Chapter 3

Statistical Process Control

3.1 Introduction

Operations managers are responsible for developing and maintaining the production processes that deliver quality products and services. Once the production process is operating, it is often necessary to constantly monitor the process to ensure that it functions the way it was designed. The statistical methods we introduce in this Chapter represent the most commonly–used applications of Statistics in Business, Marketing and Management – at any point in time, there are literally thousands of firms applying these methods. In this Chapter, we deal with the subject of *Statistical Process Control*.

3.2 Process variation

All production processes result in variation; that is, no product is exactly the same as another. For example, if you weight two boxes of 500 gram breakfast cereal,

- it is unlikely that either of them will weight exactly 500 grams;
- it is unlikely that they will have the same weight.

All products exhibit some degree of variation. This could be

1. *Chance variation* – caused by a number of randomly occurring events that are part of the production process and that cannot be eliminated without changing the process;
2. *Assignable variation* – caused by specific events or factors that are frequently temporary and that can usually be identified and eliminated.

Example
Dulux manufactures paint for indoor and outdoor domestic use; most of its paint is sold in 5 litre tins. The cans are filled by an automatic valve that regulates the amount of paint in each can. The designers of the valve acknowledge that there will be some variation in the amount of paint, even when the valve is working as it was designed to work. This is *chance variation*. Occasionally, the valve will malfunction, causing the variation in the amount delivered to each can to increase. This increase is the *assignable variation*.

The best way to understand what is happening is to consider the volume of paint in each can as a random variable. If the only sources of variation are caused by chance, then each can's volume is drawn from identical distributions. That is, each distribution has the same shape, mean, and standard deviation. Under such circumstances, the production process is said to be *under control*. In recognition of the fact that variation in output will occur even when the process is under control and operating properly, most processes are designed so that their products will fall within designated *specification limits* or "*specs*". For example the process that fills the paint cans may be designed so that the cans contain between 4.98 and 5.02 litres. Inevitably, some event or combination of factors in a production process will cause the process distribution to change. When it does, the process is said to be *out of control*. There are several possible ways for the process to go out of control. Here is a list of the most commonly occurring possibilities and their likely assignable causes.

- **Level shift**
  This is a change in the *mean* of the process distribution. Assignable causes include machine breakdown, new machine and/or operator, or a change the environment. In the paint can example, a temperature or humidity change may affect the density of the paint, resulting in less paint in each can.

- **Instability**
  This is the name we apply to the process when the *standard deviation* increases. This may be caused by a machine in need of repair, defective materials, wear of tools, or a poorly trained operator. Suppose, for example, that a part of the valve that controls the amount of paint wears down; this could cause greater variation than normal.

- **Trend**
  When there is a slow, steady shift (either up or down) in the process distribution mean, the result is a trend. This is frequently the result of less–than–regular maintenance, operator fatigue, residue or dirt build up, or gradual loss of lubricant. If the paint control valve becomes increasingly clogged, we would expect to see a steady decrease in the amount of paint delivered.

- **Cycle**
  This is a repeated series of small observations followed by large observations. Likely assignable causes include environmental changes, worn parts, or operator fatigue. If there are changes in the voltage in the electricity that runs the machines in the paint cans example, we might see series of overfilled cans and series of underfilled cans.

The key to quality is to detect when the process goes out of control so that we can correct the malfunction and restore control of the process. The *control chart* is the statistical method that we use to detect problems.

3.3 Control charts

A *control chart* is a plot of statistics over time. For example, an **$\bar{x}$–chart** plots a series of sample means taken over a period of time. Each control chart contains a *centreline* and *control limits*. The control limit above the centreline is called the *upper control limit* (UCL) and that below the centreline is called the *lower control limit* (LCL). If, when the sample statistics are plotted, all points are randomly distributed between the control limits, we conclude that the process is under control. If the points are not randomly distributed between the control limits, we conclude that the process is out of control.

3.3.1 Example: Paint tins

Suppose that in the *Dulux* paint tins example described previously, we want to determine whether the central location of the distribution has changed from one period to another. We will draw our conclusion from an $\bar{x}$–chart. For the moment, let us assume that we know the mean μ and the standard deviation σ of the process when it is under control; $\mu = 5$ litres and $\sigma = 0.15$ litres. Samples of 20 cans are taken every hour for a period of 24 hours; the resulting sample means (in litres) are shown in table 3.1 below.

Time	13:03	14:03	15:03	16:03	17:03	18:03	19:03	20:03
$\bar{x}$	5.01	4.94	4.96	5.02	5.05	4.88	4.87	5.03
Time	21:03	22:03	23:03	00:03	01:03	02:03	03:03	04:03
$\bar{x}$	5.00	5.02	4.98	4.91	5.09	4.95	4.95	5.08
Time	05:03	06:03	07:03	08:03	09:03	10:03	11:03	12:03
$\bar{x}$	4.90	5.00	5.03	5.07	4.86	4.80	4.85	4.82

Table 3.1: Sample means from 24 consecutive samples of *Dulux* paint

Recall the *Central Limit Theorem* from MAS1403. This states that, no matter what the distribution of our random variable (in this case our random variable is the amount of paint in a *Dulux* tin), the mean $\bar{x}$ of a random sample $x_1, x_2, \ldots, x_n$ from this distribution (provided n is large) is approximately Normal with mean μ and variance σ^2/n, i.e.

$$\bar{x} \sim N\left(\mu, \frac{\sigma^2}{n}\right),$$

where μ and σ^2 are the mean and variance (respectively) of the distribution of our random variable.

In the paint tins example, we are told that $\mu = 5$ litres and $\sigma = 0.15$ litres. Means are taken every hour from samples of size 20, and so we have

$$\begin{aligned} \bar{x} &\sim N\left(5, \frac{0.15^2}{20}\right) \qquad \text{i.e.} \\ \bar{x} &\sim N(5, 0.001125) \end{aligned}$$

Also recall from MAS1403 that $\bar{x} \pm 1$ standard deviation gives about 68% coverage for the Normal distribution; $\bar{x} \pm 2$ standard deviations gives about 95% coverage and $\bar{x} \pm 3$ standard deviations gives about 99% coverage. Thus, the lower and upper control limits for an $\bar{x}$–chart are often defined as:

$$\text{Lower control limit} = \mu - 3 \text{ standard errors} = \mu - 3\sqrt{\frac{\sigma^2}{n}} = \mu - 3\frac{\sigma}{\sqrt{n}}$$

$$\text{Upper control limit} = \mu + 3 \text{ standard errors} = \mu + 3\sqrt{\frac{\sigma^2}{n}} = \mu + 3\frac{\sigma}{\sqrt{n}}$$

For the *Dulux* paint example, this would give:

$$\text{Lower control limit} = 5 - 3 \times \frac{0.15}{\sqrt{20}} = 4.899 \qquad (= 5 - 3 \times \sqrt{0.001125})$$

$$\text{Upper control limit} = 5 + 3 \times \frac{0.15}{\sqrt{20}} = 5.101 \qquad (= 5 + 3 \times \sqrt{0.001125})$$

In the space below, construct an $\bar{x}$–chart for the *Dulux* paint example. Identify when the process is *out of control*.

