

Normal Distribution

- Normal distribution or Gaussian distribution is the most important one in all of probability and statistics.
- Many numerical populations have distributions that can be fit very closely by an appropriate normal curve.

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Normal Distribution

- o Heights, weights, and other physical characteristics,
- o Measurement errors in scientific experiments,
 - การวัดร่างกายมนุษย์ตามหลักวิทยาศาสตร์
- o Anthropometric measurements on fossils,
- o Reaction times in psychological experiments,
- o Measurements of intelligence and aptitude, scores on various tests, and
- o Numerous economic measures and indicators.

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Normal Distribution

Definition

Continuous random variable X is said to have **Normal distribution** with parameters μ and σ (or μ and σ^2), where $-\infty < x < \infty$ and $\sigma > 0$

, if the pdf of X is

$$f(x:\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

mathematical constant :3.14159

base of natural logarithm system and equals approximately 2.71828

- \circ Statement that X is normally distributed with parameters μ and σ^2 is often abbreviated $X \sim N(\mu, \sigma^2)$.
- Clearly $f(x; \mu, \sigma) \ge 0$, but a somewhat complicated calculus argument must be used to verify that $\int f(x:\mu,\sigma) = 1$.
- o It can be shown that $E(X) = \mu$ and $V(X) = \sigma^2$, so the parameters are mean and standard deviation of X.

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Normal Distribution

- o Each density curve is symmetric about μ and bell-shaped, so center of bell (point of symmetry) is both mean of distribution and median.
- \circ Value of σ is distance from μ to inflection points of curve (points at which curve changes from turning downward to turning upward).

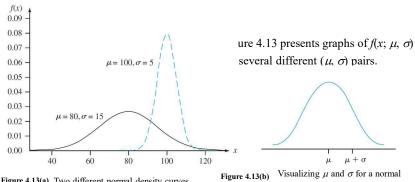


Figure 4.13(a) Two different normal density curves

distribution

Normal Distribution

- \circ Large values of σ yield graphs that are quite spread out about μ , whereas
- \circ Small values of σ yield graphs with a high peak above μ and most of the area under the graph quite close to μ .
- \circ Thus large σ implies that a value of X far from μ may well be observed, whereas such value is quite unlikely when σ is small.

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Standard Normal Distribution

Standard Normal Distribution

○ Computation of $P(a \le X \le b)$ when X is a normal rv with parameters μ and σ requires evaluating

$$P(a \le X \le b) = \int_{a}^{b} \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(x-\mu)^{2}}{2\sigma^{2}}} dx$$
 (4.4)

- o None of standard integration techniques can be used to accomplish this.
- \circ Instead, for $\mu = 0$ and $\sigma = 1$, Expression (4.4) has been calculated using numerical techniques and tabulated for certain values of a and b.
- \circ This table can also be used to compute probabilities for any other values of μ and σ under consideration.

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Standard Normal Distribution

Definition

o Normal distribution with parameter values

 $\mu = 0$ and $\sigma = 1$ is called **Standard normal distribution.**

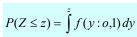
o Random variable having standard normal distribution is called

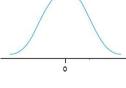
Standard normal random variable and will be denoted by Z.

 \circ The pdf of Z is

$$f(z:0,1) = \frac{1}{\sqrt{2\pi}}e^{\frac{-z^2}{2}}$$
 $-\infty < z < \infty$

- \circ Graph of f(z; 0, 1) is called *Standard normal* (or z)
- \circ Its inflection points are at 1 and -1.
- \circ The cdf of Z is



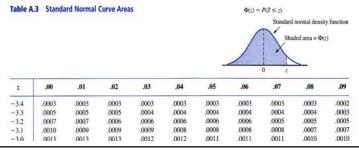


which we will denote by $\Phi(z)$

Standard Normal Distribution

- Standard normal distribution almost never serves as model for naturally arising population.
- o Instead, it is reference distribution from which information about other normal distributions can be obtained.
- Appendix Table A.3 gives $\Phi(z) = P(Z \le z)$, area under standard normal density curve to the left of z, for

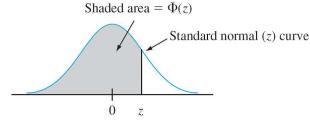
$$z = -3.49, -3.48, ..., 3.48, 3.49.$$



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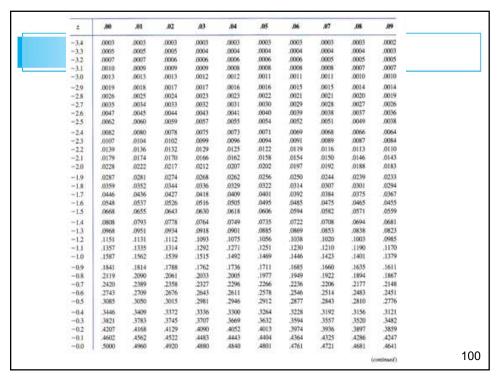
Standard Normal Distribution

