**DERIV:** The following is a simplified derivation showing that the probability density function (pdf) for the normalized sample variance,  $X = (n-1)S^2 / \sigma^2$ , is the  $\chi^2$ -distribution with v = n - 1 degrees of freedom where *n* is the number of independent, normally distributed samples,  $\sigma^2$  is the variance of each sample, and sample variance  $s^2$  is defined in the standard way:

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

where the  $X_i$  are the samples, and  $\overline{X}$  is the sample mean defined in the standard way:

$$\overline{X} = \frac{1}{n} \sum_{i=1}^{n} X_i \,. \tag{2}$$

To improve clarity and focus attention on key ideas in the derivation, we assume the samples are drawn from a standard normal distribution with mean  $\mu = 0$  and variance  $\sigma^2 = 1$ :

$$f_{X_i}(x_i) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x_i^2}.$$
(3)

Based on rules for linear combinations of random variables, the sample mean is normally distributed with variance  $\sigma^2/n = 1/n$  since we are assuming  $\sigma^2 = 1$ .

$$f_{\overline{X}}(\overline{x}) = \frac{1}{\sqrt{2\pi/n}} e^{-\frac{1}{2}\frac{\overline{x}^2}{1/n}} = \frac{1}{\sqrt{2\pi/n}} e^{-\frac{1}{2}n\overline{x}^2}$$
(4)

The pdf for all the samples is an *n*-dimensional normal distribution [1].

$$f_{(x_1,\dots,x_n)}(x_1,\dots,x_n) = \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2}\sum_{i=1}^n x_i^2}$$
(5)

With some manipulation of summations [2], we may show that the summation of the squared  $x_i$ 's may be written in terms of the sample variance and sample mean:

$$\sum_{i=1}^{n} X_i^2 = (n-1)S^2 + n\overline{X}^2.$$
(6)

$$S^{2} = \frac{1}{n-1} \left( \sum_{i=1}^{n} X_{i}^{2} - n\overline{X}^{2} \right).$$
(7)

Using (6), we rewrite the *n*-dimensional normal distribution:

$$f_{(x_1,\dots,x_n)}(x_1,\dots,x_n) = \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \left\lfloor (n-1)s^2 + n\overline{x}^2 \right\rfloor}.$$
(8)

We find the pdf of  $x = (n - 1)s^2$  by taking the derivative of the cumulative distribution function.

$$f_X(x) = f_{(n-1)S^2} \left( (n-1)s^2 \right) = \frac{d}{d(n-1)s^2} F\left( (n-1)s^2 \right)$$
$$= \frac{d}{d(n-1)s^2} P\left( (n-1)S^2 \le (n-1)s^2 \right) = \frac{d}{d(n-1)s^2} P\left( S^2 \le s^2 \right)$$
(9)
$$= \frac{d}{d(n-1)s^2} P\left( S \le s \right)$$

Given (8) and (9), our goal will be to express  $P(S \le s)$  in terms of *s*, but our starting point is to find the cumulative probability by integrating the pdf of  $(x_1, ..., x_n)$  over all the  $(x_1, ..., x_n)$  that would give a sample variance that is less than or equal to  $s^2$ .

$$P(S \le s) = \iiint_{\substack{1 \\ n-1} \left(\sum_{i=1}^{n} x_i^2 - n\overline{x}^2\right) \le s^2} f_{(x_1, \dots, x_n)}(x_1, \dots, x_n) dx_1 \dots dx_n$$
(10)

or

$$P(S \le s) = \iiint_{\substack{\sum_{i=1}^{n} x_i^2 \le (n-1)s^2 + n\overline{x}^2}} \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2}\sum_{i=1}^{n} x_i^2} dx_1 \dots dx_n$$
(11)

We observe that the pdf  $f_{(x_1,...,x_n)}(x_1,...,x_n)$  is spherically symmetric, which suggests that we might be able to use spherical coordinates for our integral. However, the spherical symmetry of  $f_{(x_1,...,x_n)}(x_1,...,x_n)$  is with respect to the origin, whereas we want to integrate over the  $(x_1, ..., x_n)$  that are within a certain squared distance from  $(\overline{x},...,\overline{x})$ . That is,  $(n-1)s^2$  may be thought of as a measure of the squared distance from  $(x_1, ..., x_n)$  to  $(\overline{x}, ..., \overline{x})$ :

$$\sum_{i=1}^{n} \left( X_i - \bar{X} \right)^2 \le (n-1)S^2 \,. \tag{12}$$

It follows that the  $(x_1, ..., x_n)$  are points in an *n*-dimensional sphere centered at  $(\overline{x}, ..., \overline{x})$  at a squared distance of at most  $(n-1)s^2$  or a radius of  $r = \sqrt{n-1} \cdot s$ .