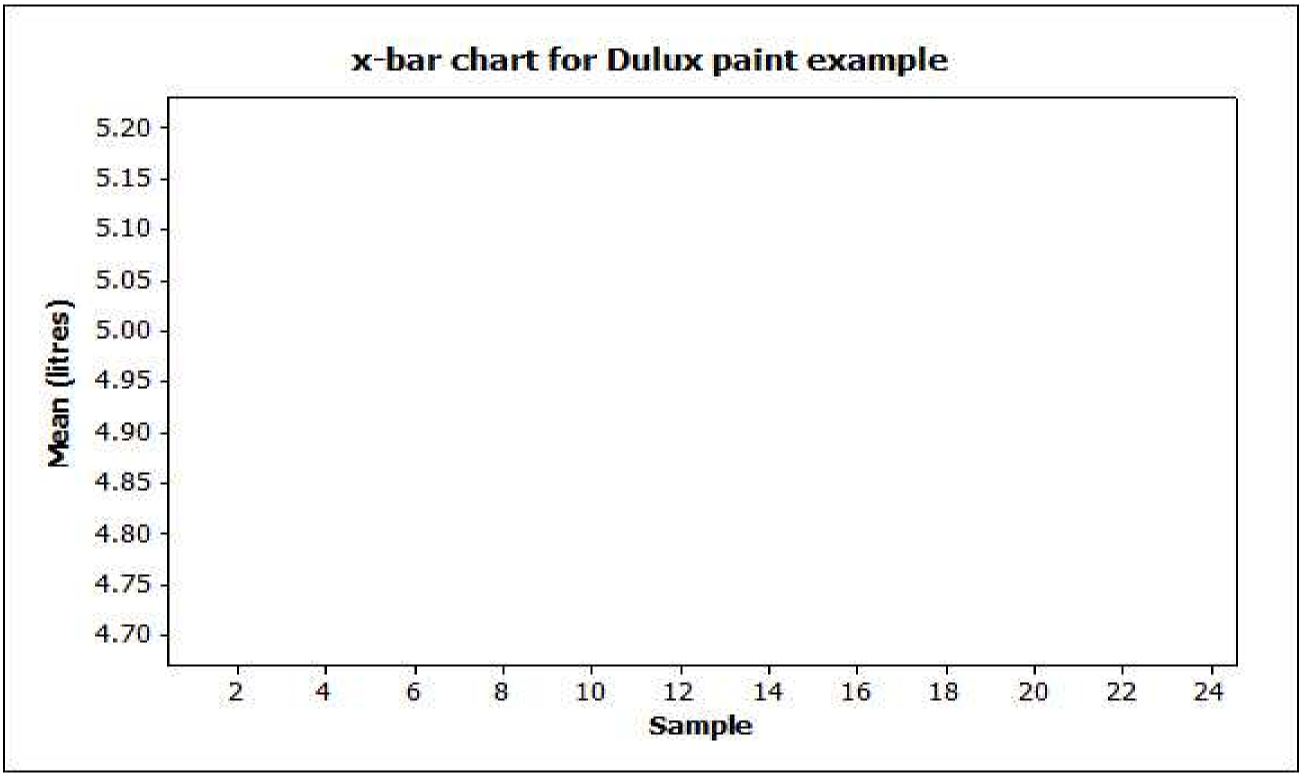

Figure 3.1: $\bar{x}$–chart for *Dulux* paint data

3.3.2 2–sigma and 3–sigma control limits

The control limits we used in the example above are called "3–sigma" control limits, since we used a distance of 3 standard errors either side of the mean as a tool to detect the process being out of control. Why not use "2–sigma" control limits? Well, sometimes these *are* used, although the following reasoning should help explain why 3–sigma control limits are often preferred.

Suppose we have

$$\begin{aligned} H_0 &: \text{ The process is under control} \\ H_1 &: \text{ The process is out of control} \end{aligned}$$

In statistical process control, a *Type I error* occurs if we conclude that the process is out of control when in fact it is not (i.e. reject H_0 when in fact it is true). This sort of error can be quite expensive: if there is evidence to suggest that the process is out of control, then the production process is usually stopped and the causes of the variation are found and repaired – stopping the production process is costly, especially if there was no need to do so! So, we would like the probability of a Type I error to be as small as possible. For the paint tins example, we can work out the probability of a Type I error as follows.

Using 3–sigma control limits gives:

$$\begin{aligned} \Pr(\bar{x} < \text{lower limit}) &= \Pr(\bar{x} < 4.899) \\ &= \Pr\left(z < \frac{4.899 - 5}{\sqrt{0.001125}}\right) \\ &= \Pr(z < -3) \\ &= 0.0013 \end{aligned}$$

Also

$$\begin{aligned} \Pr(\bar{x} > \text{upper limit}) &= \Pr(\bar{x} > 5.101) \\ &= 1 - \Pr(\bar{x} < 5.101) \\ &= 1 - \Pr\left(z < \frac{5.101 - 5}{\sqrt{0.001125}}\right) \\ &= 1 - \Pr(z < 3) \\ &= 1 - 0.9987 \\ &= 0.0013. \end{aligned}$$

Thus,

$$\begin{aligned} \Pr(\text{Type I error}) &= 0.0013 + 0.0013 \\ &= 0.0026 \end{aligned}$$

Of course, we could have turned to the standard Normal distribution immediately and, owing to the symmetry of the Normal distribution:

$$\begin{aligned}\Pr(\text{Type I error}) &= 2 \times \Pr(z < -3) \\ &= 2 \times 0.0013 \\ &= 0.0026.\end{aligned}$$

Similarly, if we use 2–sigma control limits, we would have

$$\begin{aligned}\Pr(\text{Type I error}) &= 2 \times \Pr(z < -2) \\ &= 2 \times 0.0228 \\ &= 0.046.\end{aligned}$$

Thus, using 3–sigma control limits will give a *false alarm* in about 0.26% of samples; using 2–sigma control limits increases this to about 4.6% of samples.