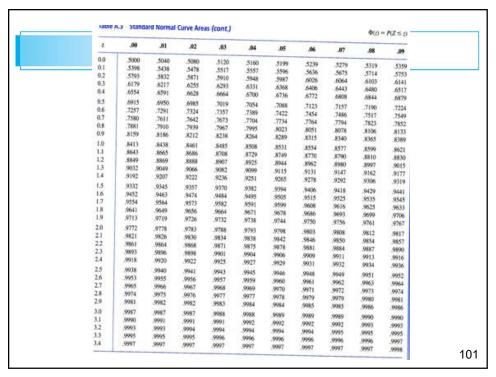
- Figure 4.14 illustrates type of cumulative area (probability) tabulated in Table A.3.
- \circ From this table, various other probabilities involving Z can be calculated.



Standard normal cumulative areas tabulated in Appendix Table A.3 Figure 4.14

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Example 4.13

Let's determine the following standard normal probabilities:

$$P(Z \le z) = \int_{-\infty}^{z} f(y:o,1) = \Phi(z)$$

- (a) $P(Z \le 1.25)$,
- (b) P(Z > 1.25),
- (c) $P(Z \le -1.25)$, and
- (d) $P(-0.38 \le Z \le 1.25)$.

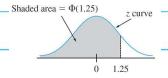
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Example 4.13

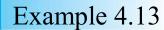
a. $P(Z \le 1.25) = \Phi(1.25)$,

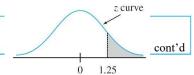


probability that is tabulated in Appendix Table A.3 at the intersection of the row marked 1.2 and the column marked 0.05.

The number there is 0.8944, so $P(Z \le 1.25) = 0.8944$.

z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	5210	-
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5319	.5359
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.5714	.5753
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406		.6103	.6141
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6443	.6480	.6517
0.5	.6915	.6950	.6985	.7019	.7054			62000	.6844	.6879
0.6	.7257	.7291	.7324	.7357	.7389	.7088	.7123	.7157	.7190	.7224
).7	.7580	.7611	.7642	.7673		.7422	.7454	.7486	.7517	.7549
0.8	.7881	.7910	.7939	.7967	.7704	.7734	.7764	.7794	.7823	.7852
).9	.8159	.8186	.8212	2000,000	.7995	.8023	.8051	.8078	.8106	.8133
				.8238	.8264	.8289	.8315	.8340	.8365	.8389
.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	
.3	.9032	.9049	.9066	.9082	9099	9115	0121	0147	.8997	.9015





b.
$$P(Z > 1.25) = 1 - P(Z \le 1.25) = 1 - \Phi (1.25)$$
,

area under the z curve to the right of 1.25 (an upper-tail area).

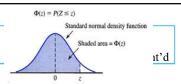
Then $\Phi(1.25) = 0.8944$ implies that

$$P(Z > 1.25) = 0.1056.$$

Table /	A.3 Standa	ard Normal	Curve Area	s (cont.)					$\Phi(z) =$	$P(Z \le z)$
z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	5310	2000 E
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636		.5319	.5359
).2	-5793	.5832	.5871	.5910	.5948	.5987	.6026	.5675	.5714	.5753
0.3	.6179	.6217	.6255	.6293	.6331	.6368		.6064	.6103	.6141
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6406	.6443	.6480	.6517
0.5	.6915	.6950					.6772	.6808	.6844	.6879
0.6	.7257		.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
		.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
).7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
).9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
0.1	.8413	.8438	.8461	.8485	.8508	.8531				
1.1	.8643	.8665	.8686	.8708			.8554	.8577	.8599	.8621
.2	.8849	.8869	.8888		.8729	.8749	.8770	.8790	.8810	.8830
1.3	.9032			.8907	.8925	.8944	.8962	.8980	.8997	.9015
-2	.9032	.9049	.9066	.9082	.9099	9115	0121	0142	01/0	

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Example 4.13



c. $P(Z \le -1.25) = \Phi(-1.25)$, a lower-tail area. Directly from Appendix Table A.3, $\Phi(-1.25) = 0.1056$.

z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
-1.2	.1151	.1131	.1112	.1093	.1075	.1056	.1038	.1020	.1003	.0985
-1.1	.1357	.1335	.1314	.1292	.1271	.1251	.1230	.1210	.1190	.1170
-1.0	.1587	.1562	.1539	.1515	.1492	.1469	.1446	.1423	.1401	.1379
-0.9	.1841	.1814	.1788	.1762	.1736	.1711	.1685	.1660	.1635	.1611
-0.8	.2119	.2090	.2061	.2033	.2005	.1977	.1949	.1922	.1894	.1867

$$P(Z \le -1.25) = 0.1056$$

By symmetry of the z curve, this is the same answer as in part (b).

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Example 4.13

cont'd

d. $P(-0.38 \le Z \le 1.25)$ is area under the standard normal curve above the interval whose left endpoint is -0.38 and whose right endpoint is 1.25.

