

## Exam 2 Review

18.05 Spring 2018

- Cannot cover everything.
- You may bring a **cheat sheet**  $5 \times 7$  inch index card (both sides) to the exam.
- You can also bring your **cheat sheet from the first exam**.
- Calculators are **not allowed** on the exam—they won't be needed.
- Get **familiar with the probability tables** for  $Z$ ,  $t$  and  $\chi^2$ . There are copies with the practice exam.

# Summary

- **Data:**  $x_1, \dots, x_n$
- Basic **statistics:** sample mean, sample variance, sample median
- **Likelihood**, maximum likelihood estimate (MLE)
- **Bayesian updating:** prior, likelihood, posterior, predictive probability, probability intervals; prior and likelihood can be discrete or continuous
- **NHST:**  $H_0$ ,  $H_A$ , significance level, rejection region, power, type 1 and type 2 errors,  $p$ -values, confidence intervals.

## Basic statistics

**Data:**  $x_1, \dots, x_n$ .

$$\text{sample mean} = \bar{x} = \frac{1}{n}(x_1 + \dots + x_n)$$

$$\text{sample variance} = s^2 = \frac{1}{n-1} \left( \sum_{i=1}^n (x_i - \bar{x})^2 \right)$$

sample median = **middle value** (or average of two middle values)

**Example.** Data: 6, 3, 8, 1, 2

$$\bar{x} = (6 + 3 + 8 + 1 + 2)/4 = 4$$

$$\begin{aligned} s^2 &= ((6 - 4)^2 + (3 - 4)^2 + (8 - 4)^2 + (1 - 4)^2 + (2 - 4)^2)/4 \\ &= (4 + 1 + 16 + 9 + 4)/4 = 8.5 \end{aligned}$$

median = 3.

# Likelihood

$x$  = data

$\theta$  = parameter of interest or hypotheses of interest

Likelihood = probability of data given hypothesis:

$p(x | \theta)$  (discrete distribution)

$f(x | \theta)$  (continuous distribution)

Log likelihood :

$\ln(p(x | \theta)).$

$\ln(f(x | \theta)).$

# Likelihood examples

**Examples.** Find the likelihood function of each of the following.

1. Coin with probability of heads  $\theta$ . Toss 10 times, get 3 heads.
2. Wait time  $\sim \exp(\lambda)$ . In 5 independent trials wait 3, 5, 4, 5, 2.
3. Usual 5 dice. Two independent rolls, 9, 5. (Make a likelihood table.)
4. Independent  $x_1, \dots, x_n \sim N(\mu, \sigma^2)$
5.  $x = 6$  drawn from  $\text{uniform}(0, \theta)$
6.  $x$  drawn from  $\text{uniform}(0, \theta)$

In each case likelihood depends on data and unknown hypotheses.

# MLE

Methods for finding the maximum likelihood estimate (MLE).

- Discrete hypotheses: compute each likelihood
- Discrete hypotheses: maximum is obvious
- Continuous parameter: compute derivative (often use log likelihood)
- Continuous parameter: maximum is obvious

**Examples.** Find the MLE for each example in the previous slide.

## Bayesian updating: discrete prior-discrete likelihood

Jon has 1 four-sided, 2 six-sided, 2 eight-sided, 2 twelve sided, and 1 twenty-sided dice. He picks one at random and rolls a 7.

- 1 For each type, find the posterior probability Jon chose that type.
- 2 What are the posterior odds Jon chose the 20-sided die?
- 3 Compute the prior predictive probability of rolling 7 on roll 1.
- 4 Compute the posterior predictive probability of rolling 8 on roll 2.

# Bayesian updating: conjugate priors

## 1. Beta prior, binomial likelihood

Data:  $x \sim \text{binomial}(n, \theta)$ .  $\theta$  is unknown.

Prior:  $f(\theta) \sim \text{beta}(a, b)$

Posterior:  $f(\theta | x) \sim \text{beta}(a + x, b + n - x)$

**Example.** Suppose  $x \sim \text{binomial}(30, \theta)$ ,  $x = 12$ .

If we have a prior  $f(\theta) \sim \text{beta}(1, 1)$  find the posterior.

## 2. Beta prior, geometric likelihood

Data:  $x$

Prior:  $f(\theta) \sim \text{beta}(a, b)$

Posterior:  $f(\theta | x) \sim \text{beta}(a + x, b + 1)$ .

**Example.** Suppose  $x \sim \text{geometric}(\theta)$ ,  $x = 6$ .

If we have a prior  $f(\theta) \sim \text{beta}(4, 2)$  find the posterior.



## Normal-normal

3. Normal prior, normal likelihood:

$$a = \frac{1}{\sigma_{\text{prior}}^2}$$

$$b = \frac{n}{\sigma^2}$$

$$\mu_{\text{post}} = \frac{a\mu_{\text{prior}} + b\bar{x}}{a + b},$$

$$\sigma_{\text{post}}^2 = \frac{1}{a + b}.$$

**Notice:**  $\mu_{\text{post}}$  **between**  $\mu_{\text{prior}}$  and  $\bar{x}$ ;  $\sigma_{\text{post}}^2$  **smaller than**  $\sigma_{\text{prior}}^2$ .

**Example.** In the population IQ is normally distributed:

$$\theta \sim N(100, 15^2).$$

An IQ test finds a person's 'true' IQ + random error  $\sim N(0, 10^2)$ .

Someone takes the test and scores 120.

Find the posterior pdf for this person's IQ.

# Bayesian updating: continuous prior-continuous likelihood

**Examples.** Update from prior to posterior for each of the following with the given data. Graph the prior and posterior in each case.

