

Math 362: Mathematical Statistics II

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Chapter 6. Hypothesis Testing

§ 6.1 Introduction

§ 6.2 The Decision Rule

§ 6.3 Testing Binomial Data – $H_0 : p = p_0$

§ 6.4 Type I and Type II Errors

§ 6.5 A Notion of Optimality: The Generalized Likelihood Ratio

Plan

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Go over the example first....

Suppose our friend Jory claims that he has some magic power to predict the side of a randomly tossed fair-coin.

Jory claims that he could do more than $\frac{1}{2}$ of the time on average.

Let's test Jory to see if we believe his claim.

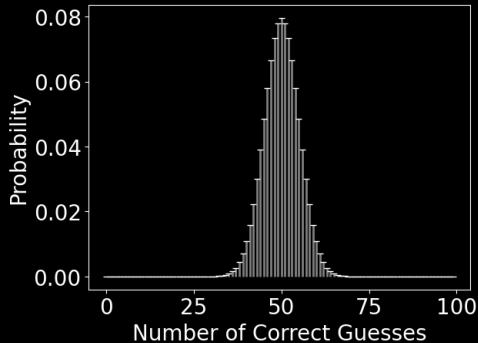
We made Jory guess a repeatedly tossed coin
for 100 times.

He guesses correctly 54 times.

Question:

Does this provide strong evidence that Jory
has the proclaimed magic power?

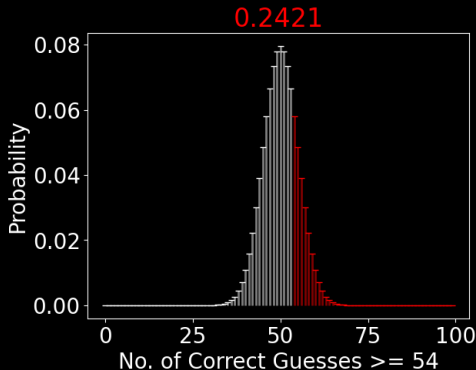
If Jory is guessing randomly, the number of correct guesses would follow a binomial distribution with parameters $n = 100$ and $p = 1/2$.



What is probability that Jory gets 54 or more correct when guessing randomly?

$$\mathbb{P}(X \geq 54) = \sum_{n=54}^{100} \binom{100}{n} \left(\frac{1}{2}\right)^n \left(\frac{1}{2}\right)^{100-n} = 0.2421.$$

What is probability that Jory gets **54 or more** correct when guessing randomly?



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It is not unlikely to get this many correct guesses due to chance.

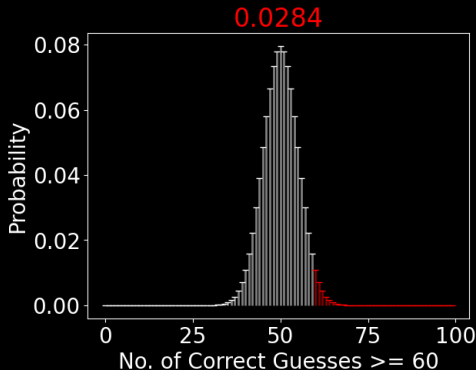
Conclusion:

There is No strong evidence that Jory has better than a $1/2$ chance of correctly guessing the coin.

What is probability that Jory gets 60 or more correct when guessing randomly?

$$\mathbb{P}(X \geq 60) = \sum_{n=60}^{100} \binom{100}{n} \left(\frac{1}{2}\right)^n \left(\frac{1}{2}\right)^{100-n} = 0.0284.$$

What is probability that Jory gets 60 or more correct when guessing randomly?



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Either

Jory is purely guessing with probability of
success of $\frac{1}{2}$, and we witnessed a very
unusual event due to chance.

Or

Jory is truly having the magic power to guess
the coin.

Conclusion:

We have strong evidence against
Red Hypothesis

Or the test is in favor of
Green Hypothesis

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Before testing Jory, could you set up a threshold above which we will believe Jory's super power?

Find smallest m such that

$$\mathbb{P}(X \geq m) = \sum_{n=m}^{100} \binom{100}{n} \left(\frac{1}{2}\right)^n \left(\frac{1}{2}\right)^{100-n} \leq 0.05$$

\Downarrow

$$\boxed{m = 59}$$

b.c. $\mathbb{P}(X \geq 58) = 0.067$ & $\mathbb{P}(X \geq 59) = 0.044$

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We have just informally conducted a hypothesis test with the null hypothesis

$$H_0 : p = \frac{1}{2}$$

against the alternative hypothesis

$$H_1 : p > \frac{1}{2}$$

under the significance level $\alpha = 0.05$

which is equivalent to either

producing the critical region
 $m \geq 59$

or

comparing with the p-value.