-.38 0 1.25

From Section 4.2, if X is a continuous rv with cdf F(x), then

$$P(a \le X \le b) = F(b) - F(a)$$

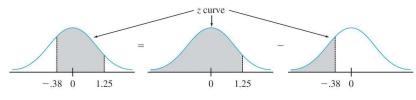


Figure 4.16 $P(-0.38 \le Z \le 1.25)$ as the difference between two cumulative areas

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Examp	le	4.	1	3

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$$P(-0.38 \le Z \le 1.25) = P(Z \le 1.25) - P(Z \le -0.38)$$
$$= \Phi(1.25) - \Phi(-0.38)$$
$$= 0.8944 - 0.3520$$
$$= 0.5424$$

z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	5160	5100	.5220	.6240	.630,5	
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554		constant,	.038
1.1	.8643	.8665	.8686	.8708	.8729	8749		.8577	.8599	.862
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8770	.8790	.8810	.8830
1.3	.9032	.9049	.9066	.9082		· · · ·	.8962	.8980	.8997	.901:
	13002	,,,,,,	.9000	.9082	.9099	.9115	.9131	9147	0162	0177

85	.3050	.3015	.2981	.2946	2012	2077	440.00	060000000	10000000000
		10010	.4701	.2940	.2912	.2877	.2843	.2810	.2776
46	.3409	.3372	.3336	.3300	.3264	.3228	.3192	3156	.3121
21	.3783	.3745	.3707	.3669	.3632	.3594	.3557	.3520	.3482
07	.4168	.4129	.4090	.4052	.4013	.3974	.3936	.3897	.3859
2	1	.1 .3783 7 .4168	.3783 .3745 .4168 .4129	.11 .3783 .3745 .3707 17 .4168 .4129 .4090	.11 .3783 .3745 .3707 .3669 .77 .4168 .4129 .4090 .4052	.11 .3783 .3745 .3707 .3669 .3632 .77 .4168 .4129 .4090 .4052 .4013	.11 .3783 .3745 .3707 .3669 .3632 .3594 .17 .4168 .4129 .4090 .4052 .4013 .3974	11 .3783 .3745 .3707 .3669 .3632 .3594 .3557 17 .4168 .4129 .4090 .4052 .4013 .3974 .3936	11 .3783 .3745 .3707 .3669 .3632 .3594 .3557 (3520) 17 .4168 .4129 .4090 .4052 .4013 .3974 .3936 .3897

Percentiles of Standard Normal Distribution

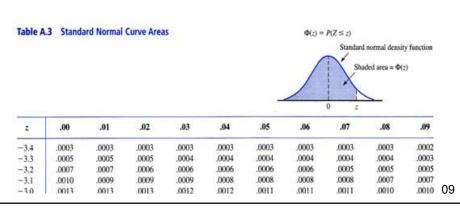
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Percentiles of the Standard Normal Distribution

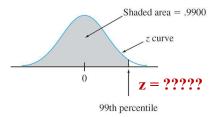
For any p between 0 and 1,

Appendix Table A.3 can be used to obtain the $(100p)^{th}$ percentile of standard normal distribution.



Example 4.14

The 99th percentile of standard normal distribution is that value on the horizontal axis such that the area under the z curve to the left of the value is 0.9900.



Appendix Table A.3 gives for fixed z the area under the standard normal curve to the left of z,

whereas here we have the area and want the value of z.

This is the "inverse" problem to $P(Z \le z) = ?$

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Example 4.14

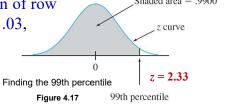
so the table is used in an inverse fashion:

- o Find in the middle of the table 0.9900;
- o Row and column in which it lies identify the 99th z percentile.

	.08	.07	.06	.05	.04	.03	.02	.01	.00	z
.98	.9854	.9850	.9840	.7044	.,رن			0064	.9861	2.2
.98	.9887	.9884	.9881	.9878	.9875	.9871	.9868	.9864	.9801	2.3
.99	.9913	.9911	.9909	.9906	.9904	.9901	.9898	.7070	.9918	2.4
.99	.9934	.9932	.9931	.9929	.9927	.9925	.9922	.9920		
	0051	0040	0048	9946	.9945	.9943	.9941	.9940	.9938	5

marked 2.3 and column marked .03,

o so the 99th percentile is (approximately) z = 2.33.



Example 4.14

cont'd

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 \circ By symmetry, the first percentile is as far below 0 as the 99th is above 0, so equals -2.33 (1% lies below the first and also above the 99th).

