Math 362, Problem set 5

Due 3/16/10

1. (3.7.6) Another estimating chi-square: Let the result of a random experiment be classifies as one of the mutually exclusive and exhaustive ways A_1, A_2, A_3 and also as one of the mutually exclusive and exhaustive ways B_1, B_2, B_3, B_4 . Two hundred independent trials of the experiment result in the following data

	B_1	B_2	B_3	B_4
A_1	10	21	15	6
A_2	11	27	21	13
A_3	6	19	27	24

Test, at the 0.05 significance level the hypothesis of independence of the A and B attribute, namely $H_0 : \mathbb{P}(A_i \cap B_i) = \mathbb{P}(A_i)\mathbb{P}(B_i)$, i = 1, 2, 3 and j = 1, 2, 3, 4 against the alternative of dependence.

Answer:

We estimate $\mathbb{P}(A_1) = \frac{10+21+15+6}{200} = \frac{13}{50}$. Likewise we estimate:

$$\mathbb{P}(A_2) = \frac{18}{50} \qquad \mathbb{P}(A_3) = \frac{19}{50} \qquad \mathbb{P}(B_1) = \frac{27}{200} \\ \mathbb{P}(B_2) = \frac{67}{200} \qquad \mathbb{P}(B_3) = \frac{63}{200} \qquad \mathbb{P}(B_4) = \frac{43}{200}$$

Note that, really, we've only estimated 5 probabilities, because $\mathbb{P}(A_3)$ is determined once $\mathbb{P}(A_2)$ and $\mathbb{P}(A_1)$ is estimated, and likewise for $\mathbb{P}(B_4)$.

Let n_{ij} denote the number of events in $A_i \cap B_j$ (so $n_{23} = 21$). We compute

$$\sum \frac{(n_{ij} - 200\mathbb{P}(A_i)\mathbb{P}(B_j)^2}{200\mathbb{P}(A_i)\mathbb{P}(B_j)} \approx 12.941$$

Since we estimated 5 parameters, we compare to a $\chi^2(12-1-5) = \chi^2(6)$ random variable. Since 12.941 > 12.592, we reject H_0 .

2. (5.8.5) Determine a method to generate random observations for the following pdf: $f(x) = 4x^3$ for 0 < x < 1, zero elsewhere.

- 3. (5.8.18) For $\alpha > 0$ and $\beta > 0$, consider the following accept/reject algorithm:
 - (1) Generate U_1 and U_2 iid uniform(0,1) random variables. Set $V_1 = U_1^{1/\alpha}$ and $V_2 = U_2^{1/\beta}$.
 - (2) Set $W = V_1 + V_2$. If $W \le 1$, set $X = V_1/W$, else goto Step(1).
 - (3) Deliver X.

Show that X has a beta distribution with parameters α and β .

Note/Hint: The analysis is quite similar to the analysis of the algorithm we did in class. That is, look for the cdf $\mathbb{P}(X \leq x)$ and note that it is some conditional probability.

Answer: Our goal is to show that $f_X(x) = Cx^{\alpha-1}(1-x)^{\beta-1}$ for some constant C. We note that

$$F_X(x) = \mathbb{P}(X \le x) = \mathbb{P}(V_1/W \le x | W \le 1)$$
$$= \frac{\mathbb{P}(V_1 \le xW, W \le 1)}{\mathbb{P}(W \le 1)}$$
$$= c\mathbb{P}(V_1 \le xW, W \le 1),$$

for some constant C. We find the joint distribution of V_1 and W as follows. First we find that $f_{V_1}(v_1) = \alpha v_1^{\alpha-1}$ for $0 < v_1 < 1$, and likewise $f_{V_2}(v_2) = \alpha v_1^{\alpha-1}$. Noting that $V_2 = W - V_1$, we have that the Jacobian of the transformation $V = V_1$ and $W = V_1 + V_2$ is 1. Thus the joint distribution of $f_{V_1,W}(v,w) = \alpha \beta v^{\alpha-1} (w-v)^{\beta-1}$ for 0 < v < 1, and v < w < v + 1. We have that

$$F_X(x) = c \int_{w=0}^{1} \int_{v=0}^{wx} \alpha \beta v^{\alpha-1} (w-v)^{\beta-1} dv dw$$

Taking the derivative and applying the fundamental theorem of calculus, we have

$$f_X(x) = c \int_{w=0}^1 \alpha \beta(wx)^{\alpha-1} (w-wx)^{\beta-1} dw = x^{\alpha-1} (1-x)^{\beta-1} c \int_{w=0}^1 \alpha \beta w^{\alpha+\beta-2} dw$$

Since this is of the proper form, the normalizing constant must be correct and this is a beta distribution as desired.