1. Romeo is late:

likelihood:  $x \sim U(0, \theta)$ , prior:  $U(0, 1)$ .

data: 0.3, 0.4, 0.4

2. Waiting times:

likelihood:  $x \sim \exp(\lambda)$ , prior:  $\lambda \sim \exp(2)$ .

data: 1, 2

3. Waiting times:

likelihood:  $x \sim \exp(\lambda)$ , prior:  $\lambda \sim \exp(2)$ .

data:  $x_1, x_2, \dots, x_n$

# NHST: Steps

- 1 Specify  $H_0$  and (perhaps)  $H_A$ .
- 2 Choose a significance level  $\alpha$ .
- 3 Choose a test statistic and determine the null distribution.
- 4 Determine how to compute a  $p$ -value and/or the rejection region.
- 5 Collect data. (At least this deserves its own color.)
- 6 Compute  $p$ -value or see if test statistic is in rejection region.
- 7 Reject or fail to reject  $H_0$ .

**It's very important that # 5 COMES AFTER #1-4!**

Make sure you are familiar with the probability tables!

# NHST: One-sample $t$ -test

- Data: we assume normal data with both  $\mu$  and  $\sigma$  unknown:

$$x_1, x_2, \dots, x_n \sim N(\mu, \sigma^2).$$

- Null hypothesis:  $\mu = \mu_0$  for some specific value  $\mu_0$ .
- Test statistic:

$$t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}}$$

where

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2.$$

- Null distribution:  $t(n-1)$ , Student  $t$  with  $n-1$  degs of freedom.
- Student  $t$  is symmetric around 0, like standard normal.

## Example: $z$ and one-sample $t$ -test

For both problems use significance level  $\alpha = 0.05$ .

Assume the data 2, 4, 4, 10 is drawn from a  $N(\mu, \sigma^2)$ .

Take  $H_0: \mu = 0$ ;  $H_A: \mu \neq 0$ .

1. Assume  $\sigma^2 = 16$  is known and test  $H_0$  against  $H_A$ .
2. Now assume  $\sigma^2$  is unknown and test  $H_0$  against  $H_A$ .

## Two-sample $t$ -test: equal variances

Data: we assume normal data with  $\mu_x, \mu_y$  and (same)  $\sigma$  unknown:

$$x_1, \dots, x_n \sim N(\mu_x, \sigma^2), \quad y_1, \dots, y_m \sim N(\mu_y, \sigma^2)$$

Null hypothesis  $H_0$ :  $\mu_x = \mu_y$ .

Pooled variance: 
$$s_p^2 = \frac{(n-1)s_x^2 + (m-1)s_y^2}{n+m-2} \left( \frac{1}{n} + \frac{1}{m} \right).$$

Test statistic: 
$$t = \frac{\bar{x} - \bar{y}}{s_p}$$

Null distribution:  $f(t | H_0)$  is the pdf of  $t(n+m-2)$

More generally we can test  $H_0: \mu_x - \mu_y = \mu_0$  using  $t = \frac{\bar{x} - \bar{y} - \mu_0}{s_p}$ .

## Example: two-sample $t$ -test

We have data from 1408 women admitted to a maternity hospital for (i) medical reasons or through (ii) unbooked emergency admission. The **duration of pregnancy** is measured in complete weeks from the beginning of the last menstrual period.

(i) Medical: 775 observations with  $\bar{x} = 39.08$  and  $s^2 = 7.77$ .

(ii) Emergency: 633 observations with  $\bar{x} = 39.60$  and  $s^2 = 4.95$

1. Set up and run a two-sample  $t$ -test to investigate whether the duration differs for the two groups.
2. What assumptions did you make?

## Chi-square test for goodness of fit

Three treatments for a disease are compared in a clinical trial, yielding the following data:

|           | Treatment 1 | Treatment 2 | Treatment 3 |
|-----------|-------------|-------------|-------------|
| Cured     | 50          | 30          | 12          |
| Not cured | 100         | 80          | 18          |

Use a chi-square test to compare the cure rates for the three treatments



## F-test = one-way ANOVA

Like  $t$ -test but for  $n$  groups of data with  $m$  data points each.

$$y_{i,j} \sim N(\mu_i, \sigma^2), \quad y_{i,j} = j^{\text{th}} \text{ point in } i^{\text{th}} \text{ group}$$

Assumptions: data for each group is an independent normal sample with (possibly) different means but the same variance.

Null hypothesis is that **means are all equal**:  $\mu_1 = \dots = \mu_n$ .

Test statistic is  $\frac{MS_B}{MS_W}$  where:

$$MS_B = \text{between group variance} = \frac{m}{n-1} \sum (\bar{y}_i - \bar{y})^2$$

$$MS_W = \text{within group variance} = \text{sample mean of } s_1^2, \dots, s_n^2$$

Idea: If  $\mu_i$  are equal, this ratio should be near 1.

Null distribution is **F-statistic with  $n-1$  and  $n(m-1)$  d.o.f.**:

$$\frac{MS_B}{MS_W} \sim F_{n-1, n(m-1)}$$

## ANOVA example

The table shows recovery time in days for three medical treatments.

1. Set up and run an F-test.
2. Based on the test, what might you conclude about the treatments?

| $T_1$ | $T_2$ | $T_3$ |
|-------|-------|-------|
| 6     | 8     | 13    |
| 8     | 12    | 9     |
| 4     | 9     | 11    |
| 5     | 11    | 8     |
| 3     | 6     | 7     |
| 4     | 8     | 12    |

For  $\alpha = 0.05$ , the critical value of  $F_{2,15}$  is 3.68.

# NHST: right and wrong 1A.

1. Significance  $\alpha$  **is not the probability of being wrong**. It's the probability of being wrong if the null hypothesis is true.
2. Likewise, power **is not the probability of being right**. It's the probability of being right if a particular alternate hypothesis is true.