For a given  $\overline{x}$ , however, these  $(x_1, ..., x_n)$  must also lie on the hyper-plane of points such that  $\frac{1}{n}(x_1+...+x_n)=\overline{x}$  since the average of the  $x_i$  is  $\overline{x}$ . This plane is perpendicular to  $(\overline{x},...,\overline{x})$  or a vector in the (1,1,1) direction. Thus, for a given  $\overline{x}$ , we are integrating over the intersection of an *n*-dimensional sphere of radius  $r = \sqrt{n-1} \cdot s$  and a hyper-plane in *n* dimensions that is perpendicular to the (1,1,1) direction. The resulting intersection is an (n-1)-dimensional sphere. As shown in Fig. 1(a), for the case of n = 2, (2-dimensional space for  $X_1, X_2$ ), the (n-1)-sphere is a 1-dimensional line of points on the constant  $\overline{x}$  line, and as shown in Fig. 1(b), for the case of n = 3, (3-dimensional space for  $X_1, X_2, X_3$ ), the (n-1)-sphere is a 2-dimensional circle of points on the constant  $\overline{x}$  plane.

We may use  $\overline{x}$  and r as orthogonal variables of integration. As we vary  $\overline{x}$ , the line of constant  $\overline{x}$  moves a distance  $\sqrt{n} \cdot \overline{x}$  in the (1,1) direction, and sphere of integrated points moves with it. This gives an extruded (n-1)-dimensional sphere as the region of integration. As shown in Fig. 2(a) for the case of n = 2, the region of integration is an infinite band in the (1,1) direction, and as shown in Fig. 2(b) for the case of n = 3, the region of integration is an infinite cylinder in the (1,1,1) direction. **CONCEPTUAL TOOLS** 

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**PROBABILITY** PROB DENSITY FUNC, f(x)Chi-squared distribution  $\chi^2$  DERIVATION



Fig. 1. Points to integrate in the *r* direction for calculation of  $P(S \le s)$  at a given value of  $\overline{x}$ : (a) 2-dimensional case, (b) 3-dimensional case.



Fig. 2. Region of integration for calculation of  $P(S \le s)$  in coordinates of  $\overline{x}$  and r: (a) 2-dimensional case is infinite band parallel to (1,1) direction,

(b) 3-dimensional case is infinite cylinder parallel to (1,1,1) direction.

For  $n \ge 2$  dimensions, the above picture generalizes to the following change of variables:

$$dx_1 \dots dx_n = \sqrt{n} \, d\overline{x} \cdot A_{n-1}(r) dr \,. \tag{13}$$

where  $\overline{x}$  varies from  $-\infty$  to  $\infty$  and  $A_{n-1}(r)$  is the surface area of an (n-1)-dimensional sphere of radius  $r = \sqrt{n-1} \cdot s$ .

From [3] we have the following formulas for sphere volumes and surface areas:

$$V_n(r) = \frac{S_n r^n}{n}$$
 is the volume of an *n*-dimensional sphere of radius *r* (14)

$$S_n(r) = \frac{2\pi^{n/2}}{\Gamma\left(\frac{n}{2}\right)}$$
 is the surface area of an *n*-dimensional sphere of radius = 1. (15)

It follows that the surface area of an *n*-dimensional unit sphere is:

$$A_n(r) = S_n r^{n-1} = \frac{2\pi^{n/2} r^{n-1}}{\Gamma\left(\frac{n}{2}\right)}.$$
 (16)

The gamma function has the following properties [4]:

 $\Gamma(n) = (n-1)! \text{ for } n > 0 \text{ a positive integer}$  $z\Gamma(z) = \Gamma(z+1) \text{ for all complex } z \text{ except integers} \le 0$  $\Gamma\left(\frac{1}{2}\right) = \sqrt{\pi}$ 

Using (16), we have:

$$A_{n-1}(r) = S_{n-1}r^{n-1} = \frac{2\pi^{(n-1)/2}r^{n-2}}{\Gamma\left(\frac{n-1}{2}\right)}.$$
(17)

**PROBABILITY** PROB DENSITY FUNC, f(x)Chi-squared distribution  $\chi^2$  DERIVATION

We now have the following integral for  $P(S \le s)$ :

$$P(S \le s) = \iiint_{\substack{\sum_{i=1}^{n} (x_i - \overline{x})^2 \le (n-1)s^2 \\ s = 0}} \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2}\sum_{i=1}^{n} x_i^2} dx_1 \dots dx_n$$

$$= \int_{s=0}^{r=\sqrt{n-1} \cdot s} \int_{\overline{x}=-\infty}^{\overline{x}=\infty} \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \left[r^2 + n\overline{x}^2\right]} \sqrt{n} d\overline{x} \frac{2\pi^{(n-1)/2} r^{n-2}}{\Gamma\left(\frac{n-1}{2}\right)} dr.$$
(18)

n

We separate variables, and perform the inner integration first (after ensuring that the inner integration is of a normal density function, thus yielding a value of unity).