A *Type II error* occurs when we do not detect when the process is out of control (i.e. we retain H_0 when in fact it is false).

3.3.3 Average run length

The *average run length* (*ARL*) is the expected number of samples that must be taken before the control chart indicates that the process has gone out of control. The *ARL* is determined by

$$ARL = \frac{1}{P}$$

where P is the probability that a sample mean falls outside the control limits. Assuming that 3–sigma control limits are used, this would give

$$ARL = \frac{1}{0.0026} = 385.$$

This means that when the process is under control, the $\bar{x}$–chart will erroneously conclude that it is *out* of control once every 385 samples, on average. If the sampling plan calls for samples to be taken once every hour (as in the paint tins example), on average there will be a *false alarm* once every 385 hours.

3.3.4 Examples

1. Find the upper and lower 2–sigma control limits for the *Dulux* paint example. Also find the *ARL* for such a control chart.

2. If the control limits of an $\bar{x}$–chart are set at 2.5 standard errors from the centreline, what is the probability that on any sample the control chart will give a false alarm?

3. A firm manufactures notebook computers. For one component, the company draws samples of size 10 every half an hour. The company makes 4000 of these components every hour. The control limits of the $\bar{x}$–chart are set at 3 standard errors from the mean. When the process goes out of control, it usually shifts the mean by about 0.75 standard deviations.

(a) On average, how many units will be produced until the control chart gives a false alarm?

(b) Find the probability that the $\bar{x}$–chart does not detect a shift of 0.75 standard deviations on the first sample after the shift occurs.

In the examples presented so far, we have assumed that the process parameters (μ and σ) were known. When the parameters are *unknown*, we estimate their values from the sample data. In the next section, we discuss how to construct and use control charts in more realistic situations. We will re–visit $\bar{x}$–charts in section 3.4, as well as S–charts, and we call these *control charts for variables.* In section 3.5 we will also consider *control charts for attributes.*

3.4 Control charts for variables

There are several ways to determine whether a change in the process distribution has occurred. To determine whether the distribution means have changed, we employ the $\bar{x}$–chart. To determine whether the process distribution standard deviation has changed, we can use the S–chart or the R–chart (S for standard deviation, R for range).

3.4.1 $\bar{x}$–chart

In the previous section we determined the centreline and the control limits of an $\bar{x}$–chart using the mean and standard deviation of the process distribution. However, it is unrealistic to believe that the mean and standard deviation of the process distribution will be known. Thus, to construct the $\bar{x}$–chart, we need to *estimate* the relevant parameters from the data.

We begin by drawing samples when we have determined that the process is under control. For each sample, we compute the mean and standard deviation. The estimator of the mean of the distribution is the mean of the sample means (denoted $\bar{\bar{x}}$ and pronounced "x bar bar" or "x double bar"), given by

$$\bar{\bar{x}} = \frac{\sum_{j=1}^{k} \bar{x}_j}{k},$$

where $\bar{x}_j$ is the mean of the jth sample and there are k samples. To estimate the standard deviation of the process distribution, we calculate the "pooled standard deviation", which we denote S and define as

$$S = \sqrt{\frac{\sum_{j=1}^{k} s_j^2}{k}}.$$

In the previous section, where we assumed that the process distribution mean and variance were known, the centreline and control limits were defined as

$$\begin{aligned} \text{centreline} &= \mu \\ \text{Lower control limit} &= \mu - 3\frac{\sigma}{\sqrt{n}} \\ \text{Upper control limit} &= \mu + 3\frac{\sigma}{\sqrt{n}} \end{aligned}$$

Because the values of μ and σ are now unknown, we must use the sample data to estimate them. The estimator of μ is $\bar{\bar{x}}$ and the estimator of σ is S. Therefore, the centreline and control limits are now:

$$\begin{aligned} \text{centreline} &= \bar{\bar{x}} \\ \text{Lower control limit} &= \bar{\bar{x}} - 3\frac{S}{\sqrt{n}} \\ \text{Upper control limit} &= \bar{\bar{x}} + 3\frac{S}{\sqrt{n}} \end{aligned}$$

Example: Car Giant car seats

Car Giant manufactures seats for Mazda and Lexus cars. One of the components of a front seat cushion is a wire spring, produced from 4mm steel wire. A machine is used to bend the wire so that the spring's length is 500mm. If the springs are longer than 500mm they will loosen and eventually fall out. If they are too short, they won't easily fit into position. To determine whether the process is under control, random samples of four springs are taken every hour. The last 25 samples are shown in the table below.

Sample	Spring 1	Spring 2	Spring 3	Spring 4	Mean ($\bar{x}_j$)	St. dev. (s_j)
1	501.02	501.65	504.34	501.10	502.027	1.56689
2	499.80	498.89	499.47	497.90	499.015	0.83309
3	497.12	498.35	500.34	499.33	498.785	1.37556
4	500.68	501.39	499.74	500.41	500.555	0.68267
5	495.87	500.92	498.00	499.44	498.558	2.15203
6	497.89	499.22	502.10	500.03	499.810	1.76324
7	497.24	501.04	498.74	503.51	500.132	2.74084
8	501.22	504.53	499.06	505.37	502.545	2.93381
9	499.15	501.11	497.96	502.39	500.152	1.97782
10	498.90	505.99	500.05	499.33	501.068	3.31578
11	497.38	497.80	497.57	500.72	498.368	1.57771
12	499.70	500.99	501.35	496.48	499.630	2.21626
13	501.44	500.46	502.07	500.50	501.118	0.77993
14	498.26	495.54	495.21	501.27	497.570	2.81996
15	497.57	497.00	500.32	501.22	499.027	2.05853
16	500.95	502.07	500.60	500.44	501.015	0.73487
17	499.70	500.56	501.18	502.36	500.950	1.11887
18	501.57	502.09	501.18	504.98	502.455	1.72411
19	504.20	500.92	500.02	501.71	501.712	1.79632
20	498.61	499.63	498.68	501.84	499.690	1.50694
21	499.05	501.82	500.67	497.36		
22	497.85	494.08	501.79	501.95		
23	501.08	503.12	503.06	503.56		
24	500.75	501.18	501.09	502.88		
25	502.03	501.44	498.76	499.39		

Table 3.2: Spring data for *Car Giant* car seats

Complete the table by finding the mean and standard deviation for samples 21–25.

