

## Topic 19

### Extensions on the Likelihood Ratio

#### One-Sided Tests

## Outline

### One-Sided Tests

Karlin-Rubin Theorem

Binomial Test

Proportion Test

## Introduction

For a **composite hypothesis**

$$H_0 : \theta \in \Theta_0 \quad \text{versus} \quad H_1 : \theta \in \Theta_1,$$

we have seen critical regions defined by taking a **statistic**  $T(\mathbf{x})$  and defining the **critical region** based on a **critical value**  $\tilde{k}_\alpha$ . For a **one-sided test**, we have seen critical regions

$$\{\mathbf{x}; T(\mathbf{x}) \geq \tilde{k}_\alpha\} \quad \text{or} \quad \{\mathbf{x}; T(\mathbf{x}) \leq \tilde{k}_\alpha\}.$$

For a **two-sided test**, we saw

$$\{\mathbf{x}; |T(\mathbf{x})| \geq \tilde{k}_\alpha\}.$$

$\tilde{k}_\alpha$  is determined by the level  $\alpha$ . We thus use commands **qnorm**, **qbinom**, or **qhyper** when  $T(\mathbf{x})$  has, respectively, a **normal**, **binomial**, or **hypergeometric** distribution under a appropriate choice of  $\theta \in \Theta_0$ . We now examine extensions of the **likelihood ratio test** for simple hypotheses that have desirable properties for a critical region.

## One-Sided Tests

In testing for the invasion of a **mimic** butterfly by a **model** species, we collected a simple random sample modeled as independent normal observations with **unknown mean** and known variance  $\sigma_0^2$ .

We discovered, in the case of a **simple hypothesis** test,

$$H_0 : \mu = \mu_0 \quad \text{versus} \quad H_1 : \mu = \mu_1$$

that the critical region as determined by the **Neyman-Pearson lemma** depends only on whether or not  $\mu_1$  was greater than  $\mu_0$ . For example, if  $\mu_1 > \mu_0$ , then the critical region

$$C = \{\mathbf{x}; \bar{x} \geq \tilde{k}_\alpha\}$$

shows that we reject  $H_0$  whenever the sample mean is higher than some threshold value  $\tilde{k}_\alpha$  **irrespective** of the difference between  $\mu_0$  and  $\mu_1$ .

## One-Sided Tests

- If a test is most powerful against *each* possible alternative in a simple hypothesis test, when we can say that this test is in some sense *best overall* for a composite hypothesis?
- Does this test have the property that its *power function*  $\pi$  is greater for every value of  $\theta \in \Theta_1$  than the power function of *any* other test. Such a test is called *uniformly most powerful*.
- We can hope such a test if the procedures from simple hypotheses results in a *common critical region* for all values of the alternative.
- In the example above using independent normal data. In this case, the power function

$$\pi(\mu) = P_{\mu}\{\bar{X} \geq k_{\alpha}\}$$

increases as  $\mu$  increases and so the test has the intuitive property of becoming more powerful with increasing  $\mu$ .

## Karlin-Rubin Theorem

In general, we look for a **test statistic**  $T(\mathbf{x})$ . Next, we check that the **likelihood ratio**,

$$\frac{L(\theta_2|\mathbf{x})}{L(\theta_1|\mathbf{x})}, \quad \theta_1 < \theta_2.$$

depends on the **data**  $\mathbf{x}$  only through the value of statistic  $T(\mathbf{x})$  and, in addition, this ratio is a **monotone increasing function** of  $T(\mathbf{x})$ .

The **Karlinin-Rubin theorem** states:

If these conditions hold, then for an appropriate value of  $\tilde{k}_\alpha$ ,

$$C = \{\mathbf{x}; T(\mathbf{x}) \geq \tilde{k}_\alpha\}$$

is the critical region for a **uniformly most powerful**  $\alpha$  level test for the one-sided alternative hypothesis

$$H_0 : \theta \leq \theta_0 \quad \text{versus} \quad H_1 : \theta > \theta_0.$$



## Karlin-Rubin Theorem

A corresponding criterion holds for the one sided test a “less than” alternative.

**Exercise.** Verify that the likelihood ratio is an appropriate monotone function of the given test statistic,  $T$ .

1. For mark and recapture, use the hypothesis

$$H_0 : N \geq N_0 \quad \text{versus} \quad H_1 : N < N_0,$$

use the test statistic  $T(\mathbf{x}) = r(\mathbf{x})$ , the number tagged in the second capture.

