§24. Sampling Distribution of the Sampling Variance

Let X be a random variable and let X_1, \ldots, X_n be a random sample from X.

Definition 1

A quantity computed from a sample is called a **statistic**.

Example 1

The sample mean

 $\overline{X} = \frac{1}{n} \sum_{i=1}^{n} X_i$

is a statistic.

So is the sample variance

$$s^{2} = \frac{1}{n-1} \sum_{i=1}^{n} \left(X_{i} - \bar{X} \right)^{2}$$

Example 2

 $p(\overline{x})$ sampling distribution of the mean.

 $p(s^2)$ sampling distribution of the sampling variance.

To keep the discussion reasonably simple we will only consider the case of a sample X_1, \ldots, X_n from a Gaussian population $X \sim N(\mu, \sigma)$

Let's find out what is the distribution of s^2 .

$$\sum_{i=1}^{n} (x_i - \bar{x})^2 = \sum_{i=1}^{n} [(x_i - \mu) - (\bar{x} - \mu)]^2$$
$$= \sum_{i=1}^{n} (x_i - \mu)^2 - 2\sum_{i=1}^{n} (x_i - \mu) (\bar{x} - \mu) + \sum_{i=1}^{n} (\bar{x} - \mu)^2$$

Remark The statistics are r.v. themselves ∵ they depend on the random sample and their distributions are called sampling distributions.

$$= \sum_{i=1}^{n} (x_i - \mu)^2 - 2n(\bar{x} - \mu)^2 + n(\bar{x} - \mu)^2$$
$$= \sum_{i=1}^{n} (x_i - \mu)^2 - n(\bar{x} - \mu)^2$$
$$\Rightarrow \quad \frac{(n-1)s^2}{\sigma^2} + \frac{(\bar{x} - \mu)^2}{\sigma^2/n} = \sum_{i=1}^{n} \frac{(x_i - \mu)^2}{\sigma^2}$$

It can be shown that in a sampling distribution from a Gaussian \overline{x} and s^2 are independent.

$$M\frac{(n-1)s^{2}}{\sigma^{2}}(t) \cdot M\frac{(\bar{x}-\mu)^{2}}{\sigma^{2}/n}(t)}{\sum_{\substack{\text{Square of }N(0,1)\\\chi^{2}(1)}}^{\text{Square of }N(0,1)}} = M\sum_{\substack{i=1\\sum \text{ of } n \text{ squares}\\N(0,1)\sim\chi^{2}(n)}}^{u}$$

$$M\frac{(n-1)s^{2}}{\sigma^{2}}(t) \cdot (1-2t)^{-1/2} = (1-2t)^{-n/2}$$

$$M\frac{(n-1)s^{2}(t)}{\sigma^{2}} = (1-2t)^{-\frac{n-1}{2}}$$

$$M\frac{(n-1)s^{2}(t)}{\sigma^{2}} = (1-2t)^{-\frac{n-1}{2}} \Rightarrow \frac{(n-1)s^{2}}{\sigma^{2}} \sim \chi^{2}(n-1)$$

Since the expected value of $\chi^2(k)$ random variable is k, we have

$$E(s^2) = \frac{n-1}{n-1}\sigma^2 \Rightarrow E(s^2) = \sigma^2$$

Thus with

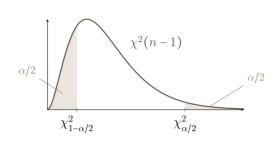
$$s^{2} = \frac{1}{n-1} \sum_{i=1}^{n} (x_{i} - \bar{x})^{2}$$

 s^2 is an unbiased estimation for σ^2

The variance of $\chi^2(k)$ is 2k, so we have

$$\operatorname{Var}\left(\frac{(n-1)s^2}{\sigma^2}\right) = \frac{(n-1)^2}{\sigma^4} \operatorname{Var}\left(s^2\right) = 2(n-1) \quad \Rightarrow \quad \operatorname{Var}\left(s^2\right) = \frac{2\sigma^4}{n-1}$$

Confidence Interval of the Variance and Standard Deviation of a Gaussian Random Variable



$$P\left(\chi_{1-\alpha/2}^2 \le \frac{(n-1)s^2}{\sigma^2} \le \chi_{\alpha/2}^2\right) = 1 - \alpha$$

 $1 - \alpha$ of all samples have sample variance not in the $\alpha/2$ tails

$$\Rightarrow P\left(\frac{(n-1)s^2}{\chi^2_{\alpha/2}} \le \sigma^2 \le \frac{(n-1)s^2}{\chi^2_{1-\alpha/2}}\right) = 1 - \alpha$$

$$\frac{(n-1)s^2}{\chi^2_{\alpha/2}} \le \sigma^2 \le \frac{(n-1)s^2}{\chi^2_{1-\alpha/2}}$$

 $100(1-\alpha)\%$ CI for the variance of normal

Example 3

Data on pH of rain in Michigan.