The mean of the means – $\bar{\bar{x}}$ – is given by

$$\begin{aligned}\bar{\bar{x}} &= \frac{502.027 + 499.015 + \ldots}{25} \\ &= 500.296.\end{aligned}$$

Also, the pooled standard deviation S is found as

$$\begin{aligned}S &= \sqrt{\frac{1.56689^2 + 0.83309^2 + \ldots}{25}} \\ &= \sqrt{\frac{97.125}{25}} \\ &= 1.971\end{aligned}$$

Thus, the centreline and control limits are

$$\text{Centreline} = \bar{\bar{x}} = 500.296$$
$$\text{Lower control limit} = \bar{\bar{x}} - 3\frac{S}{\sqrt{n}} = 500.296 - 3 \times \frac{1.971}{\sqrt{4}} = 497.34$$
$$\text{Upper control limit} = \bar{\bar{x}} + 3\frac{S}{\sqrt{n}} = 500.296 + 3 \times \frac{1.971}{\sqrt{4}} = 503.253$$

This produces the $\bar{x}$–chart shown in figure 3.2. *Don't forget – you should be able to produce these plots by hand!* Is the process in control or out of control?

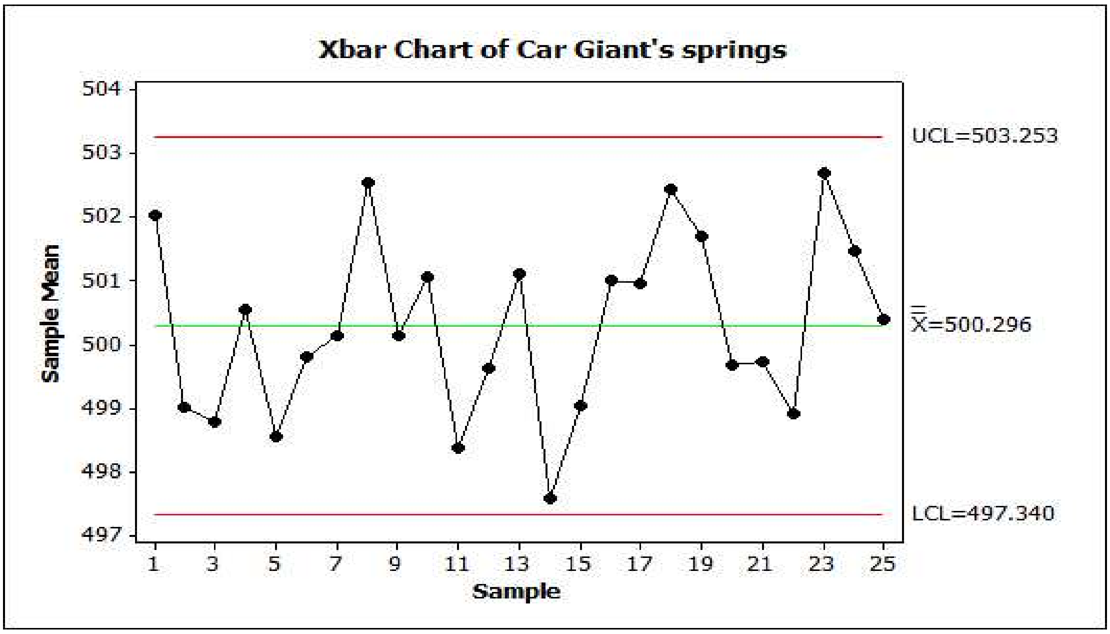

Figure 3.2: $\bar{x}$–chart for *Car Giant* springs dataset

As you can probably tell, I produced the plot shown in figure 3.2 using `Minitab`. To do this, all the data need to be in a single column, i.e.

```
501.02
501.65
504.34
501.10
499.80
498.89
499.47
497.90
497.12
   .
   .
   .
501.44
498.76
499.39
```

You then click on `Stat`–`Control Charts`–`Variable Charts for Subgroups`–`Xbar`. Enter the column that contains the data, and enter the `Subgroup sizes` (here this is 4). Figure 3.3 below shows a screenshot from `Minitab` illustrating this.