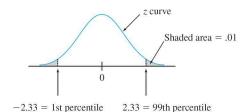


Figure 4.18 The relationship between the 1st and 99th percentiles

z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
-2.4 -2.3 ← -2.2	.0082 .0107 .0139	.0080 .0104 .0136	.0078 .0102 .0132	.0075 .0099 .0129	.0073 .0096 .0125	.0071 .0094 .0122	.0069 .0091 .0119	.0068 .0089 .0116	.0066 .0087 .0113	.0064 .0084 .0110
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Percentiles of Standard Normal Distribution

o In general, the $(100p)^{th}$ percentile is identified by the row and column of Appendix Table A.3 in which entry \underline{p} is found

o (e.g., the 67th percentile is obtained by finding 0.6700 in body of table, which gives z = 0.44).

	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
	.5793	.5832	.5871	5010	,	00ردر.	.2020	.36/3	.5714	.575
	.6179	.6217	.6255	.5910 .6293	.59 <mark>4</mark> 8 .6331	.5987	.6026	.6064	.6103	.61
\leftarrow	.6554	.6591	.6628	.6664	.6700	.6368 .6736	.6406 .6772	.6443 .6808	.6480	.65
	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.6844	.68
	.7257	.7291	.7324	.7357	.7389	7422	7454	7106	.7190	.722

Percentiles of Standard Normal Distribution

o If *p* does not appear, the number closest to it is often used, although linear interpolation gives a more accurate answer.

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Percentiles of Standard Normal Distribution

For example, to find the 95th percentile, we look for 0.9500 inside the table representation.

									$\Psi(z) = P(Z \le z)$		
z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09	
1.4	.9192	.9207	.9222	.9236	.9099 .92 5 1	.9 <mark>115</mark> .9265	.9131 .9278	.9147 .9292	.9162 .9306	.9177 .9319	
1.5 1.6	.9332 .9452	.9345	.9357 .9474	.9370 .9484	.9382	9394	.9406	.9418	.9429	.9319	
1.7 1.8	.9554 .9641	.9564	.9573	.9582	.9591	.9505 .9599	.9515 .9608	.9525 .9616	.9535 .9625	.9545 .9633	
1.9	.9713	.9719	.9656 .9726	.9664 .9732	.9671 .9738	.9678 .9744	.9686 .9750	.9693 .9756	.9699 .9761	.9706 .9767	
20	0772	0770	0700							.2707	

Although 0.9500 does not appear, both 0.9495 and 0.9505 do, corresponding to z = 1.64 and 1.65, respectively.

Since 0.9500 is halfway between the two probabilities that do appear, we will use **1.645** as the 95th percentile and -1.645 as the 5th percentile.

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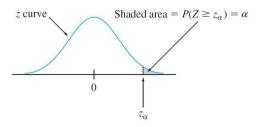
 z_{α} Notation for z Critical Values

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z_{α} Notation for z Critical Values

 \circ In statistical inference, we will need values on horizontal z axis that capture certain small tail areas under standard normal curve.



Notation

 z_{α} will denote value on the z axis for which α of area under z curve lies to the right of z_{α} .

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z_{α} Notation for z Critical Values

For example, $z_{0.10}$ captures upper-tail area 0.10,

Since α of area under the z curve lies to the right of z_{α} . $1 - \alpha$ of the area lies to its left. Thus z_{α} is the $100(1 - \alpha)^{th}$ percentile of standard normal distribution.

By symmetry the area under the standard normal curve to the left of $-z_{\alpha}$ is also α .

The z_{α} 's are usually referred to as z critical values.

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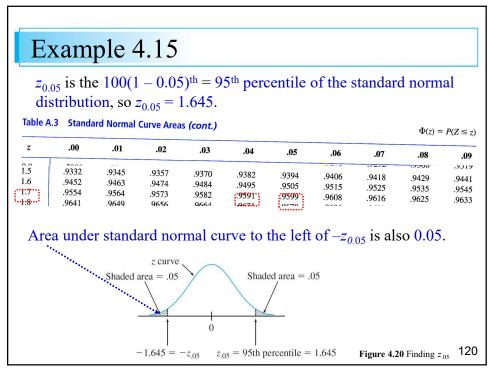
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z_{α} Notation for z Critical Values Table 4.1 lists the most useful z percentiles and z_{α} values. **Percentile** 90 95 97.5 99.5 99.9 99.95 0.05 0.025 0.01 0.005 0.001 0.0005 α (tail area) 0.1 1.96 2.33 2.58 3.08 $z_{\alpha} = 100(1-\alpha)^{\text{th}}$ percentile 1.285 1.645 3.27 Table A.3 Standard Normal Curve Areas (cont.) $\Phi(z) = P(Z \leq z)$.02 .06 .07 .8708 .8729 .8749 .8770 .8790 .8810 8830 .8849 .8869 .8888 .8925 .8944 .8962 .8980 .9015 .9032 .9049 9066 .9082 .9115 .9131 .9147 .9162 .9177 .9192 9303 .9337 .93% 9382 0304 .9406 .9429 .9441 .9452 9463 9474 .9495 .9505 .9515 .9535 .9545 .9564 .9573 .9582 .9608 .9616 .9625 .9633 .9649 .9656 .9664 .9686 .9693 9699 .9706 .9713 .9719 .9726 .9732 .9738 .9744 .9750 .9756 .9761 .9767 986 .9864 .9868 .9871 .9875 .9878 .9881 .9884 .9887 .9890 .9893 9896 .9898 .9901 .9904 .9906 .9909 .9913 .9916 .9918 .9920 .9922 .9929 .9931 9932 9934 .9936 .9938 .9940 .9941 .9943 .9945 .၁၁၀+ .9946 .9949 .9985 .9951 9986 .9987 9987 .9987 .9988 .9989 .9989 .9989 .9990 .9991 .9991 .9991 .9992 .9992 9992 .9993 .9995