- ▶ **Test statistic:** Any function of the observed data whose numerical value dictates whether H_0 is accepted or rejected.

- ▶ **Critical region C :** The set of values for the test statistic that result in the null hypothesis being rejected.

Critical value: The particular point in C that separates the rejection region from the acceptance region.

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Test Normal mean $H_0 : \mu = \mu_0$ (σ known)

Setup:

1. Let $Y_1 = y_1, \dots, Y_n = y_n$ be a random sample of size n from $N(\mu, \sigma^2)$ with σ known.
2. Set $\bar{y} = \frac{1}{n}(y_1 + \dots + y_n)$ and $z = \frac{\bar{y} - \mu_0}{\sigma/\sqrt{n}}$.
3. The level of significance is α .

Test:

$$\begin{cases} H_0 : \mu = \mu_0 \\ H_1 : \mu > \mu_0 \end{cases}$$

reject H_0 if $z \geq z_\alpha$.

$$\begin{cases} H_0 : \mu = \mu_0 \\ H_1 : \mu < \mu_0 \end{cases}$$

reject H_0 if $z \leq -z_\alpha$.

$$\begin{cases} H_0 : \mu = \mu_0 \\ H_1 : \mu \neq \mu_0 \end{cases}$$

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Definition. The **P-value** associated with an observed test statistic is the probability of getting a value for that test statistic as extreme as or more extreme than what was actually observed (relative to H_1) given that H_0 is true.

Note: Test statistics that yield small P-values should be interpreted as evidence against H_0 .

E.g., Suppose that test statistic $z = 1.90$. Find P-value for

$$\begin{array}{lll} \left\{ \begin{array}{l} H_0: \mu = \mu_0 \\ H_1: \mu > \mu_0 \end{array} \right. & \left\{ \begin{array}{l} H_0: \mu = \mu_0 \\ H_1: \mu < \mu_0 \end{array} \right. & \left\{ \begin{array}{l} H_0: \mu = \mu_0 \\ H_1: \mu \neq \mu_0 \end{array} \right. \end{array}$$

$$\begin{array}{lll} P(Z > 1.90) = 0.0287 & P(Z < 1.90) = 0.9713 & P(Z > 1.90) = 0.0287 \\ P(Z < 1.90) = 0.9713 & P(Z > 1.90) = 0.0287 & P(Z < 1.90) = 0.9713 \\ P(Z < 1.90) = 0.9713 & P(Z < 1.90) = 0.9713 & P(Z < 1.90) = 0.9713 \end{array}$$

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$$\begin{array}{lll} \left\{ \begin{array}{l} H_0: \mu = 0 \\ H_1: \mu > 0 \end{array} \right. & \left\{ \begin{array}{l} H_0: \mu = 0 \\ H_1: \mu < 0 \end{array} \right. & \left\{ \begin{array}{l} H_0: \mu = 0 \\ H_1: \mu \neq 0 \end{array} \right. \\ \left\{ \begin{array}{l} H_0: \mu = 0 \\ H_1: \mu > 0 \end{array} \right. & \left\{ \begin{array}{l} H_0: \mu = 0 \\ H_1: \mu < 0 \end{array} \right. & \left\{ \begin{array}{l} H_0: \mu = 0 \\ H_1: \mu \neq 0 \end{array} \right. \end{array}$$

$$\begin{aligned} P(Z \geq 1.96) &= 1 - P(Z \leq 1.96) = 1 - \Phi(1.96) = 1 - 0.9750 = 0.0250 \\ P(Z \leq -1.96) &= \Phi(-1.96) = 0.0250 \\ P(Z \leq 1.96 \text{ or } Z \leq -1.96) &= P(Z \leq 1.96) + P(Z \leq -1.96) \\ &= \Phi(1.96) + \Phi(-1.96) = 0.9750 + 0.0250 = 0.1000 \end{aligned}$$

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E.g. Suppose that test statistic $z = 0.60$. Find P-value for

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$$\mathbb{P}(Z \geq 0.60) = 0.2743.$$

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