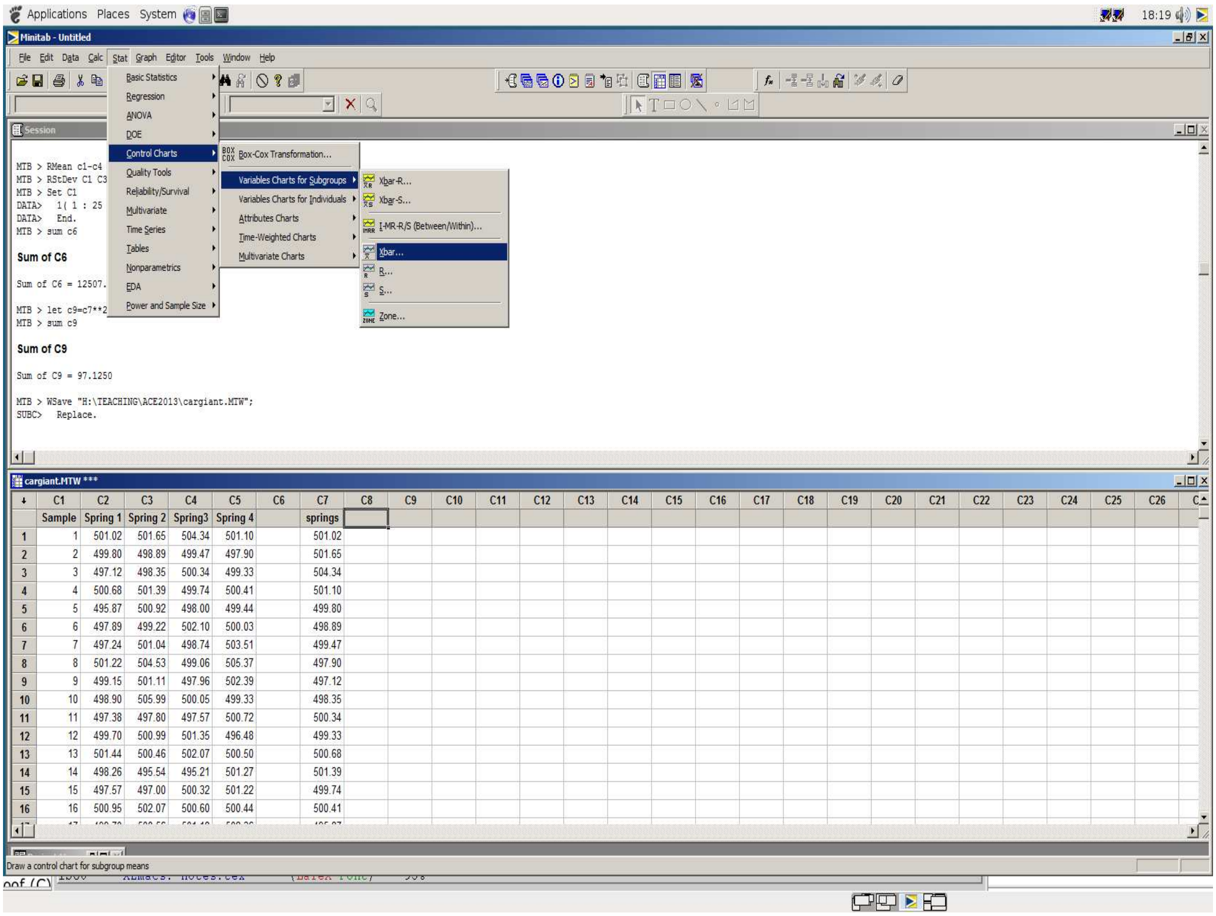

Figure 3.3: `Minitab` screenshot showing the options for the $\bar{x}$–chart

3.4.2 S–charts

The S–chart graphs sample standard deviations to determine whether the process distribution standard deviation has changed. The format is similar to that of the $\bar{x}$ chart. The S chart will display a centreline and control limits. However, the formulae for the centreline and control limits are more complicated than those for the $\bar{x}$–chart; Consequently, we will let `Minitab` do the work here!

With the data stacked as before (see page 94), we click on `Stat–Control Charts–Variables Charts for Subgroups–S`; we enter the column with the stacked data, and we enter the `Subgroup sizes` as 4. In `S options`, we need to make sure that the `Pooled standard deviation` is selected under `Method for estimating standard deviation` within `Estimate`. Clicking `OK` gives the plot shown in figure 3.4.

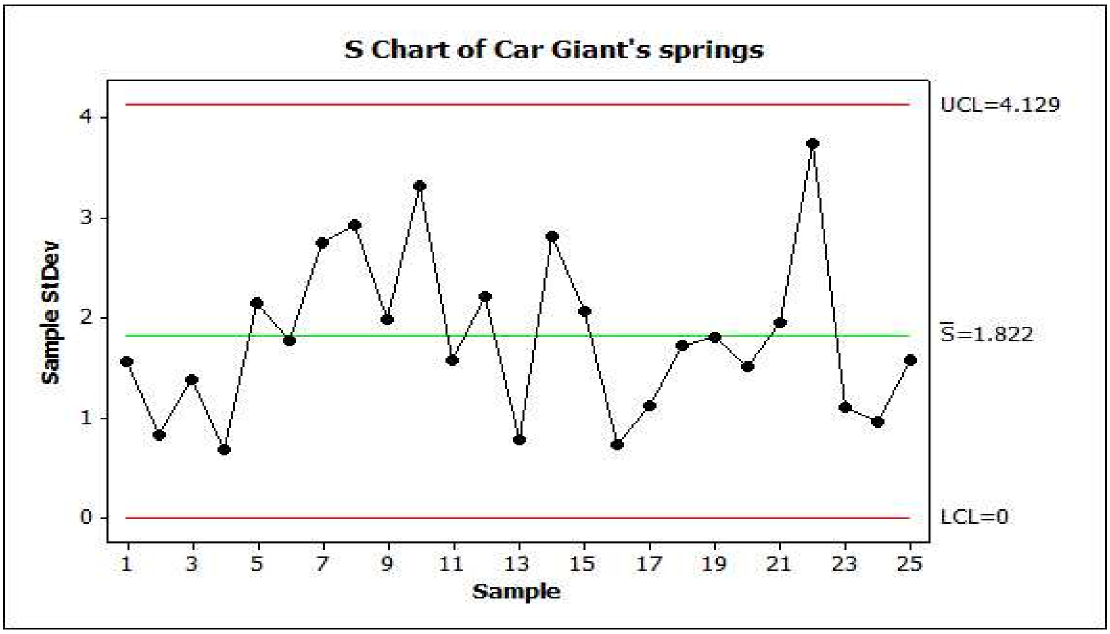

Figure 3.4: S–chart for *Car Giant* springs dataset

Comments

3.4.3 $\bar{x}$–charts and S–charts in practice: Monitoring the production process

In this section, we have introduced $\bar{x}$–charts and S–charts as separate procedures. In actual practice, however, the two charts must be drawn and assessed together. The reason for this is that the $\bar{x}$–chart uses S to calculate the control limits. Consequently, if the S–chart indicates that the process is out of control, the value of S will not lead to an accurate estimate of the standard deviation of the process distribution. The usual procedure is:

1. Draw the S–chart first;
2. If this indicates that the process is under control, then draw the $\bar{x}$–chart;
3. If the $\bar{x}$–chart also indicates that the process is under control, we can then use both charts to maintain control;
4. If either chart shows that the process was out of control at some time during the creation of the charts, we can detect and fix the problem and then re–draw the charts with new data.

When the process is under control, we can use the control chart limits and centreline to monitor the process in the future. We do so by plotting all future statistics on the control chart.

Example: Back to Car Giant car seats
We have determined that the process is under control – none of the points in the S–chart nor the $\bar{x}$–chart fell outside the control limits. We now use the statistics generated in the creation of these charts to monitor the production process. Recall that the sampling plan calls for samples of size 4 every hour. The following table lists the lengths of the springs taken during the *next* six hours.

Sample	Spring 1	Spring 2	Spring 3	Spring 4	Mean ($\bar{x}_j$)	St. dev. (s_j)
26	502.653	498.354	502.209	500.080		
27	501.212	494.454	500.918	501.855		
28	500.086	500.826	496.426	503.591		
29	502.994	500.481	502.996	503.113		
30	506.549	508.708	502.480	504.442		
31	500.441	508.887	505.005	503.254		

