# **Chapter 1: A Review of Basic Concepts A**

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## **A Review of Basic Concepts**

## **Describing Quantitative Data Numerically**

The mean of a sample of *n* measurements  $y_1, \ldots, y_n$  is

$$\overline{y} = \frac{1}{n} \sum_{i=1}^{n} y_i$$

The mean of a population is  $E(y)=\mu$ .

The variance of a sample of *n* measurements  $y_1, \ldots, y_n$  is

$$s^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (y_{i} - \overline{y})^{2}$$

The mean of a population is  $E[(y-\mu)^2] = \sigma^2$ .

The sample standard deviation is s and the population standard deviation is  $\sigma$ .

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## **A Review of Basic Concepts**

## **The Normal Probability Distribution**







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### **The Normal Probability Distribution**







## **A Review of Basic Concepts**

## **The Normal Probability Distribution**

Areas of continuous functions are found with Calculus.

$$A = \int_{a}^{b} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^{2}} dy = P(a < y < b)$$
$$f(y)$$



But we can't integrate the normal distribution. So, we transform to standard normal.

$$z = \frac{y - \mu}{\sigma}$$
  
And look up the areas in a table.





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### The Normal Probability Distribution Convert *a* and *b* to $z_1$ and $z_2$ .

$$z_1 = \frac{a - \mu}{\sigma}$$
$$z_2 = \frac{b - \mu}{\sigma}$$

Look up area between  $z_1$  and 0 as 0 to  $z_1$ .

Look up area between 0 and  $z_2$ .

Add together.







## **A Review of Basic Concepts**



			$\frown$			R Coc	le				
				<b>\</b>		df <	4		mean	<- 0	
				$\backslash$		pval <	<- 0.975		sd <-	1	
						qt(pv	al, df = 0	df,	y <- 1	.96	
				$\rightarrow$ lower.tail = FALS			ALSE)	1-pnorm(y, mu, sd)			
	7	00	01	- 02	03	04	05	06	07		09
	<i>4</i> .	.00	.01	.02	.05	.04	.05	.00	.07	.00	.07
	0	.0000	.0040	.0080	.0120	.0160	.0199	.0239	.0279	.0319	.0359
	.1	.0398	.0438	.0478	.0517	.0557	.0596	.0636	.0675	.0714	.0753
	.2	.0793	.0832	.0871	.0910	.0948	.0987	.1026	.1064	.1103	.1141
	.3	.1179	.1217	.1255	.1293	.1331	.1368	.1406	.1443	.1480	.1517
	.4	.1554	.1591	.1628	.1664	.1700	.1736	.1772	.1808	.1844	.1879
	.5	.1915	.1950	.1985	.2019	.2054	.2088	.2123	.2157	.2190	.2224
	.6	.2257	.2291	.2324	.2357	.2389	.2422	.2454	.2486	.2517	.2549
	.7	.2580	.2611	.2642	.2673	.2704	.2734	.2764	.2794	.2823	.2852
,	.8	.2881	.2910	.2939	.2967	.2995	.3023	.3051	.3078	.3106	.3133
·1	.9	.3159	.3186	.3212	.3238	.3264	.3289	.3315	.3340	.3365	.3389
	1.0	.3413	.3438	.3461	.3485	.3508	.3531	.3554	.3577	.3599	.3621
	1.1	.3643	.3665	.3686	.3708	.3729	.3749	.3770	.3790	.3810	.3830
	1.2	.3849	.3869	.3888	.3907	.3925	.3944	.3962	.3980	.3997	.4015
	1.3	.4032	.4049	.4066	.4082	.4099	.4115	.4131	.4147	.4162	.4177
	1.4	.4192	.4207	.4222	.4236	.4251	.4265	.4279	.4292	.4306	.4319
	1.5	.4332	.4345	.4357	.4370	.4382	.4394	.4406	.4418	.4429	.4441



## **A Review of Basic Concepts**

### Sampling Distribution and the Central Limit Theorem

### **Theorem 1.1: Sampling distribution of the Sampling Mean**

If  $y_1, \ldots, y_n$  represent a random sample of *n* measurements from a large (or infinite) population with mean  $\mu$  and standard deviation  $\sigma$  then, regardless of the form of the population relative distribution, the mean and standard error of estimate of the sampling distribution of  $\overline{y}$  will be

Mean: 
$$\mu_{\overline{y}} = E(y) = \mu$$

Standard error of estimate: 
$$\sigma_{\overline{y}} = \sqrt{E[(y-\mu)^2]} = \frac{\sigma}{\sqrt{n}}$$

$$\mu = \int y$$

$$\sigma^2 = \int ($$



 $yf(y)dy < \infty$ 

 $(y-\mu)^2 f(y) dy < \infty$ 

## **A Review of Basic Concepts**

### Sampling Distribution and the Central Limit Theorem

#### **Theorem 1.2: Central Limit Theorem**

For large sample sizes, the mean  $\overline{y}$  of a sample from a population with mean  $\mu$  and standard deviation  $\sigma$  has a sampling distribution that is approximately normal, regardless of the probability distribution of the sampled population. The larger the sample size, the better will be the normal approximation to the sampling distribution of  $\overline{y}$ .