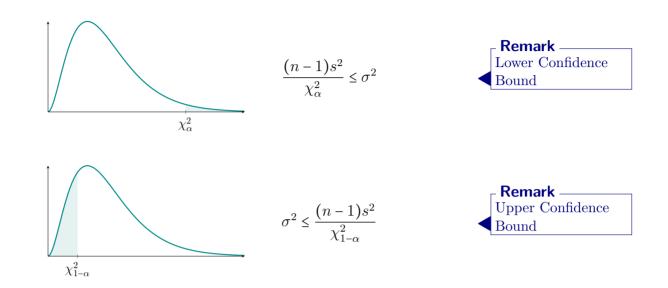
Assuming that the pH is Gaussian compute a 95% CI for the rain pH variance and for the standard deviation.

Using Open Office: $s^2 = 0.4508, n - 1 = 10$ d.f.

$$\begin{split} \chi^2_{\alpha/2} &= 20.48, \qquad \chi^2_{1-\alpha/2} = 3.25 \\ \hline \frac{(10) \cdot (0.4508)}{20.48} &\leq \sigma^2 &\leq \frac{10(0.4508)}{3.25} \\ \hline 0.2201 &\leq \sigma^2 &\leq 1.3871 \quad \text{with } 95\% \text{ confidence} \\ 0.4691 &\leq \sigma^2 &\leq 1.1777 \quad \text{with } 95\% \text{ confidence} \end{split}$$

Lower and Upper Confidence Bounds

The $100(1-\alpha)\%$ lower and upper confidence bounds on σ^2 are



Example 4

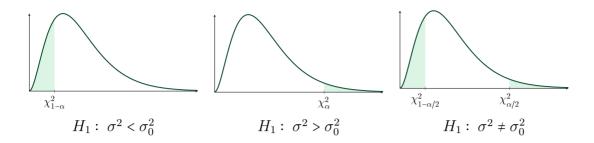
An automatic filling machine fills bottles with beer. A random sample of 20 bottles has a sample variance of the fill volume of $s^2 = 2.957 \, ml^2$. If the variance of the fill volume is too high an acceptable portion of the bottles will be under-or over filled. Assuming that the fill volume is normal construct a 95% upper confidence bound for σ .

$$\begin{split} \sigma^2 &\leq \frac{(n-1)s^2}{\chi^2_{0.95}} \\ \sigma^2 &\leq \frac{19(2.957)}{10 \cdot 117} \quad \Rightarrow \quad \sigma^2 \leq 5.5533 \quad \text{with } 95\% \text{ confidence} \\ \Rightarrow \quad \sigma \leq 2.3565 \text{ ml} \quad \text{with } 95\% \text{ confidence} \end{split}$$

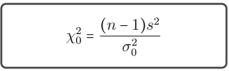
Hypothesis Testing for the Variance and Standard Deviation of Gaussian

Let X be a normal random variable and let X_1, \ldots, X_n be a random sample from X. Let s^2 be the sample variance.

We would like to test the hypothesis that $H_0: \sigma^2 = \sigma_0^2$ against $H_1: \sigma^2 > \sigma_0^2$ or $\sigma^2 < \sigma_0^2$ or $\sigma^2 \neq \sigma_0^2$ at significance level α (probability for Type I error). The critical (rejection) regions are:



with test statistic



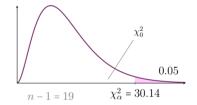
Example 5

For the beer bottle example test $H_0: \sigma^2 = 2$ versus $H_1: \sigma^2 > 2$ at the 5% level of significance.

$$\chi_0^2 = \frac{(19)(2.957)}{2} = 28.09 < 30.14 = x_\alpha^2$$

Fail to reject H_0 . This sample does not provide enough evidence that the fill volume variance exceeds 2 mL².

The *p*-value for the test is $P(\chi^2 > \chi_0^2) = 0.0817$. The sample is not unlikely enough to contradict H₀.



Example 6

The sugar content of the syrup in canned peaches is normal and the variance is thought to be $\sigma^2 = 18 \text{ mg}^2$. A sample of a dozen cans gives $s^2 = 6.7 \text{ mg}^2$. Test $H_0 : \sigma^2 = 18 \text{ vs.}$ $H_1 : \sigma^2 < 18 \text{ at}$ $\alpha = 0.05$ level of significance. What is the *p*-value of this test.

$$\chi_0^2 = \frac{(4-1)s^2}{\sigma_0^2} = \frac{11(6.7)}{18} = 4.0944 < \chi_{1-\alpha}$$

Reject H_0 . Accept H_1 . The variance of the sugar content of canned peaches is less that 18 mg².

 $p - value = 0.0329 < 0.05 = \alpha$

The sample contradicts H_0 strongly enough.