.9994

.9995

.9994



Nonstandard Normal Distributions

Nonstandard Normal Distributions

- When $X \sim N(\mu, \sigma^2)$, probabilities involving X are computed by "standardizing."
- o Standardized variable is $(X \mu)/\sigma$.
- \circ Subtracting μ shifts mean from μ to zero, and then dividing by σ scales the variable so that standard deviation is 1 rather than σ .

Proposition

If X has Normal distribution with mean μ and standard deviation σ , then

$$Z = \frac{X - \mu}{\sigma}$$

has a standard normal distribution. Thus

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Nonstandard Normal Distributions

Thus

$$P(a \le X \le b) = P\left(\frac{a - \mu}{\sigma} \le Z \le \frac{b - \mu}{\sigma}\right)$$
$$= \Phi\left(\frac{b - \mu}{\sigma}\right) - \Phi\left(\frac{a - \mu}{\sigma}\right)$$

$$P(X \le a) = \Phi\left(\frac{a - \mu}{\sigma}\right)$$

$$P(X \ge b) = 1 - \Phi\left(\frac{b - \mu}{\sigma}\right)$$

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Nonstandard Normal Distributions

 \circ Key idea of proposition is that by standardizing, any probability involving X can be expressed as a probability involving a standard normal random variable Z, so that Appendix Table A.3 can be used.

This is illustrated in Figure 4.21.

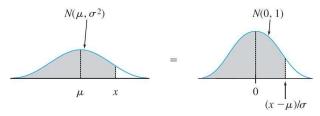


Figure 4.21: Equality of nonstandard and standard normal curve areas

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Example 4.16





o The time that it takes a driver to react to the brake lights on a decelerating vehicle is critical in helping to avoid rear-end collisions.



• The article "Fast-Rise Brake Lamp as a Collision-Prevention Device" (*Ergonomics*, 1993: 391–395) suggests that reaction time for an in-traffic response to a brake signal from standard brake lights can be modeled with a normal distribution having mean value 1.25 sec and standard deviation of 0.46 sec.

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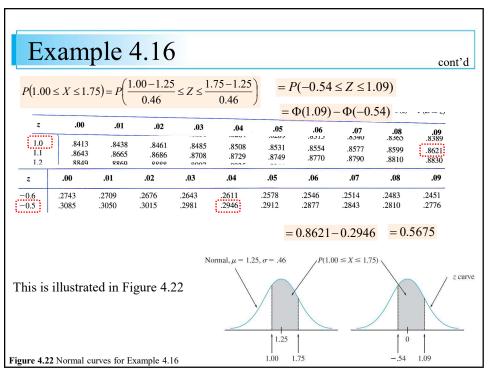
Example 4.16

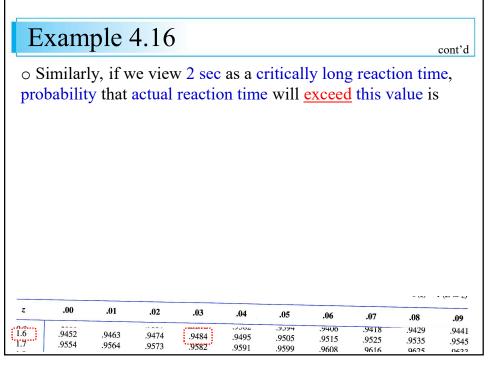
cont'd

- o What is the probability that reaction time is between 1.00 sec and 1.75 sec?
- \circ If we let X denote reaction time, then standardizing gives

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Percentiles of Arbitrary Normal Distribution

Percentiles of Arbitrary Normal Distribution

o The $(100p)^{\text{th}}$ percentile of normal distribution with mean μ and standard deviation σ is easily related to the $(100p)^{\text{th}}$ percentile of standard normal distribution.

Proposition

$$\frac{(100p)\text{th percentile}}{\text{for normal } (\mu, \sigma)} = \mu + \begin{bmatrix} (100p)\text{th for } \\ \text{standard normal} \end{bmatrix} \cdot \sigma$$

o Another way of saying this is that if z is desired percentile for standard normal distribution, then desired percentile for normal (μ, σ) distribution is z standard deviations from μ .