1. Complete the last two columns of this table.

2. Update the S–chart and $\bar{x}$–chart shown in figures 3.5 and 3.6 below (respectively).

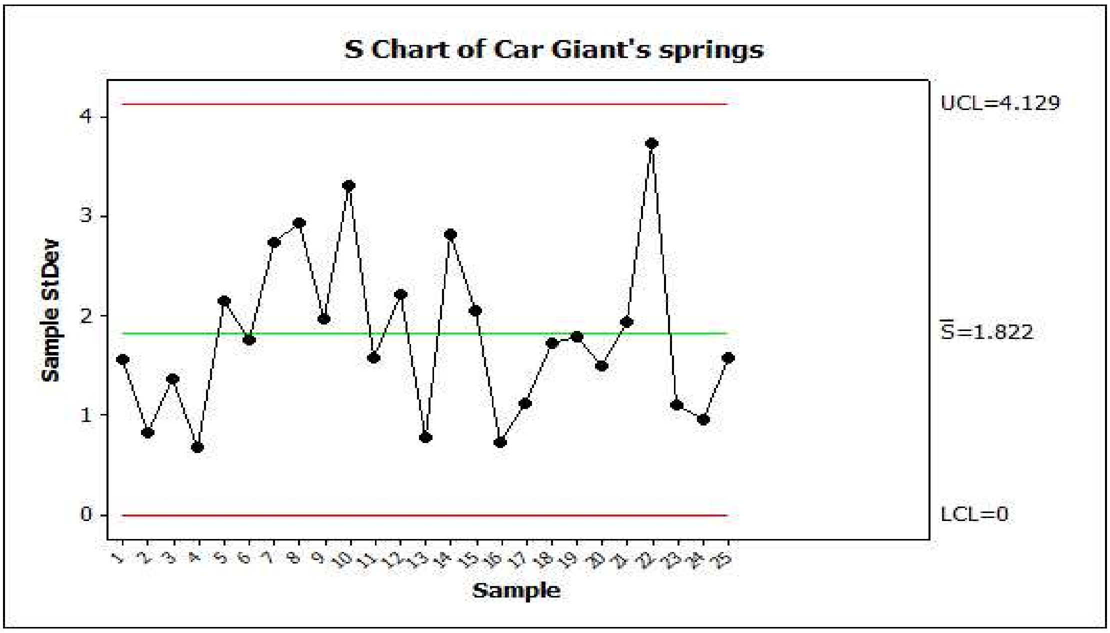

Figure 3.5: S–chart for *Car Giant* springs dataset, with updated results

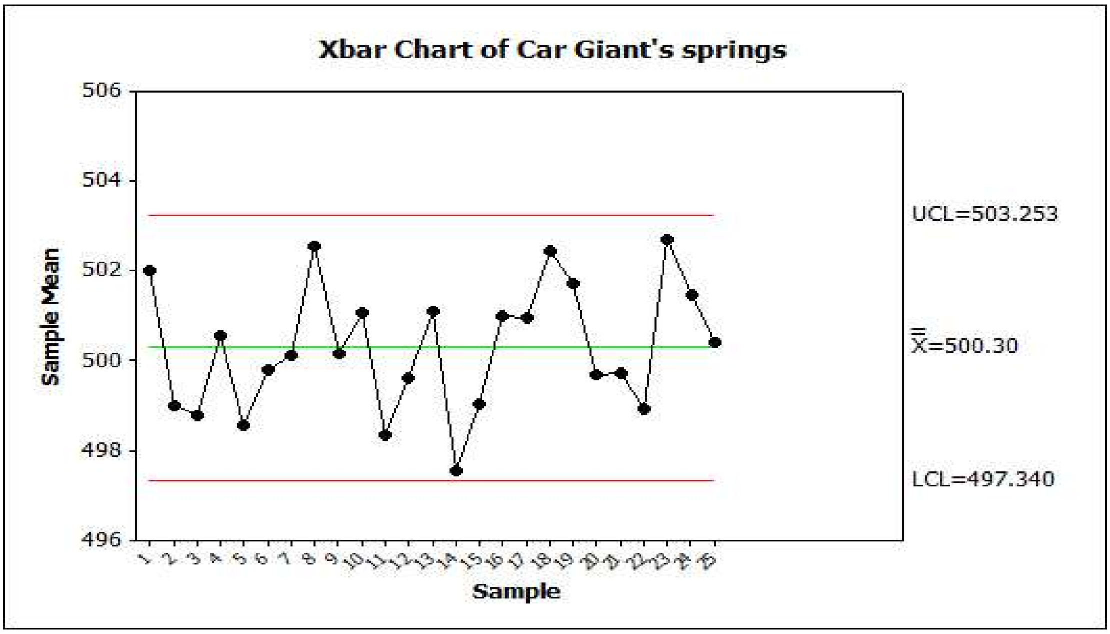

Figure 3.6: $\bar{x}$–chart for *Car Giant* springs dataset, with updated results

3. Comment.

3.4.4 Process Capability Index

The *Process Capability Index*, C_p, measures the theoretical or potential process capability, and we use statistics computed in the construction of the control chart to calculate this. Suppose that the operations manager of *Car Giant* determined that the springs will fit provided that their lengths fall between 493mm and 507mm. These are known as the *lower* and *upper specification limits* (*LSL* and *USL*), respectively. Recall that, in the *Car Giant* example, we had

$$\bar{\bar{x}} = 500.296 \qquad \text{and} \qquad S = 1.971.$$

We now define

$$CPL = \frac{\bar{\bar{x}} - LSL}{3S} = \frac{500.296 - 493}{3 \times 1.971} = 1.23$$

and

$$CPU = \frac{USL - \bar{\bar{x}}}{3S} = \frac{507 - 500.296}{3 \times 1.971} = 1.13.$$

We then define the process capability index C_p as

$$C_p = \text{Min}(CPL, CPU) = 1.13.$$

The higher the value of C_p, the better the production process meets specifications. By determining this value, operations managers can measure improvements in the production process.

3.5 Control charts for attributes

The quality characteristic of interest is not always a numerical measurement (e.g. mean or standard deviation). Sometimes, the product or service has, or does have, a particular feature or *attribute*. In particular, we are usually interested in whether it is satisfactory or defective. In this case the *proportion* of items in the sample that possess the attribute is recorded on the control chart instead of the sample mean or standard deviation. A control chart produced in this way is often called a p–chart.

Suppose that when the process is in control the proportion of items with the characteristic of interest is known and is p. The 3–sigma lower and upper control limits for a proportion are

$$\begin{aligned} \text{Lower control limit} &= p - 3\sqrt{\frac{p(1-p)}{n}} \\ \text{Upper control limit} &= p + 3\sqrt{\frac{p(1-p)}{n}} \end{aligned}$$

and the centreline is p itself. If the lower limit is negative, you should set it equal to zero. As was the case with $\bar{x}$–charts, we very rarely know the process characteristics. If

p is unknown, we estimate it from the data. In the above formulae, we replace p with $\bar{p}$, where

$$\bar{p} = \frac{\sum_{j=1}^{k} \hat{p}_j}{k},$$

where $\hat{p}_j$ is the sample proportion of items with the attribute of interest in sample j, and there are k samples in total.

