LECTURE 03

SAMPLING DISTRIBUTIONS AND CENTRAL LIMIT THEOREM - II

Outline of today's lecture:

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I. The Central Limit Theorem (CLT)

The Central Limit Theorem (CLT) The mean of a random sample has a <u>sampling distribution</u> whose shape can be approximated by a Normal distribution. The larger the sample, the better the approximation will be.

Theorem 7.4 Let Y_1 , Y_2 , ..., Y_n be independent and identically distributed random variables with $E(Y_i) = \mu$ and $V(Y_i) = \sigma^2 < \infty$. Define

$$U_n = \left(\frac{\overline{Y} - \mu}{\sigma / \sqrt{n}}\right)$$
 where $\overline{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$

Then the distribution of U_n converges to a standard normal distribution function as $n \rightarrow \infty$.

- That is, probability statements about U_n can be approximated by corresponding probabilities for the standard normal random variable if n is large.
 - Usually a value of *n* greater than 30 will ensure that the distribution of U_n can be closely approximated by a normal distribution.
- The conclusion of the central limit theorem is often replaced with the simpler statement that \overline{Y} is <u>asymptotically normally</u> <u>distributed</u> with mean μ and variance σ^2 .
- EXAMPLE 7.7 Achievement test scores of all high school seniors in a state have mean 60 and variance 64. A random sample of n = 100 students from one large high school had a mean score of 58. Is there evidence to suggest that this high school is inferior? (Calculate the probability that the sample mean is at most 58 when n = 100.)
 - **Solution** Let \overline{Y} denote the mean of a random sample of n = 100 scores from a population with $\mu = 60$ and $\sigma^2 = 64$. We want to approximate $P(\overline{Y} \le 58)$. We know from Theorem 7.4 that $\sqrt{n}(\overline{Y} \mu)/\sigma$ is approximately a standard normal random variable, which we denote by Z. Hence, using Table 4, Appendix III, we have

$$P(\overline{Y} \le 58) \approx P\left(Z \le \frac{\sqrt{100}(58 - 60)}{\sqrt{64}}\right) = P(Z \le -2.5) = .0062.$$

Because this probability is so small, it is unlikely that the sample from the school of interest can be regarded as a random sample from a population with $\mu = 60$ and

 $\sigma^2 = 64$. The evidence suggests that the average score for this high school is lower than the overall average of $\mu = 60$.

This example illustrates the use of probability in the process of testing hypotheses, a common technique of statistical inference that will be further discussed in Chapter 10.

EXAMPLE 7.8 The service times for customers coming through a checkout counter in a retail store are independent random variables with mean 1.5 minutes and variance 1.0. Approximate the probability that 100 customers can be served in less than 2 hours of total service time. **Solution** If we let Y_i denote the service time for the *i*th customer, then we want

$$P\left(\sum_{i=1}^{100} Y_i \le 120\right) = P\left(\overline{Y} \le \frac{120}{100}\right) = P(\overline{Y} \le 1.20).$$

Because the sample size is large, the central limit theorem tells us that \overline{Y} is approximately normally distributed with mean $\mu_{\overline{Y}} = \mu = 1.5$ and variance $\sigma_{\overline{Y}}^2 = \sigma^2/n = 1.0/100$. Therefore, using Table 4, Appendix III, we have

$$P(\overline{Y} \le 1.20) = P\left(\frac{\overline{Y} - 1.50}{1/\sqrt{100}} \le \frac{1.20 - 1.50}{1/\sqrt{100}}\right)$$
$$\approx P[Z \le (1.2 - 1.5)\sqrt{100}] = P(Z \le -3) = .0013.$$

Thus the probability that 100 customers can be served in less than 2 hours is approximately .0013. This small probability indicates that it is virtually impossible to serve 100 customers in only 2 hours.

II. Sampling Distributions Related to Normal Distribution

A. Sampling Distribution of Mean

Theorem 7.1 Let Y_1 , Y_2 , ..., Y_n be independent, normal random variables, each with mean μ and variance σ^2 . Then:

$$\overline{Y} = \frac{1}{n} \sum_{i=1}^{n} Y_i$$

is normally distributed with mean $\mu_{\overline{Y}} = \mu$ and variance $\sigma_{\overline{Y}}^2 = \frac{\sigma^2}{n}$.

Example 7.1 and 7.2 A bottling machine can be regulated so that it discharges an average of μ ounces per bottle. It has been observed that the amount of fill dispensed by the machine is normally

distributed with $\sigma = 1.0$ ounce. A sample of n = 9 filled bottles is randomly selected from the output of the machine on a given day (all bottled with the same machine setting) and the ounces of fill measured for each.

