Non-Central Chi-squared¹ STA442/2101 Fall 2016

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Definition

If $X \sim N(\mu, 1)$ then $Y = X^2$ is said to have a *non-central* chi-squared distribution with degrees of freedom one and non-centrality parameter $\lambda = \mu^2$.

Write $Y \sim \chi^2(1, \lambda)$.

Facts about the non-central chi-squared distribution $Y = X^2$ where $X \sim N(\mu, 1)$

$Y \sim \chi^2(1,\lambda)$, where $\lambda \ge 0$

• $Pr{Y > 0} = 1$, of course.

- If $\lambda = 0$, the non-central chi-squared reduces to the ordinary central chi-squared.
- The distribution is "stochastically increasing" in λ , meaning that if $Y_1 \sim \chi^2(1, \lambda_1)$ and $Y_2 \sim \chi^2(1, \lambda_2)$ with $\lambda_1 > \lambda_2$, then $Pr\{Y_1 > y\} > Pr\{Y_2 > y\}$ for any y > 0.

$$\lim_{\lambda \to \infty} \Pr\{Y > y\} = 1$$

• There are efficient algorithms for calculating non-central chi-squared probabilities. R's pchisq function does it.

Why is it called "non-central?" Recall that if $X \sim N(\mu, 1)$ then $Y = X^2 \sim \chi^2(1, \lambda = \mu^2)$

If $X \sim N(\mu, \sigma^2)$, then if we center it and scale it,

•
$$Z^2 = \left(\frac{X-\mu}{\sigma}\right)^2 \sim \chi^2(1)$$
, the *central* chi-squared.

- What if we scale it correctly, but center it to the wrong place?
- $Z = \frac{X \mu_0}{\sigma} \sim N(\frac{\mu \mu_0}{\sigma}, 1)$
- And Z^2 is chi-squared with df = 1 and non-centrality parameter

$$\lambda = \left(\frac{\mu - \mu_0}{\sigma}\right)^2$$

This applies whether the normality is exact or asymptotic.

An example Back to the coffee taste test

$$Y_1, \dots, Y_n \stackrel{i.i.d.}{\sim} B(1, \theta)$$

$$H_0: \theta = \theta_0 = \frac{1}{2}$$

Reject H_0 if $|Z_2| = \left| \frac{\sqrt{n}(\overline{Y} - \theta_0)}{\sqrt{\overline{Y}(1 - \overline{Y})}} \right| > z_{\alpha/2}$

Suppose that in the population, 60% of consumers would prefer the new blend. If we test 100 consumers, what is the probability of obtaining results that are statistically significant?

That is, if $\theta = 0.60$, what is the power for n = 100? Earlier, got 0.53 with a direct standard normal calculation.

Non-central chi-squared

Recall that if
$$X \sim N(\mu, \sigma^2)$$
, then $\left(\frac{X-\mu_0}{\sigma}\right)^2 \sim \chi^2 \left(1, \left(\frac{\mu-\mu_0}{\sigma}\right)^2\right)$.

For large n, the sample proportion \overline{Y} is approximately normal with mean $\mu = \theta$ and variance $\sigma^2 = \frac{\theta(1-\theta)}{n}$. So,

$$Z_2^2 = \left(\frac{\sqrt{n}(\overline{Y} - \theta_0)}{\overline{Y}(1 - \overline{Y})}\right)^2$$
$$\approx \frac{(\overline{Y} - \theta_0)^2}{\theta(1 - \theta)/n}$$
$$= \left(\frac{\overline{Y} - \theta_0}{\sigma}\right)^2$$
$$\stackrel{approx}{\sim} \chi^2 \left(1, n \frac{(\theta - \theta_0)^2}{\theta(1 - \theta)}\right)^2$$

We have found that

The Wald chi-squared test statistic of $H_0: \theta = \theta_0$

$$Z_2^2 = \frac{n(\overline{Y} - \theta_0)^2}{\overline{Y}(1 - \overline{Y})}$$

has an asymptotic non-central chi-squared distribution with df = 1 and non-centrality parameter

$$\lambda = \frac{n(\theta - \theta_0)^2}{\theta(1 - \theta)}$$

Notice the similarity of test statistic and non-centrality parameter, and also that

- If $\theta = \theta_0$, then $\lambda = 0$ and Z_2^2 has a central chi-squared distribution.
- The probability of exceeding any critical value (power) can be made as large as desired by making λ bigger.
- There are 2 ways to make λ bigger. What are they?

Power calculation with R For n = 100, $\theta_0 = 0.50$ and $\theta = 0.60$

> # Power for Wald chisquare test of H0: theta=theta0
> n=100; theta0=0.50; theta=0.60
> lambda = n * (theta-theta0)^2 / (theta*(1-theta))
> critval = qchisq(0.95,1)
> power = 1-pchisq(critval,1,lambda); power
[1] 0.5324209

Earlier, had

> Z2power(0.60,100)
[1] 0.5324209

Check power calculations by simulation First develop and illustrate the code

```
# Try a simulation to test it.
set.seed(9999) # Set seed for "random" number generation
theta = 0.50; theta0 = 0.50; n = 100; m = 10
critval = qchisq(0.95,1); critval
p = rbinom(m,n,theta)/n; p
Z2 = sqrt(n)*(p-theta0)/sqrt(p*(1-p))
rbind(p,Z2)
sig = (Z2^2>critval); sig
sum(sig)/n
```