- 4. (5.9.1) Let x_1, \ldots, x_n be the values of a random sample. A bootstrap sample $\mathbf{x}^{*'} = (x_1^*, \ldots, x_n^*)$ is a random sample of x_1, \ldots, x_n drawn with replacement.
 - (a) Show that $\mathbb{E}[x_i^*] = \bar{x}$
 - (b) If n is odd, show that median $\{x_i^*\} = x_{((n+1)/2)}$
 - (c) Show that $\operatorname{Var}(x_i^*) = \frac{1}{n} \sum_{i=1}^n (x_i \bar{x})^2$

Notes: There was a part (a) on the book problem, which I cut as it's obvious but hard to write up nicely. It asks you to show that the x_i^* are independent (which they are because I chose with replacement) and have the CDF \hat{F}_n which is $\hat{F}_n(x) = \frac{1}{n} \times (\# \text{ of } x_i < x)$, which is obvious because I select the x_i^* uniformly from x_1, \ldots, x_n . Note that in (c), you have $\frac{1}{n}$ and not $\frac{1}{n-1}$ because \bar{x} is the *real* mean of the x_i^* as opposed to the sample mean of the x_i^* .

Answer:

$$\mathbb{E}[x_i^*] = \sum x_i \mathbb{P}(x_i^* = x_i) = \frac{1}{n} \sum x_i = \bar{x}_i$$

For (b), since half of the values are above, and half are below $x_{(n+1)/2}$, this is the median as desired.

For (c), we have

$$\operatorname{Var}(x_i^*) = \mathbb{E}[(x_i^* - \mathbb{E}[x_i^*])^2] = \frac{1}{n} \sum (x_i^* - \bar{x})^2.$$

- 5. (5.9.2) Let X_1, \ldots, X_n be a random sample from a $\Gamma(1, \beta)$ distribution.
 - (a.) Show that the confidence interval (2nX̄/(χ²_{2n})^{(1-(α/2))}, 2nX̄/(χ²_{2n})^{α/2}) is an exact (1 − α)100% confidence interval for β.
 Notation note: (χ²_{2n})^{(1-(α/2))} is the books (rather confusing) way of saying 'the number such that P(χ²(2n) < (χ²_{2n})^{(1-(α/2))}) = 1 − α/2; for instance for α = .5 and n = 4, so that 2n = 8, we have (by our chart) (χ²₈)^{(1-(α/2))} = 17.535. Unfortunately the notation makes the problem look harder than it is.
 - (b.) Using part (a), show that the 90% confidence interval discussed in Example 5.9.1 is (64.99, 136.69).

Answer: For (a) note that $2n\bar{X}$ has a $\Gamma(n,2\beta)$ distribution and $\frac{2n\bar{X}}{\beta}$ has a $\Gamma(n,2) = \chi^2(2n)$ distribution. Thus:

$$\mathbb{P}((\chi_{2n}^2)^{\alpha/2} \le \frac{2n\bar{X}}{\beta} \le (\chi_2^2 n)^{1-\alpha/2}) = 1 - \alpha.$$

Solving the interval for β , we get the desired answer.

For (b), we get that $(\chi^2_{40})^{.05} = 26.5$ and $(\chi^2_{40})^{.95} = 55.8$ (sadly from the internet). Then we compute to see the hypothesized interval.

6. (5.9.10) Let z^* be drawn at random from the discrete distribution which has mass n^{-1} at each point $z_i = x_i - \bar{x} + \mu_0$, where (x_1, \ldots, x_n) is the realization of a random sample. Determine $\mathbb{E}[z^*]$ and $\operatorname{Var}(z^*)$.

Answer:

$$\mathbb{E}[z^*] = \frac{1}{n} \sum (x_i - \bar{x} + \mu_0) = \mu_0.$$

Likewise

$$\operatorname{Var}(z^*) = \frac{1}{n} \sum (x_i - \bar{x} + \mu_0 - \mu_0)^2 = \frac{1}{n} \sum (x_i - \bar{x})^* = \operatorname{Var}(x^*).$$

where x^* is as in problem 3.