

Lecture #16

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Recall: Want a way to do hypothesis testing on the parameters of a multinomial distribution $\text{Multi}(\vec{p}; n)$ where n (# trials) is known but $\vec{p} = (p_1, \dots, p_k)$ is not.

• So, we would consider hypotheses of the form $H_0: \vec{p} = \vec{p}_0 = (p_1^0, \dots, p_k^0)$
 $H_1: \vec{p} \neq \vec{p}_0$

To understand how to evaluate such hypotheses, we should understand the behavior of a particular observation under the assumption H_0 holds.

• So, suppose (X_1, \dots, X_k) is observed from $\text{Multi}(\vec{p}; n)$. We saw that while an individual X_i is asymptotically normal in the sense that

$$\frac{X_i - np_i}{\sqrt{np_i}} \rightsquigarrow N(0, \sqrt{1-p_i}),$$

the global correlation amongst the $\left\{ \frac{X_i - np_i}{\sqrt{np_i}} \right\}_{i=1}^k$, due to the constraint $\sum_{i=1}^k X_i = n$, prevents a simple analysis of something like $\sum_{i=1}^k \frac{X_i - np_i}{\sqrt{np_i}}$. (approximate/asymptotic)

• Instead, we saw that a delicate linear algebraic analysis of the joint distribution

$\left(\frac{X_1 - np_1}{\sqrt{np_1}}, \dots, \frac{X_k - np_k}{\sqrt{np_k}} \right)^2$ yields that under H_0 ,

$$\sum_{i=1}^k \frac{[X_i - np_i]^2}{np_i} \rightsquigarrow \chi^2(k-1),$$

where $\chi^2(k-1)$ is a χ^2 -distribution with $(k-1)$ degrees of freedom. (2)

$$\chi^2(k-1) = \sum_{i=1}^{k-1} Z_i^2, \text{ where } \{Z_i\}_{i=1}^{k-1} \text{ are i.i.d. standard normals.}$$

• This gives us a framework for testing if $\sum_{i=1}^k \frac{[x_i - np_i]^2}{np_i}$ is anomalous

or not: compare it to a cut-off ~~value~~ χ_α^2 where

$$P(\chi^2(k-1) > \chi_\alpha^2) = \alpha$$

for some significance level α .

• Just like for a Wald Test, we can use a computer/standard table to compute

χ_α^2 for fixed (α, k) values.

• To summarize: To run a Pearson's χ^2 test on $H_0: \vec{p} = \vec{p}_0 = (p_1^0, \dots, p_k^0)$
 $H_1: \vec{p} \neq \vec{p}_0,$

compute the test statistic $T = \sum_{i=1}^k \frac{[x_i - np_i^0]^2}{np_i^0}$. Let α be the specified

significance level. We reject H_0 at level α if $T > \chi_\alpha^2$, where χ_α^2 is
chosen s.t. $P(\chi^2(k-1) > \chi_\alpha^2) = \alpha$.

Note: The cut-off ~~value~~ χ_α^2 depends on both the significance level (α) and
the number of degrees of freedom $(k-1)$.

ex: Suppose we have a 6-sided die. We roll it 6,000 times and observe ③

The following outcome:

| Roll | Frequency |
|------|-----------|
| 1 | 971 |
| 2 | 1084 |
| 3 | 1013 |
| 4 | 918 |
| 5 | 972 |
| 6 | 1042 |

Can we argue the die is unfair? Let's phrase "fairness" as a statement about multinomial distributions. $\vec{X} = (X_1, X_2, \dots, X_6) \sim \text{Multi}(\vec{p}, 6000)$

$$H_0: \vec{p} = \left(\frac{1}{6}, \frac{1}{6}, \dots, \frac{1}{6}\right)$$

$$H_1: \vec{p} \neq \left(\frac{1}{6}, \dots, \frac{1}{6}\right)$$

Well, the χ^2 test statistic is $T = \sum_{i=1}^k \frac{[x_i - n p_i^0]^2}{n p_i^0}$

In our case, $p_i^0 = 1/6$ for all $i=1, \dots, 6$; this is the quantification of fairness.

Then $n = 6000$, $k = 6$, and we compute

$$\begin{aligned}
 T &= \sum_{i=1}^6 \frac{[x_i - 6000 \cdot \frac{1}{6}]^2}{6000 \cdot \frac{1}{6}} \\
 &= \frac{[971 - 1000]^2}{1000} + \frac{[1084 - 1000]^2}{1000} + \frac{[1013 - 1000]^2}{1000} \\
 &\quad + \frac{[918 - 1000]^2}{1000} + \frac{[972 - 1000]^2}{1000} + \frac{[1042 - 1000]^2}{1000} \\
 &\approx 17.3380
 \end{aligned}$$

So, how do we use this to evaluate H_0 ? Let's run the test at $\alpha = .01$.

The cut-off χ^2_α associated to $\alpha = .01$ at $6-1=5$ degrees of freedom (4)
is (using computer) $\chi^2_\alpha = 15.0863$. Then since $T = 17.3380 > 15.0863$,

we reject H_0 at the $\alpha = .01$ level.

What is the p-value? Well, what is the value $P(\chi^2(5) > 17.3380)$
 $= .0039$.

So, quite decent evidence the die is "unfair", albeit not very unfair.

Remark: Unlike Gaussian r.v., χ^2 r.v. are not symmetric:



As # d.o.f. increase, the bulk/center of the distribution increases, as does the variance (HW)

- Notice that $P(\chi^2(k) > 0) = 1 \quad \forall k$, but $P(\chi^2(k) < N) < 1$ for all k, N

In other words, χ^2 distributions have only 1 infinite tail, the one towards $+\infty$.

Recap of Hypothesis Testing: We consider hypotheses around parameters of models,

ie. $H_0: \mu = \mu_0$
 $H_1: \mu \neq \mu_0$

or $H_0: \vec{p} = (p_1^0, \dots, p_k^0)$
 $H_1: \vec{p} \neq (p_1^0, \dots, p_k^0)$

for μ the mean of a Gaussian

for \vec{p} the probabilities associated to a multinomial distribution

- To evaluate these hypotheses (or any), we needed to answer: "what is the distribution of the sample statistic under the assumption H_0 holds?"
- The Wald Test answered that question by leveraging the CLT.
- The Pearson χ^2 test leveraged delicate linear algebra.
- In general, one can be creative and try to develop understanding of the test statistic under H_0 ; this is part of what research in mathematical statistics looks like!
- Going forward, we will consider more non-parametric/vaguer hypothesis tests.
- Our focus will be on tests for independence: are two R.V. \bar{X}, \bar{Y} independent?