- a) Find the probability that the sample mean will be within 0.3 ounce of the true mean μ for that particular setting.
- b) How many observations should be included in the sample if we wish \overline{Y} to be within 0.3 ounce of μ with probability 0.95?

Solution

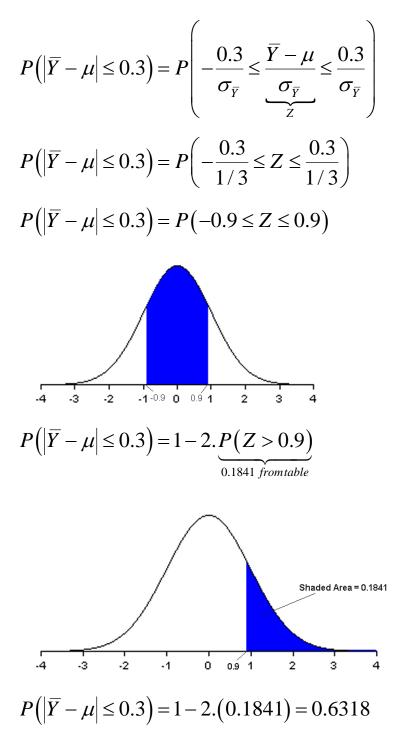
a)

If Y_1, Y_2, \ldots, Y_9 denote the ounces of fill to be observed, then we know that the Y_i are normally distributed with mean μ and variance $\sigma^2 = 1$ for $i = 1, 2, \ldots, 9$.

Therefore \overline{Y} possesses a normal sampling distribution with mean $\mu_{\overline{Y}} = \mu$ and variance $\sigma_{\overline{Y}}^2 = \frac{\sigma^2}{n} = \frac{1}{9}$.

In the problem, we are asked to find:

$$P(|\overline{Y} - \mu| \le 0.3) = P(-0.3 \le \overline{Y} - \mu \le 0.3)$$



Thus the chance is only 0.6318 that the sample mean will be within 0.3 ounce of the true population mean.

b) Now we want:

$$P(|\overline{Y} - \mu| \le 0.3) = P[-0.3 \le \overline{Y} - \mu \le 0.3] = 0.95$$
$$P(|\overline{Y} - \mu| \le 0.3) = P\left(-\frac{0.3}{\frac{\sigma}{\sqrt{n}}} \le \frac{\overline{Y} - \mu}{\frac{\sigma}{\sqrt{n}}} \le \frac{0.3}{\frac{\sigma}{\sqrt{n}}}\right) = 0.95$$

It is given that $\sigma=1$, hence we can write:

$$P(|\overline{Y} - \mu| \le 0.3) = P(-0.3\sqrt{n} \le Z \le 0.3\sqrt{n}) = 0.95$$

From Standard Normal Distribution table, we know that:

$$P(-1.96 \le Z \le 1.96) = 0.95$$

It implies that $0.3\sqrt{n} = 1.96$. Hence

$$n = \left(\frac{1.96}{0.3}\right)^2 = \left(6.5\overline{3}\right)^2 = 42.68$$
, which is impractical for sample size.

So we can decide to n=43, since if n=43, $P(|\overline{Y} - \mu| \le 0.3)$ slightly exceeds 0.95.

B. Chi-Square Distribution

In statistics, the sampling distribution of the *sum of the squares* of independent, standard normal random variables is also widely used.

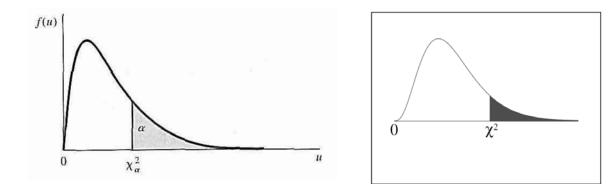
Theorem 7.2 Let $Y_1, Y_2, ..., Y_n$ be a random sample of size *n* from a normal distribution with mean μ and variance σ^2 . Then $\sum_{i=1}^{n} Z_i^2 = \sum_{i=1}^{n} \left(\frac{Y_i - \mu}{\sigma} \right)$ has a Chi-square, χ^2 , distribution with *n* degrees of freedom.

Note: We can denote a chi-square distribution variable with *n* degrees of freedom (*df*) for α level of significance as $\chi^2_{\alpha,df}$.

From Chi-square tables, we can find values χ^2_{α} so that:

$$P(\chi^2 > \chi^2_\alpha) = \alpha$$

for random variables with χ^2 distributions.



