0 = 0.1, \quad k_1 = 1.98$$

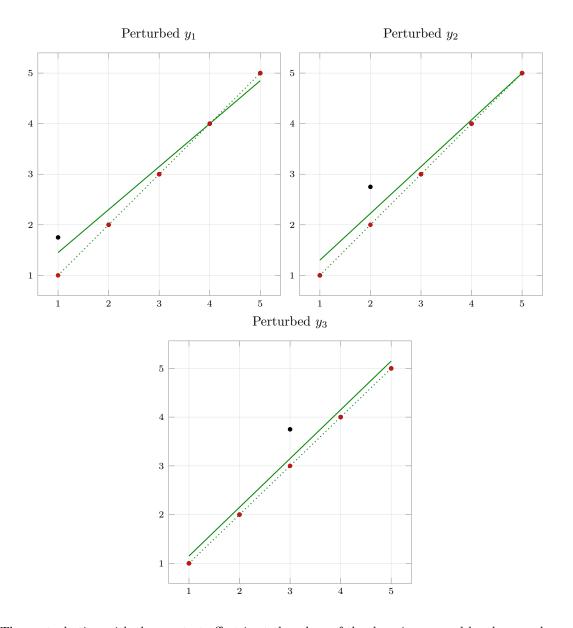


**9.** At room temperature,  $x = 66 \implies y = 0.351$ 

10. At room temperature,  $x = 35 \implies y = 199.75$ 



11. Looking at the effect of perturbations,



The perturbation with the greatest effect is at the edges of the domain spanned by the sample.

### 12. Using the data in Problem 2,

Quantity	Value
$\gamma$	0.95
$k_1$	-0.4542
$q_0$	0.1314
n	4
c	4.3027
Lower Limit	-0.6674
Upper Limit	-0.2410

### 13. Using the data in Problem 3,

Quantity	Value
$\gamma$	0.95
$k_1$	43.1829
$q_0$	97256.0976
n	5
c	3.1824
Lower Limit	41.1819
Upper Limit	45.1839

## **14.** Using the data in Problem 4,

Quantity	Value
$\overline{\gamma}$	0.95
$k_1$	-1.3196
$q_0$	77.1543
n	9
c	2.3646
Lower Limit	-1.5751
Upper Limit	-1.0641

## 15. Using the given data,

Quantity	Value
$\gamma$	0.95
$k_1$	0.0670
$q_0$	0.0230
n	4
c	4.3027
Lower Limit	0.0464
Upper Limit	0.0876