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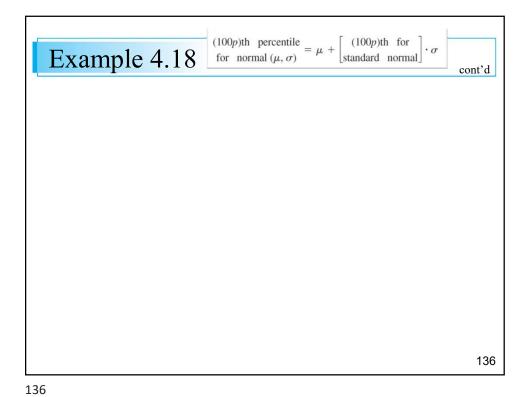
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Example 4.18



- The amount of distilled water dispensed by a certain machine is normally distributed with mean value 64 oz and standard deviation 0.78 oz.
- \circ What container size c will ensure that overflow occurs only 0.5% of the time?
- o If X denotes the amount dispensed, the desired condition is that P(X > c) = 0.005, or, equivalently, that $P(X \le c) = 0.995$.
- Thus c is the 99.5th percentile of normal distribution with $\mu = 64$ and $\sigma = 0.78$.

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Example 4.18 cont'd .03 .07 .09 .9930 .9938 .9953 .9940 .9946 .9960 .9945 .9948 .9949 .9951 .9952 .9961 .9964 The 99.5th percentile of the standard normal distribution is 2.58, so Shaded area = .995 $\mu = 64$ c = 99.5th percentile = 66.0

This is illustrated in Figure 4.23.

Figure 4.23 Distribution of amount dispensed for Example 18

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Normal Distribution and Discrete Populations

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Normal Distribution and Discrete Populations

- Normal distribution is often used as an approximation to the distribution of values in discrete population.
- o In such situations, extra care should be taken to ensure that probabilities are computed in an accurate manner.

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ระดับ ไลลิว ร้อยละ อัจฉริยะ >144 0.13 Example 4.19 ปัญญาเลิศ 130-144 2.14 เหนือค่าเฉลี่ 115-129 13.59 สงกว่าค่าเฉลี่ 100-114 34.13 ค่อมข้างตำ 34.13 ค่ากว่าค่าเฉลี่ย 13.59 o Intelligence Quotient (IQ) in a particular คาบเส้น 55-69 2.14

population (as measured by a standard test) is

known to be approximately normally distributed with $\mu = 100$ and $\sigma = 15$.

- What is the probability that a randomly selected individual has an **IQ** of at least 125?
- \circ Letting X = the IQ of a randomly chosen person, we wish

$$P(X \ge 125)$$
.

- The temptation here is to standardize $X \ge 125$ as in previous examples.
- o However, the IQ population distribution is actually discrete, since IQs are integer-valued.

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Example 4.19

cont'd

 So the normal curve is an approximation to a discrete probability histogram, as pictured in Figure 4.24.

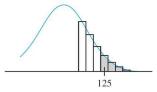
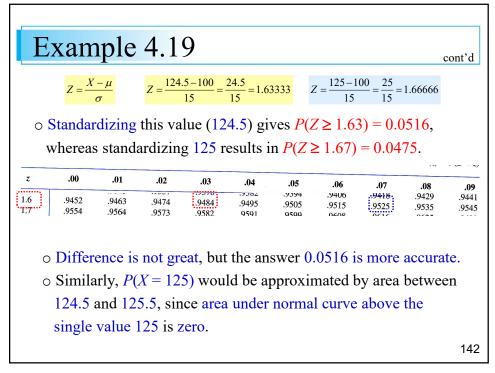


Figure 4.24 Normal approximation to a discrete distribution

- Rectangles of histogram are *centered* at integers,
 so IQs of at least 125 correspond to rectangles beginning at 124.5,
 as shaded in Figure 4.24.
- o Thus we really want the area under the approximating normal curve to the right of 124.5.

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Example 4.19

cont'd

- o Correction for discreteness of the underlying distribution in Example 19 is often called a **continuity correction.**
- o It is useful in the following application of normal distribution to the computation of binomial probabilities.

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Approximating Binomial Distribution

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Approximating Binomial Distribution

• Recall that mean value and standard deviation of binomial random variable *X* are

$$\mu_X = np$$

$$\sigma_X = \sqrt{npq}$$

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Approximating Binomial Distribution

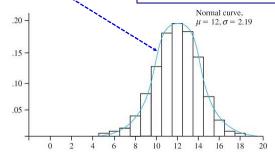
Figure 4.25 displays a binomial probability histogram for binomial distribution with n = 20, p = 0.6, for which

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Approximating Binomial Distribution

Normal curve with this μ and σ has been superimposed on probability histogram.

Although probability histogram is a bit skewed (because $p \neq 0.5$), normal curve gives a very good approximation, especially in the middle part of picture.



Area of any rectangle (probability of any particular *X* value) except those in the extreme tails can be accurately approximated by the corresponding normal curve area.