A distribution χ^2 showingAttention! The shaded area isupper-tail area α equal to α for $\chi^2 = \chi^2_{\alpha}$

For example, if the χ^2 random variable of interest has 10 degrees of freedom, we can use χ^2 Tables to find $\chi^2_{0.90}$. We look in the row labeled 10 df. and the column headed $\chi^2_{0.90}$ and read the value 4.86518. Therefore if Y has a χ^2 distribution with df=10: $P(\chi^2 > 4.86518) = 0.10$

Table 6. Percentage points of the χ^2 distributions

			a Xa	_		
d.f.	x _{0.995}	x _{0.990}	X ² _{0.975}	x ² _{0.950}	x ² _{0.900}	
1	0.0000393	0.0001571	0.0009821	0.0039321	0.0157908	
2	0.0100251	0.0201007	0.0506356	0.102587	0.210720	
2 3	0.0717212	0.114832	0.215795	0.351846	0.584375	
4	0.206990	0.297110	0.484419	0.710721	1.063623	
5	0.411740	0.554300	0.831211	1.145476	1.61031	
6	0.675727	0.872085	1.237347	1.63539	2.20413	
7	0.989265	1.239043	1.68987	2.16735	2.83311	
8	1.344419	1.646482	2.17973	2.73264	3.48954	
9	1.734926	2.087912	2.70039	3.32511	4.168	
10	2.15585	2.55821	3.24697	3.94030	4.86518	
11	2.60321	3.05347	3.81575	4.57481	5.57779	
12	3.07382	3.57056	4.40379	5.22603	6.30380	
12	2 56502	4 10601	5 00974	5 80186	7 04150	

Example 7.3 If $Z_1, Z_2, ..., Z_6$ denotes a random sample from the standard normal distribution, find a number *b* such that: $P\left(\sum_{i=1}^{6} Z_i^2\right) = 0.95$

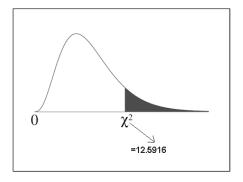
Solution

 $\sum_{i=1}^{6} Z_i^2$ has a χ^2 distribution with 6 degrees of freedom (df) since it

represents the summation of 6 squared normally distributed random variables, Z. Equivalently:

$$P\left(\sum_{i=1}^{6} Z_i^2\right) = 0.95$$

From Chi-square table, we find that:



$$P\left(\sum_{i=1}^{6} Z_i^2 > b\right) = 0.05 \Longrightarrow b = 12.5916$$

Table 6. Percentage points of the χ^2 distributions $ \int_{0}^{\alpha} \frac{\alpha}{\chi_{\alpha}^2} $					
$\chi^2_{0.100}$	x ² _{0.050}	x ² _{0.025}	$x_{0.010}^2$	$\chi^2_{0.005}$	d.f.
2.70554	3.84146	5.02389	6.63490	7.87944	1
4.60517	5.99147	7.37776	9.21034	10.5966	2
6.25139	7.81473	9.34840	11.3449	12.8381	3
7.77944	9.48773	11.1433	13.2767	14.8602	4
9.23635	11.0705	12.8325	15.0863	16.7496	3 🔇
10.6446	12.5916 🧲	194	16.8119	18.5476)e
12.0170	14.0671	H 128	18.4753	20.2777	7
13.3616	15.5073	17.5346	20.0902	21.9550	7 8 9
14.6837	16.9190	19.0228	21.6660	23.5893	9
15.9871	18.3070	20.4831	23.2093	25.1882	10
17.2750	19.6751	21.9200	24.7250	26.7569	11
18.5494	21.0261	23.3367	26.2170	28.2995	12
19.8119	22.3621	24.7356	27.6883	29.8194	13

The χ^2 distribution plays an important role in many inferential procedures. For example, suppose that we wish to make an inference about the population variable σ^2 based on a random sample Y_1 , Y_2 , ..., Y_n from a normal population. A good estimator for *population variance* σ^2 (we will see in Ch. 8) is the *sample variance*, S^2 :

$$S^{2} = \frac{1}{n-1} \sum_{i=1}^{n} \left(Y_{i} - \overline{Y} \right)^{2}$$

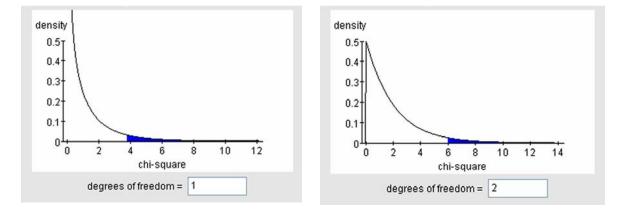
The following theorem gives the probability distribution for a function of the statistic S^2 :