Output from the last slide

> # Trv a simulation to test it. > set.seed(9999) # Set seed for "random" number generation > theta = 0.50; theta0 = 0.50; n = 100; m = 10 > critval = qchisq(0.95,1); critval [1] 3.841459 > p = rbinom(m,n,theta)/n; p [1] 0.40 0.56 0.47 0.57 0.47 0.50 0.58 0.48 0.40 0.53 > Z2 = sqrt(n)*(p-theta0)/sqrt(p*(1-p)) > rbind(p,Z2) [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] p 0.400000 0.560000 0.4700000 0.570000 0.4700000 0.5 0.580000 0.4800000 0.400000 22 -2.041241 1.208734 -0.6010829 1.413925 -0.6010829 0.0 1.620882 -0.4003204 -2.041241 [,10] p 0.5300000 Z2 0.6010829 > sig = (Z2^2>critval); sig [1] TRUE FALSE FALSE FALSE FALSE FALSE FALSE TRUE FALSE > sum(sig)/n [1] 0.02

Now the real simulation

First estimated probability should equal about 0.05 because $\theta=\theta_0$

```
> # Check Type I error probability
> set.seed(9999)
> theta = 0.50; theta0 = 0.50; n = 100; m = 10000
> critval = qchisq(0.95,1)
> p = rbinom(m,n,theta)/n; Z2 = sqrt(n)*(p-theta0)/sqrt(p*(1-p))
> sig = (Z2<sup>2</sup>>critval)
> sum(sig)/m
[1] 0.0574
> # Exact power calculation for theta=0.60 gives power = 0.5324209
> set.seed(9998)
> theta = 0.60; theta0 = 0.50; n = 100; m = 10000
> critval = qchisq(0.95,1)
> p = rbinom(m,n,theta)/n; Z2 = sqrt(n)*(p-theta0)/sqrt(p*(1-p))
> sig = (Z2<sup>2</sup>>critval)
> sum(sig)/m
[1] 0.5353
```

Conclusions from the power analysis

- Power for n = 100 is pathetic.
- As Fisher said, "To call in the statistician after the experiment is done may be no more than asking him to perform a postmortem examination: he may be able to say what the experiment died of."
- n = 200 is better.

> n=200; theta0=0.50; theta=0.60
> lambda = n * (theta-theta0)^2 / (theta*(1-theta))
> power = 1-pchisq(critval,1,lambda); power
[1] 0.8229822

• What sample size is required for power of 90%?

What sample size is required for power of 90%?

```
> # Find sample size needed for power = 0.90
> theta0=0.50; theta=0.60; critval = qchisq(0.95,1)
> effectsize = (theta-theta0)^2 / (theta*(1-theta))
> n = 0
> power=0
> while(power < 0.90)
+ {
+ n = n+1
+ lambda = n * effectsize
+ power = 1-pchisq(critval,1,lambda)
+ }
> n; power
[1] 253
[1] 0.9009232
```

General non-central chi-squared

Let X_1, \ldots, X_n be independent $N(\mu_i, \sigma_i^2)$. Then

$$Y = \sum_{i=1}^n \frac{X_i^2}{\sigma_i^2} \sim \chi^2(n, \lambda), \text{ where } \lambda = \sum_{i=1}^n \frac{\mu_i^2}{\sigma_i^2}$$

- Density is a bit messy a Poisson mixture of central chi-squares.
- Reduces to central chi-squared when $\lambda = 0$.
- Generalizes to $Y \sim \chi^2(\nu, \lambda)$, where $\nu > 0$ as well as $\lambda > 0$.
- Stochastically increasing in λ , meaning $Pr\{Y > y\}$ can be increased by increasing λ .
- $\lim_{\lambda \to \infty} \Pr\{Y > y\} = 1$
- Probabilities are easy to calculate numerically.



Non-central Chi-squared with df = 3

R code for the record

```
# Plotting non-central chi-squared in R with Greek letters
lambda1 = 1; lambda2=2; top = 15; DF=3
titlestring = paste("Non-central Chi-squared with df =",DF)
x = seq(from=0, to=top, by=0.01)
Density = dchisq(x,df=DF)
d1 = dchisq(x,df=DF,ncp=lambda1); d2 = dchisq(x,df=DF,ncp=lambda2)
plot(x,Density,type="1",main=titlestring) # That's a lower case L
lines(x,d1,lty=2); lines(x,d2,lty=3)
# Make line labels
x1 <- c(11,14) ; y1 <- c(0.20,0.20) ; lines(x1,y1,lty=1)</pre>
x2 <- c(11,14) ; y2 <- c(0.19,0.19) ; lines(x2,y2,lty=2)
x3 <- c(11,14) ; y3 <- c(0.18,0.18) ; lines(x3,y3,lty=3)
caption0 = expression(paste(lambda," = 0")); text(10,0.20,caption0);
# Ugly but flexible: * means concatenation in expressions, and we
#
                       need to substitute numerical values. First comes
#
                       an expression, and then a list of substitutions.
caption1 = substitute( lambda * " = " * L1, list(L1=lambda1) )
text(10,0.19,caption1)
caption2 = substitute( lambda * " = " * L2, list(L2=lambda2) )
text(10,0.18,caption2)
```

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