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For example, P(X = 10) = B(10; 20, 0.6) - B(9; 20, 0.6)= 0.245 - 0.128 = 0.117,

n=20		0.01	0.05	0.10	0.20	0.25	0.30	0.40	0.50	0.60	0.70	0.75	0.80	0.90	0.95	0.99
	9	1.000	1.000	1.000	.997	.986	.952	.755	.412	.128	.017	.004	.001	.000	.000	.000
A	10	1.000	1.000	1.000	.999	.996	.983	.872	.588	.245	.048	.014	.003	.000	.000	.000
	11	1.000	1.000	1.000	1.000	999	995	943	748	404	113	041	010	Ω	000	000

whereas area under the normal curve between 9.5 and 10.5 is

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Approximating Binomial Distribution

o More generally, as long as binomial probability histogram is not too skewed, binomial probabilities can be well approximated by normal curve areas.

 \circ It is then customary to say that X has approximately a normal distribution.

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Approximating Binomial Distribution

Proposition

- Let X be binomial random variable based on n trials with success probability p.
- Then if binomial probability histogram is not too skewed, X has approximately normal distribution with $\mu = np$ and $\sigma = \sqrt{npq}$

In particular, for x = possible value of X,

$$P(X \le x) = B(x, n, p) \approx \begin{pmatrix} area & under & normal & curve \\ to & the & left & of & x + 0.5 \end{pmatrix} = \Phi\left(\frac{x + 0.5 - np}{\sqrt{npq}}\right)$$

○ In practice, approximation is adequate provided that both $np \ge 10$ and $nq \ge 10$, since there is enough symmetry in underlying binomial distribution.

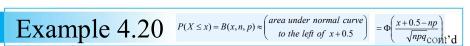
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Example 4.20

- Suppose that 25% of all students at a large public university receive financial aid.
- Let X be the number of students in a random sample of size 50 who receive financial aid, so that p = 0.25.

Then $\mu = 12.5$ and $\sigma = 3.06$.

○ Since $np = 50(0.25) = 12.5 \ge 10$ and $nq = 50(0.75) = 37.5 \ge 10$, the approximation can safely be applied.



o Probability that at most 10 students receive aid is

 Similarly, probability that between 5 and 15 (inclusive) of selected students receive aid is

$$P(5 \le X \le 15) = B(15;50,0.25) - B(4;50,0.25)$$

$$\approx \Phi\left(\frac{15.5 - 12.5}{3.06}\right) - \Phi\left(\frac{4.5 - 12.5}{3.06}\right) = \Phi(0.98) - \Phi(-2.61) = 0.8320$$

o Exact probabilities are 0.2622 and 0.8348, respectively, so approximations are quite good.

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Exponential Distribution

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Exponential Distributions

The family of exponential distributions provides probability models that are very widely used in engineering and science disciplines.

ตัวอย่างเช่น

- ปัญหาในระบบแถวคอย เวลาในการให้บริการและช่วงห่างระหว่างการเข้ามารับบริการของลูกค้า
- ความน่าจะเป็นที่ผลิตภัณฑ์ยังคงทำงานได้
- ความน่าจะเป็นที่ผลิตภัณฑ์จะเกิดการพังของอุปกรณ์หรือเครื่องจักรก่อนช่วงเวลาที่กำหนด
- อายุการใช้งานของอุปกรณ์

Definition

X is said to have an **exponential distribution** with parameter λ ($\lambda > 0$) if the pdf of X is

$$f(x;\lambda) = \begin{cases} \lambda e^{-\lambda x} & x \ge 0\\ 0 & otherwise \end{cases}$$
 (4.5)

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Exponential Distributions

- ο Some sources write the exponential pdf in the form $(1/\beta)e^{-x/\beta}$, so that $\beta = 1/\lambda$.
- \circ Expected value of an exponentially distributed random variable X is

$$E(X) = \int_0^\infty x \lambda e^{-\lambda x} \, dx$$

o Obtaining this expected value necessitates doing an integration by parts.

The variance of X can be computed using the fact that

$$V(X) = E(X^2) - [E(X)]^2.$$

 \circ The determination of $E(X^2)$ requires integrating by parts twice in succession.

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3/16/2021

Exponential Distributions

The results of these integrations are as follows:

$$\mu = \frac{1}{\lambda}$$
 $\sigma^2 = \frac{1}{\lambda^2}$

Both the mean and standard deviation of the exponential distribution equal $1/\lambda$.

Graphs of several exponential pdf's are illustrated in Figure 4.26.

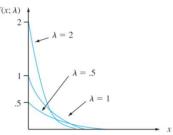


Figure 4.26 Exponential density curves

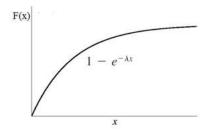
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Exponential Distributions

The exponential pdf is easily integrated to obtain the cdf.

$$F(x; \lambda) = \begin{cases} 0 & x < 0 \\ 1 - e^{-\lambda x} & x \ge 0 \end{cases}$$



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Example 4.21

MPa: MegaPascals

The article "Probabilistic Fatigue Evaluation of Riveted Railway Bridges" (*J. of Bridge Engr.*, 2008: 237–244) suggested the exponential distribution with mean value 6 MPa as a model for the distribution of stress range in certain bridge connections.