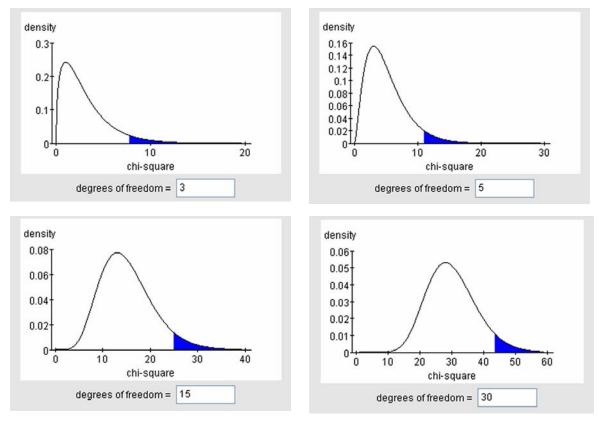
Theorem 7.3 Let $Y_1, Y_2, ..., Y_n$ be a random sample from a normal distribution with mean μ and variance σ^2 . Then:

$$\frac{(n-1)S^{2}}{\sigma^{2}} = \frac{1}{\sigma^{2}} \sum_{i=1}^{n} (Y_{i} - \overline{Y})^{2}$$

has a χ^2 distribution with (n-1) degrees of freedom (df). Hence $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{\alpha,(n-1)}$. Also \overline{Y} and S^2 are independent random variables.

Impact of Degrees of Freedom in the χ^2 Distribution





Note: Shaded areas in the graphs represent 0.05. *Source of Graph Applet:* <u>http://www.stat.tamu.edu/~west/applets/chisqdemo.html</u>

Example 7.4 Recall the bottle example, where the ounces of fill from the bottling machine are assumed to have a normal distribution with $\sigma^2 = 1$.

- Suppose that we plan to select a random sample of 10 bottles and measure the amount of fill in each bottle. If these ten observations are used to calculate S^2 , it might be useful to specify an interval of values that will include S^2 with a high probability.
- Find numbers b_1 and b_2 such that:

$$P\left(b_1 \le S^2 \le b_2\right) = 0.90$$

Solution

For our case, α =0.90 and degrees of freedom, *df*=10-1=9.

$$P[b_{1} \le S^{2} \le b_{2}] = P\left[\frac{(n-1)b_{1}}{\sigma^{2}} \le \frac{(n-1)S^{2}}{\sigma^{2}} \le \frac{(n-1)b_{2}}{\sigma^{2}}\right] = 0.90$$

We are given that $\sigma^2 = 1$ so it follows that $(n-1)S^2$ has a χ^2 distribution with n-1=10-1=9 degrees of freedom (*df*):

$$P\left[b_{1} \le S^{2} \le b_{2}\right] = P\left[\underbrace{(n-1)b_{1}}_{a_{1}} \le (n-1)S^{2} \le \underbrace{(n-1)b_{2}}_{a_{2}}\right] = 0.90$$

From a chi-square table we can find two numbers a_1 and a_2 such that:

$$P\left[a_1 \le (n-1)S^2 \le a_2\right] = 0.90$$

One method of doing this to find the value of a_2 that represents an area of 0.05 in the upper tail and the value of a_1 that represents 0.05 in the lower tail (0.95 in the upper tail).

Because there are *n*-1 degrees of freedom, the Chi-square table gives $a_2=16.919$ and $a_1=3.32511$.

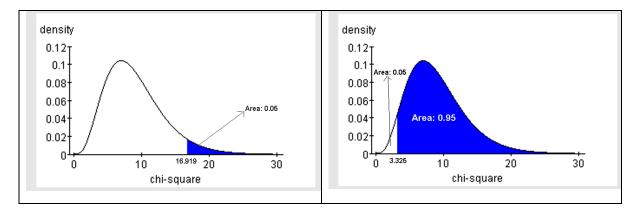


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10	2 02202	2 57056	4 40270	5 22602	6 20200

Consequently, values for b_1 and b_2 are given by:

•
$$a_1 = \frac{(n-1)b_1}{\sigma^2} = \frac{9b_1}{1} = 3.32511 \Longrightarrow b_1 = \frac{3.32511}{9} \approx 0,369$$

• $a_2 = \frac{(n-1)b_2}{\sigma^2} = \frac{9b_2}{1} = 16.9190 \Longrightarrow b_2 = \frac{16.9190}{9} \approx 1,880$

Thus, if we want to have an interval that will include S^2 with probability 0.90, this interval is given by (0.369,1.880). Note that this interval is quite wide.