$$P(S \le s) = \int_{r=0}^{r=\sqrt{n-1} \cdot s} \left[ \int_{\overline{x}=-\infty}^{\overline{x}=\infty} \frac{1}{\sqrt{2\pi/n}} e^{-\frac{1}{2}n\overline{x}^2} d\overline{x} \right] \frac{1}{(2\pi)^{(n-1)/2}} e^{-\frac{1}{2}r^2} \frac{2\pi^{(n-1)/2}r^{n-2}}{\Gamma\left(\frac{n-1}{2}\right)} dr \quad (19)$$

The value inside the square brackets is our integral (of a normal density function) that has a value of unity. Thus, we have

$$P(S \le s) = \int_{r=0}^{r=\sqrt{n-1} \cdot s} \frac{1}{(2\pi)^{(n-1)/2}} e^{-\frac{1}{2}r^2} \frac{2\pi^{(n-1)/2}r^{n-2}}{\Gamma\left(\frac{n-1}{2}\right)} dr .$$
(20)

We now use v = n - 1 as the "degrees of freedom" to simplify the expression and reflect the idea that the pdf is analogous to one for n - 1 variables.

$$P(S \le s) = \int_{r=0}^{r=\sqrt{n-1}/s} \frac{1}{(2\pi)^{\nu/2}} e^{-\frac{1}{2}r^2} \frac{2\pi^{\frac{\nu}{2}}r^{\nu-1}}{\Gamma\left(\frac{\nu}{2}\right)} dr$$
(21)

Fortunately, we will take the derivative of the cumulative distribution, so computing the integral is unnecessary. However, we do have to deal with a change of variables for the derivative.

As a preliminary to using the chain rule, we have the following calculations:

$$x = (n-1)s^2 = r^2$$
(22)

so

$$r = \sqrt{x} \tag{23}$$

and

$$\frac{dr}{dx} = \frac{1}{2\sqrt{x}}.$$
(24)

Using the chain rule, we have the following result:

$$f_X(x) = \frac{d}{dx} P(S \le s) = \frac{dr}{dx} \frac{d}{dr} P(S \le s \text{ i.e., } r = \sqrt{x})$$
  
$$= \frac{1}{2\sqrt{x}} \frac{d}{dr} P\left(S \le s; r = \sqrt{x}\right) \qquad (25)$$

The final derivative is the derivative of an integral, so the final derivative is just the integrand from (21):

$$f_X(x) = \begin{cases} \frac{1}{2\sqrt{x}} \frac{1}{(2\pi)^{\nu/2}} e^{-\frac{1}{2}r^2} \frac{2\pi^2 r^{\nu-1}}{\Gamma\left(\frac{\nu}{2}\right)} & x > 0\\ 0 & \text{otherwise} \end{cases}$$
(26)

or, since  $r^2 = x$  and several constants cancel out,

$$f_X(x) = \begin{cases} \frac{1}{2^{\nu/2} \Gamma\left(\frac{\nu}{2}\right)} e^{-\frac{1}{2}x} x^{\frac{\nu}{2}-1} & x > 0\\ 0 & \text{otherwise} \end{cases}$$
(27)

In conclusion, the distribution of  $x = (n - 1)s^2$  when  $\sigma^2 = 1$  is a chi-squared distribution. Without proof, we state the following result when  $\sigma^2 \neq 1$ :

The probability density function of  $x = \frac{(n-1)S^2}{\sigma^2}$  is a chi-squared distribution with

v = n - 1 degrees of freedom [2]:

$$f_{\chi^{2},v}(x) = \begin{cases} \frac{1}{2^{\frac{v}{2}}} x^{\frac{v}{2}-1} e^{-\frac{x}{2}} & x > 0\\ 2^{\frac{v}{2}} \Gamma\left(\frac{v}{2}\right) & 0 \\ 0 & \text{otherwise} \end{cases}$$
(28)

- **REF:** [1] "The Multivariate Normal Distribution." http://www.math.uah.edu/stat/special/MultiNormal.html
  - [2] Ronald E. Walpole, Raymond H. Myers, Sharon L. Myers, and Keying Ye, *Probability and Statistics for Engineers and Scientists*, 8th Ed., Upper Saddle River, NJ: Prentice Hall, 2007.
  - [3] <u>Weisstein, Eric W.</u> "Hypersphere." From <u>MathWorld</u>--A Wolfram Web Resource. <u>http://mathworld.wolfram.com/Hypersphere.html</u>
  - [4] <u>Weisstein, Eric W.</u> "Gamma Function." From <u>MathWorld</u>--A Wolfram Web Resource. <u>http://mathworld.wolfram.com/GammaFunction.html</u>