Let's assume that this is in fact the true model. Then



 $E(X) = 1/\lambda = 6$ implies that $\lambda = 0.1667$.

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Example 4.21

cont'd

The probability that stress range is at most 10 MPa is

$$P(X \le 10) = F(10; 0.1667)$$

$$= 1 - e^{-(0.1667)(10)}$$

$$F(x; \lambda) = \begin{cases} 0 & x < 0 \\ 1 - e^{-\lambda x} & x \ge 0 \end{cases}$$

$$= 1 - 0.189$$

$$= 0.811$$

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Example 4.21
$$F(x; \lambda) = \begin{cases} 0 & x < 0 \\ 1 - e^{-\lambda x} & x \ge 0 \end{cases}$$

cont'd

The probability that stress range is between 5 and 10 MPa is

$$P(5 \le X \le 10) = F(10; 0.1667) - F(5; 0.1667)$$

$$= (1 - e^{-0.1667(10)}) - (1 - e^{-0.1667(5)})$$

$$= (1 - e^{-1.667}) - (1 - e^{-0.8335})$$

$$= 0.246$$

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Exponential Distributions

- o Exponential distribution is frequently used as a model for distribution of times between occurrence of successive events, such as
 - customers arriving at a service facility or
 - calls coming in to a switchboard.

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Exponential Distributions

Proposition

- o Suppose that the number of events occurring in any time interval of length t has a Poisson distribution with parameter αt (where α , rate of event process, is expected number of events occurring in 1 unit of time) and that numbers of occurrences in nonoverlapping intervals are independent of one another.
- Then distribution of elapsed time between occurrence of two successive events is exponential with parameter $\lambda = \alpha$.

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Exponential Distributions

$$p(x;\lambda) = \frac{e^{-\lambda}\lambda^x}{x!}$$

Although a complete proof is beyond the scope of the text, the result is easily verified for the time X_1 until the first event occurs:

$$P(X_1 \le t) = 1 - P(X_1 > t) = 1 - P$$
 [no events in $(0, t)$]

$$= 1 - \frac{e^{-\alpha t} \cdot (\alpha t)^0}{0!} = 1 - e^{-\alpha t}$$

which is exactly the cdf of the exponential distribution.

$$F(x; \lambda) = \begin{cases} 0 & x < 0 \\ 1 - e^{-\lambda x} & x \ge 0 \end{cases}$$

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Example 4.22

- \circ Suppose that calls are received at a 24-hour "suicide hotline" according to a Poisson process with rate $\alpha = 0.5$ call per day.
- \circ Then the number of days X between successive calls has an exponential distribution with parameter value 0.5, so the probability that more than 2 days elapse between calls is

$$P(X>2) = 1 - P(X \le 2)$$

$$= 1 - F(2; 0.5)$$

$$= e^{-(0.5)(2)}$$

$$= 0.368$$

$$F(x; \lambda) = \begin{cases} 0 & x < 0 \\ 1 - e^{-\lambda x} & x \ge 0 \end{cases}$$

The expected time between successive calls is 1/0.5 = 2 days.

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Exponential Distributions

Another important application of the exponential distribution is to model the distribution of component lifetime.

A partial reason for the popularity of such applications is the "memoryless" property of the exponential distribution.

Suppose component lifetime is exponentially distributed with parameter λ .

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Exponential Distributions

After putting the component into service, we leave for a period of t_0 hours and then return to find the component still working; what now is the probability that it lasts at least an additional t hours?

In symbols, we wish $P(X \ge t + t_0 \mid X \ge t_0)$.

By the definition of conditional probability,

$$P(X \ge t + t_0 | X \ge t_0) = \frac{P[(X \ge t + t_0) \cap (X \ge t_0)]}{P(X \ge t_0)}$$

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Exponential Distributions $F(x; \lambda) = \begin{cases} 0 & x < 0 \\ 1 - e^{-\lambda x} & x \ge 0 \end{cases}$

But the event $X \ge t_0$ in the numerator is redundant, since both events can occur if $X \ge t + t_0$ and only if. Therefore,

$$P(X \ge t + t_0 | X \ge t_0) = \frac{P(X \ge t + t_0)}{P(X \ge t_0)} = \frac{1 - F(t + t_0; \lambda)}{1 - F(t_0; \lambda)} = e^{-\lambda t}$$

This conditional probability is identical to the original probability $P(X \ge t)$ that the component lasted t hours.

o Thus distribution of additional lifetime is exactly the same as the original distribution of lifetime, so at each point in time the component shows no effect of wear.

o In other words, the distribution of remaining lifetime is independent of current age.

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