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## **A Review of Basic Concepts**

### **Sampling Distribution and the CLT** When *n* is large,

$$\overline{y} \sim N\left(\mu_{\overline{y}} = \mu, \sigma_{\overline{y}}^2 = \frac{\sigma^2}{n}\right),$$

no matter what distribution our original measurements come from, when *n* is large,  $\overline{y}$  has a normal distribution

This means that we can use the z table to get areas!

$$z = \frac{\overline{y} - \mu}{\sigma / \sqrt{n}}$$





## **A Review of Basic Concepts**

#### **Estimating a Population Mean**

When we estimate a parameter like  $\mu$  with a single value like y, it is called a point estimator. We often are interested in a range of values within which we have a prespecified level of confidence that the interval contains  $\mu$ .

We know that P(-1.96 < z < 1.96) = 0.95, or more generally,  $P(-z_{\alpha/2} < z < z_{\alpha/2}) = 1 - \alpha$ .

Where  $z_{\alpha/2}$  is called the confidence coefficient.  $z_{\alpha/2}$  is the value of z with an area  $\alpha/2$  larger than it.







### **A Review of Basic Concepts**

#### **Estimating a Population Mean**

With some algebra on  $P(-z_{\alpha/2} < z < z_{\alpha/2}) = 1 - \alpha$ , we can see that ...

 $\begin{aligned} -z_{\alpha/2} &< z \\ -z_{\alpha/2} &< \frac{\overline{y} - \mu_{\overline{y}}}{\sigma_{\overline{y}}} \end{aligned}$  $\frac{z}{\overline{y} - \mu_{\overline{y}}} < z_{\alpha/2}$   $\frac{\overline{y} - \mu_{\overline{y}}}{\sigma_{\overline{y}}} < z_{\alpha/2}$  $-z_{\alpha/2}\frac{\sigma}{\sqrt{n}} < \overline{y}-\mu$  $\overline{y} - \mu < z_{\alpha/2} \frac{\partial}{\sqrt{n}}$  $-\mu < z_{\alpha/2} \frac{\sigma}{\sqrt{n}} - \overline{y}$  $-z_{\alpha/2}\frac{\sigma}{\sqrt{n}}-\overline{y} < -\mu$  $\overline{y} - z_{\alpha/2} \frac{\sigma}{\sqrt{n}} < \mu$  $\mu < \overline{y} + z_{\alpha/2} \frac{\sigma}{\sqrt{n}}$ 











### **A Review of Basic Concepts**

#### **Estimating a Population Mean**

Thus, a  $(1-\alpha) \times 100\%$  confidence interval for  $\mu$  is

$$\overline{y} - z_{\alpha/2} \frac{\sigma}{\sqrt{n}}$$
 to  $\overline{y} + z_{\alpha/2} \frac{\sigma}{\sqrt{n}}$ 

which if  $\alpha$ =0.05, a 95% confidence interval for  $\mu$  is

$$\overline{y} - 1.96 \frac{\sigma}{\sqrt{n}}$$
 to  $\overline{y} + 1.96 \frac{\sigma}{\sqrt{n}}$ 





### **A Review of Basic Concepts**

#### **Estimating a Population Mean**

However, we never know the true value of  $\sigma$ , so we replace it by *s* 

$$\overline{y} - z_{\alpha/2} \frac{s}{\sqrt{n}}$$
 to  $\overline{y} + z_{\alpha/2} \frac{s}{\sqrt{n}}$ 

but then we also need to replace z by t, so our CI for  $\mu$  is

$$\overline{y} - t_{\alpha/2,df} \frac{S}{\sqrt{n}}$$
 to  $\overline{y} + t_{\alpha/2,df} \frac{S}{\sqrt{n}}$ ,

where df = n-1 is our degrees of freedom.



## **A Review of Basic Concepts**

### **Estimating a Population Mean**

Since we estimated  $\sigma$  by s and changed z to t, the distribution and areas have changed.



$$f(t \mid v) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)} \frac{1}{\sqrt{\nu\pi}}$$







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as *n* increases, so does v=df=n-1 and Student *t* becomes standard normal

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df <- 4 tval <- 2.776 pt(tval, df = df,lower.tail = FALSE)

<i>t</i> .025	<i>t</i> .010	<i>t</i> .005
2.706	31.821	63.657
4.303	6.965	9.925
3.182	4.541	5.841
2.776	3.747	4.604
2.571	3.365	4.032
2.447	3.143	3.707
2.365	2.998	3.499
2.306	2.896	3.355
2.262	2.821	3.250
2.228	2.764	3.169
2.201	2.718	3.106
2.179	2.681	3.055
2.160	2.650	3.012
2.145	2.624	2.977
2.131	2.602	2.947

## A Review of Basic Concepts

Homework: Read Chapter 1

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# **Questions?**