2. For  $X = (X_1, \dots, X_n)$  is a sequence of Bernoulli trials with unknown success probability  $p$ , and the one-sided test

$$H_0 : p \leq p_0 \quad \text{versus} \quad H_1 : p > p_0,$$

use the test statistic  $T(\mathbf{x}) = \hat{p}(\mathbf{x})$ , the sample proportion of successes.

## Binomial Test

If 20 out of 36 bee hives survive a severe winter, for an  $\alpha = 0.05$  level test for

$$H_0 : p \geq 0.7 \quad \text{versus} \quad H_1 : p < 0.7,$$

we use the binomial distribution for the number of successes using `binom.test`.

```
> binom.test(20,36,p=0.7,alternative=c("less"))
```

Exact binomial test

data: 20 and 36

number of successes = 20, number of trials = 36, p-value = 0.04704

alternative hypothesis: true probability of success is less than 0.7

**Exercise.** Do we reject the hypothesis at the 5% level? the 1% level? Find the *p-value* using the `pbinom` command.



## Proportion Test

If 250 out of 336 bee hives survive a mild winter, for an  $\alpha = 0.05$  level test for

$$H_0 : p \leq 0.7 \quad \text{versus} \quad H_1 : p > 0.7,$$

we use the normal approximation for the number of successes using `prop.test`.

```
> prop.test(250,336,p=0.7,alternative=c("greater"))
```

1-sample proportions test with continuity correction

```
data: 250 out of 336, null probability 0.7  
X-squared = 2.8981, df = 1, p-value = 0.04434
```

and we *reject* the null hypothesis.

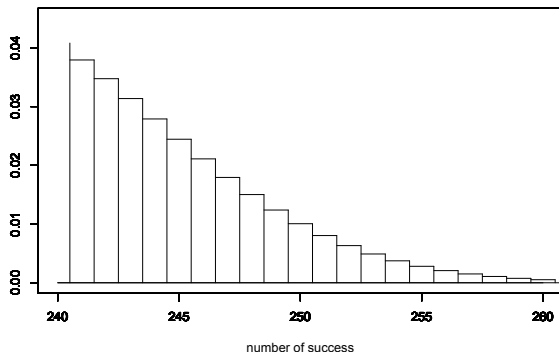
## Continuity Correction

The  $p$ -value is  $P\{X \geq 250\}$  where  $X$  is  $\text{Bin}(336, 0.7)$ . We compute this using R.

$$P\{X \geq 250\} = 1 - P\{X \leq 249\}$$

```
> 1-pbinom(249,336,0.7)
[1] 0.0428047
```

The command `prop.test` uses a normal approximation and a continuity correction to obtain a  $p$ -value 0.04434



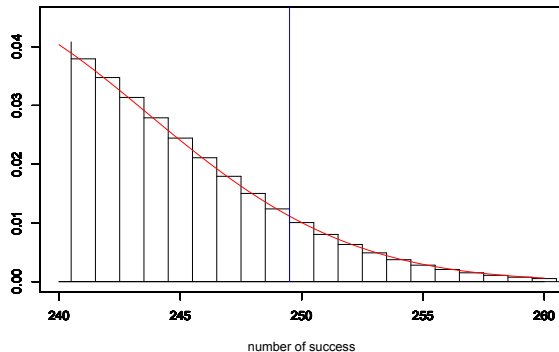
The  $p$ -value  $P\{X \geq x\} = \sum_{y=x}^n P\{X = y\}$  can be realized as the area of rectangles, height  $P\{X = y\}$  and width 1.

## Continuity Correction

The rectangles look like a **Riemann sum** for the integral of the density of a  $N(np_0, \sqrt{np_0(1-p_0)})$  random variable with **lower limit**  $x - 1/2$ .

```
> mu<-0.7*336
> sigma<-sqrt(336*0.7*0.3)
> x<-c(249,249.5,250)
> prob<-1-pnorm(x,mu,sigma)
> data.frame(x,prob)
```

	x	prob
1	249.0	0.05020625
2	249.5	0.04434199
3	250.0	0.03904269



The **continuity correction** replaces the binomial by finding the area under the normal density with **lower limit**  $x - 1/2$ .

## Continuity Correction

### Exercise.

1. Create a table of  $p$ -values for the hypothesis above for the values  $x = 240, \dots, 260$  for the number of hives that survive the winter. Compare the  $p$ -values using the **binomial distribution** and using the **normal distribution** with the **continuity correction**.
2. Use the normal approximation to create a **95%** confidence interval for the proportion of hives that survive the winter.