Example
A company that produces USB memory sticks has been receiving complaints from its customers about the large number of devices that will not store data properly. Company management has decided to institute statistical process control to remedy the problem. Every hour, a random sample of 200 memory sticks is taken, and each is tested to determine whether it is defective. The number of defective memory sticks in the samples of size 200 for the first 40 hours is shown in table 3.3 below. Using these data, draw a p–chart to monitor the production process. Was the process out of control when the sample results were generated?

19	5	16	20	6	12	18	6	13	15
10	6	7	10	18	20	13	6	8	3
8	7	4	19	3	19	9	10	10	18
15	16	5	14	3	10	19	13	19	9

Table 3.3: Number of defective memory sticks in 40 consecutive samples of size 200

Outline solution
For each sample we compute the proportion of defective memory sticks, i.e. for sample 1:

$$\hat{p}_1 = \frac{19}{200} = 0.095.$$

Similarly, for sample 2:

$$\hat{p}_2 = \frac{5}{200} = 0.025.$$

We then find the mean of all these proportions ($\bar{p}$), which for the control chart gives

$$\text{Centreline} = \bar{p} = 0.05762.$$

The lower and upper control limits are then found as:

$$\begin{aligned}\text{Lower control limit} &= \bar{p} - 3\sqrt{\frac{\bar{p}(1-\bar{p})}{n}} \\ &= 0.05762 - 3 \times \sqrt{\frac{0.05762 \times 0.94238}{200}} \\ &= 0.008188 \qquad \text{and}\end{aligned}$$

$$\begin{aligned}
\text{Upper control limit} &= \bar{p} + 3\sqrt{\frac{\bar{p}(1-\bar{p})}{n}} \\
&= 0.05762 + 3 \times \sqrt{\frac{0.05762 \times 0.94238}{200}} \\
&= 0.1071.
\end{aligned}$$

We then produce a plot of the calculated proportions $\hat{p}_j$, along with the centreline and control limits, giving the plot shown in figure 3.7.

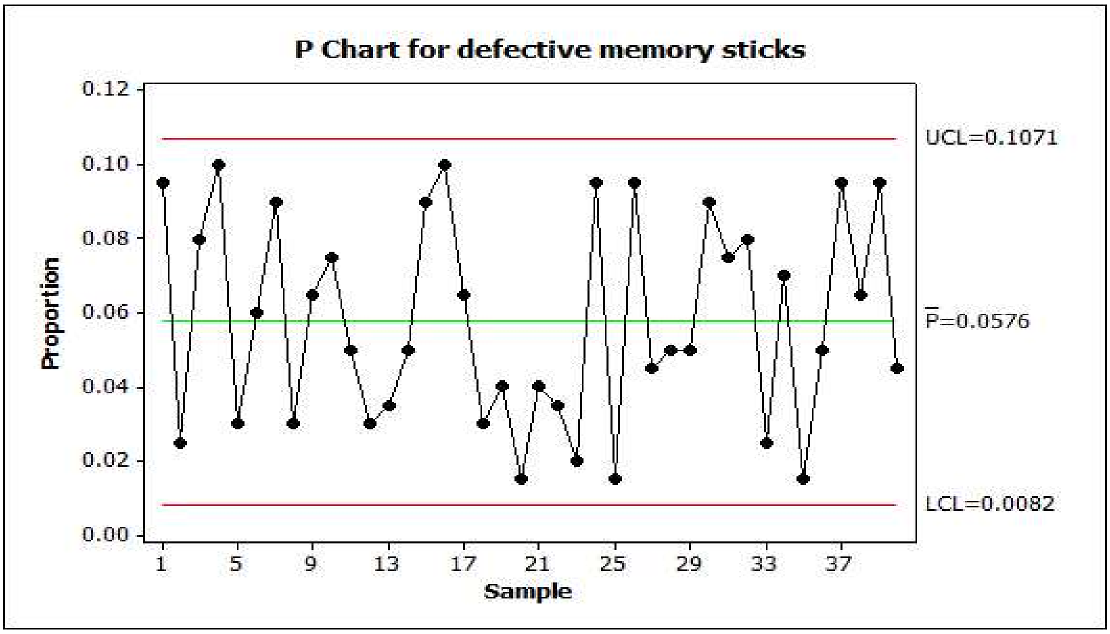

Figure 3.7: p–chart for the proportion of defective memory sticks

In `Minitab`, we would click on `Stat`–`Control Charts`–`Attributes Charts`–`P`; enter the column with the (stacked) data in in `Variables`, enter the `Subgroup sizes` (200 here), and then click `OK`.

Comments

Probability Tables for the Standard Normal Distribution

The table contains values of $P(Z < z)$, where $Z \sim N(0,1)$.

z	-0.09	-0.08	-0.07	-0.06	-0.05	-0.04	-0.03	-0.02	-0.01	0.00
-3.0	0.0000	0.0000	0.0001	0.0002	0.0002	0.0003	0.0005	0.0007	0.0010	0.0013
-2.9	0.0014	0.0014	0.0015	0.0015	0.0016	0.0016	0.0017	0.0018	0.0018	0.0019
-2.8	0.0019	0.0020	0.0021	0.0021	0.0022	0.0023	0.0023	0.0024	0.0025	0.0026
-2.7	0.0026	0.0027	0.0028	0.0029	0.0030	0.0031	0.0032	0.0033	0.0034	0.0035
-2.6	0.0036	0.0037	0.0038	0.0039	0.0040	0.0041	0.0043	0.0044	0.0045	0.0047
-2.5	0.0048	0.0049	0.0051	0.0052	0.0054	0.0055	0.0057	0.0059	0.0060	0.0062
-2.4	0.0064	0.0066	0.0068	0.0069	0.0071	0.0073	0.0075	0.0078	0.0080	0.0082
-2.3	0.0084	0.0087	0.0089	0.0091	0.0094	0.0096	0.0099	0.0102	0.0104	0.0107
-2.2	0.0110	0.0113	0.0116	0.0119	0.0122	0.0125	0.0129	0.0132	0.0136	0.0139
-2.1	0.0143	0.0146	0.0150	0.0154	0.0158	0.0162	0.0166	0.0170	0.0174	0.0179
-2.0	0.0183	0.0188	0.0192	0.0197	0.0202	0.0207	0.0212	0.0217	0.0222	0.0228
-1.9	0.0233	0.0239	0.0244	0.0250	0.0256	0.0262	0.0268	0.0274	0.0281	0.0287
-1.8	0.0294	0.0301	0.0307	0.0314	0.0322	0.0329	0.0336	0.0344	0.0351	0.0359
-1.7	0.0367	0.0375	0.0384	0.0392	0.0401	0.0409	0.0418	0.0427	0.0436	0.0446
-1.6	0.0455	0.0465	0.0475	0.0485	0.0495	0.0505	0.0516	0.0526	0.0537	0.0548
-1.5	0.0559	0.0571	0.0582	0.0594	0.0606	0.0618	0.0630	0.0643	0.0655	0.0668
-1.4	0.0681	0.0694	0.0708	0.0721	0.0735	0.0749	0.0764	0.0778	0.0793	0.0808
-1.3	0.0823	0.0838	0.0853	0.0869	0.0885	0.0901	0.0918	0.0934	0.0951	0.0968
-1.2	0.0985	0.1003	0.1020	0.1038	0.1056	0.1075	0.1093	0.1112	0.1131	0.1151
-1.1	0.1170	0.1190	0.1210	0.1230	0.1251	0.1271	0.1292	0.1314	0.1335	0.1357
-1.0	0.1379	0.1401	0.1423	0.1446	0.1469	0.1492	0.1515	0.1539	0.1562	0.1587
-0.9	0.1611	0.1635	0.1660	0.1685	0.1711	0.1736	0.1762	0.1788	0.1814	0.1841
-0.8	0.1867	0.1894	0.1922	0.1949	0.1977	0.2005	0.2033	0.2061	0.2090	0.2119
-0.7	0.2148	0.2177	0.2206	0.2236	0.2266	0.2296	0.2327	0.2358	0.2389	0.2420
-0.6	0.2451	0.2483	0.2514	0.2546	0.2578	0.2611	0.2643	0.2676	0.2709	0.2743
-0.5	0.2776	0.2810	0.2843	0.2877	0.2912	0.2946	0.2981	0.3015	0.3050	0.3085
-0.4	0.3121	0.3156	0.3192	0.3228	0.3264	0.3300	0.3336	0.3372	0.3409	0.3446
-0.3	0.3483	0.3520	0.3557	0.3594	0.3632	0.3669	0.3707	0.3745	0.3783	0.3821
-0.2	0.3859	0.3897	0.3936	0.3974	0.4013	0.4052	0.4090	0.4129	0.4168	0.4207
-0.1	0.4247	0.4286	0.4325	0.4364	0.4404	0.4443	0.4483	0.4522	0.4562	0.4602
0.0	0.4641	0.4681	0.4721	0.4761	0.4801	0.4840	0.4880	0.4920	0.4960	0.5000

z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0.0	0.5000	0.5040	0.5080	0.5120	0.5160	0.5199	0.5239	0.5279	0.5319	0.5359
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	0.5596	0.5636	0.5675	0.5714	0.5753
0.2	0.5793	0.5832	0.5871	0.5910	0.5948	0.5987	0.6026	0.6064	0.6103	0.6141
0.3	0.6179	0.6217	0.6255	0.6293	0.6331	0.6368	0.6406	0.6443	0.6480	0.6517
0.4	0.6554	0.6591	0.6628	0.6664	0.6700	0.6736	0.6772	0.6808	0.6844	0.6879
0.5	0.6915	0.6950	0.6985	0.7019	0.7054	0.7088	0.7123	0.7157	0.7190	0.7224
0.6	0.7257	0.7291	0.7324	0.7357	0.7389	0.7422	0.7454	0.7486	0.7517	0.7549
0.7	0.7580	0.7611	0.7642	0.7673	0.7704	0.7734	0.7764	0.7794	0.7823	0.7852
0.8	0.7881	0.7910	0.7939	0.7967	0.7995	0.8023	0.8051	0.8078	0.8106	0.8133
0.9	0.8159	0.8186	0.8212	0.8238	0.8264	0.8289	0.8315	0.8340	0.8365	0.8389
1.0	0.8413	0.8438	0.8461	0.8485	0.8508	0.8531	0.8554	0.8577	0.8599	0.8621
1.1	0.8643	0.8665	0.8686	0.8708	0.8729	0.8749	0.8770	0.8790	0.8810	0.8830
1.2	0.8849	0.8869	0.8888	0.8907	0.8925	0.8944	0.8962	0.8980	0.8997	0.9015
1.3	0.9032	0.9049	0.9066	0.9082	0.9099	0.9115	0.9131	0.9147	0.9162	0.9177
1.4	0.9192	0.9207	0.9222	0.9236	0.9251	0.9265	0.9279	0.9292	0.9306	0.9319
1.5	0.9332	0.9345	0.9357	0.9370	0.9382	0.9394	0.9406	0.9418	0.9429	0.9441
1.6	0.9452	0.9463	0.9474	0.9484	0.9495	0.9505	0.9515	0.9525	0.9535	0.9545
1.7	0.9554	0.9564	0.9573	0.9582	0.9591	0.9599	0.9608	0.9616	0.9625	0.9633
1.8	0.9641	0.9649	0.9656	0.9664	0.9671	0.9678	0.9686	0.9693	0.9699	0.9706
1.9	0.9713	0.9719	0.9726	0.9732	0.9738	0.9744	0.9750	0.9756	0.9761	0.9767
2.0	0.9772	0.9778	0.9783	0.9788	0.9793	0.9798	0.9803	0.9808	0.9812	0.9817
2.1	0.9821	0.9826	0.9830	0.9834	0.9838	0.9842	0.9846	0.9850	0.9854	0.9857
2.2	0.9861	0.9864	0.9868	0.9871	0.9875	0.9878	0.9881	0.9884	0.9887	0.9890
2.3	0.9893	0.9896	0.9898	0.9901	0.9904	0.9906	0.9909	0.9911	0.9913	0.9916
2.4	0.9918	0.9920	0.9922	0.9925	0.9927	0.9929	0.9931	0.9932	0.9934	0.9936
2.5	0.9938	0.9940	0.9941	0.9943	0.9945	0.9946	0.9948	0.9949	0.9951	0.9952
2.6	0.9953	0.9955	0.9956	0.9957	0.9959	0.9960	0.9961	0.9962	0.9963	0.9964
2.7	0.9965	0.9966	0.9967	0.9968	0.9969	0.9970	0.9971	0.9972	0.9973	0.9974
2.8	0.9974	0.9975	0.9976	0.9977	0.9977	0.9978	0.9979	0.9979	0.9980	0.9981
2.9	0.9981	0.9982	0.9982	0.9983	0.9984	0.9984	0.9985	0.9985	0.9986	0.9986
3.0	0.9987	0.9990	0.9993	0.9995	0.9997	0.9998	0.9998	0.9999	0.9999	0.9999