Mathematical Statistics Week 5 exercises

1. Let us have a realisation of a random sample x_1, \ldots, x_n from Be(p), where the parameter p is an unknown parameter. Consider the following two estimates of p:

$$\hat{p}_1 = \overline{x}$$
 and $\hat{p}_2 = \frac{x_1 + x_2}{2}$.

- (a) Are the estimates \hat{p}_1 and \hat{p}_2 unbiased?
- (b) Which of the estimates is more efficient?
- (c) Are the estimates \hat{p}_1 and \hat{p}_2 consistent?
- 2. Two methods are available for determining a certain chemical quantity p. Using these methods, we have obtained two independent estimates \hat{p}_1 and \hat{p}_2 , which are both unbiased. The standard deviations of the estimates are 0.4 and 0.6, respectively. Combine the estimates into a single unbiased estimate by forming the expression

$$\hat{p} = \alpha \hat{p}_1 + (1 - \alpha)\hat{p}_2$$
, where $0 \le \alpha \le 1$.

- (a) Prove that \hat{p} is an unbiased estimate of p.
- (b) Find the value of α for which the variance of \hat{p} is as small as possible.
- 3. Show that if we assume the random sample to have a distribution $N(\mu, \sigma^2)$, where μ is known and σ is unknown, then the estimate

$$\hat{\sigma}_1^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2$$

is an unbiased estimate for the parameter σ^2 , and if the estimate

$$\hat{\sigma}_2^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \mu)^2$$

is used, we obtain a biased estimate for the parameter σ^2 . Find the bias.

4. For two data sets x_1, \ldots, x_4 and y_1, \ldots, y_5 the arithmetic means and variances are

$$\bar{x} = 1.38, \quad \bar{y} = 2.10,$$

$$s_x^2 = 0.0552, \quad s_y^2 = 0.0792.$$

Compute the arithmetic mean and variance, assuming that all nine values are regarded as one data set.

5. Let $X \sim Bin(m, p)$, where p is unknown. We have an observation x on X. Find an unbiased estimate of the variance Var(X).

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- 6. Let x = 16 be an observation on $X \sim Bin(25, p)$.
 - (a) Estimate p.
 - (b) Find the standard deviation of the estimate.
- 7. Non-parametric statistics In this course we will mainly deal with **parametric statistics**, where somewhere along the way we assume that our data or statistic follows or is drawn from a given parametric family of probability distributions (that is determined by fixing parameters, and hence the name). For example, in applying t-test we assume that our data is normally distributed with certain mean and variance.

If this assumption is not justified, then non-parametric statistics - a special branch of statistics - comes to help and loosens these assumptions. But be aware, results found using non-parametric statistics are not that powerful (i.e. we need a lot more data to reach the same level of confidence when using parametric statistics).

A fun video that explains the difference once more.

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realised random sample from X1,..., Xn ~ Be (P)

$$\hat{P}_2 = \frac{\chi_1 + \chi_2}{2}$$

according to Bernoulli distribution

$$E[P_{1}] = E[\frac{1}{n} \sum_{i=1}^{n} x_{i}] = \frac{1}{n} E[X_{i}] = P$$

$$E[X_{i}] = P$$

$$E[P_2] - E[X_1 + X_2] = \frac{2P}{2} = P$$

$$V_{ar} \chi_2 E[X^2] - (EX)$$

$$= P - P^2$$

b)
$$Var P_1 - \frac{1}{n^2} Var \sum X_i = \frac{1}{n^2} \sum Var X_i = \frac{1}{n^2} \frac{P(1-P)}{n^2}$$
 $Var P_2 - \frac{1}{4} (P(1-P) + P(1-P)) = \frac{1}{2} P(1-P)$
 P_1 is more efficient

[2]
6)
$$E[\hat{p}] = E[\lambda \hat{p}_1 + (1 - \lambda) \hat{p}_2] = \lambda E\hat{p}_1 + (1 - \lambda) E\hat{p}_2 - 2E[\lambda \hat{p}_1 + (1 - \lambda) \hat{p}_2] = \lambda E[\lambda \hat{p}_1 + (1 -$$

b)
$$Var[P] = Var[LP, +(I-d)P_2] =$$

$$= d^2 Var[P_1] + (I-d)^2 Vur[P_2] = d^2 O_1 4 + (I-d)^2 O_2^2$$

next derivative

$$2-0.4^{2}\lambda-2\cdot0.6^{2}+2\cdot0.6\lambda=0$$

$$0.32\lambda-0.72+0.72\lambda=0$$

$$\lambda=\frac{0.72}{1.04}\approx0.6923$$

L=0,6923

Solution

Blandom sample has disdribertion

$$N(\mu, 5^2)$$
 where μ is known and 5^2 is not.

 $\hat{G}_L^2 = \frac{1}{N} \sum_{i=1}^{N} (\chi_i - \mu)^2$

thom \hat{G}_S^2 is unbiased

$$\hat{G}_{L}^{2} = \frac{1}{N} \sum_{i=1}^{N} (\chi_{i} - \mu)^{2}$$
show \hat{G}_{1}^{2} is unbiased
$$\sum_{i=1}^{N} (\chi_{i} - \mu)^{2}$$

$$\sum_{i=1}^{N} (\chi_{i} - \mu)^{2}$$

show of is unbrased
$$E\left[\frac{c^2}{c^2}\right]^2 = \frac{1}{n} E\left[\frac{c}{x_i} - \mu\right]^2 = \frac{1}{n} E\left[\frac{c}{x_i$$

$$= \frac{1}{h} \left(\sum E x_{i}^{2} - 2 n \sum E x_{i} + n \mu^{2} \right) =$$

$$= \frac{1}{h} \left(h \left(S^{2} + \mu^{2} \right) - 2 n \mu^{2} + n \mu^{2} \right) =$$

$$= \frac{1}{h} \left(n G^{2} + n \mu^{2} - 2 n \mu^{2} + n \mu^{2} \right) = G^{2}$$

show
$$\delta_2^2$$
 is biased
$$E[\delta_2] = \frac{1}{n-1} E[(x_i - \mu)^2] = \frac{n}{n-1} \delta^2$$

$$E[G_{2}] = N-L$$

$$= N-1 E[G_{2}] = N-1 G^{2}$$

62= EX2-(EX)2

$$\begin{array}{l} \underbrace{\nabla} & \times \cdot (\chi_{1}, ..., \chi_{4}) \\ & \overline{\chi} = \frac{\chi_{1} + ... + \chi_{4}}{4} = 1,38 \\ & \overline{y} = \frac{y_{1} + ... + y_{5}}{5} = 2,10 \\ & S_{x}^{2} = \frac{1}{3} \underbrace{\frac{z}{z} (\chi_{1} - \overline{\chi})^{2}}_{z=1} = \frac{1}{3} \left(E \chi^{2} - (E \overline{\chi})^{2} \right) \\ & S_{y}^{2} = \frac{1}{4} \underbrace{\frac{z}{z} (y_{1} - \overline{y})^{2}}_{z=1} = \frac{1}{4} \left(E y^{2} - (E \overline{y})^{2} \right) \\ & Assume all 9 items belong to a \\ & single data set 2. \\ & \overline{z} = \frac{4 \overline{\chi} + 5 \overline{y}}{g} = \frac{(6 \overline{\chi} - 1) \overline{\chi}}{g} = \frac{1}{8} \left(\frac{z}{z} (\chi_{1} - \overline{z})^{2} + \frac{z}{z} (y_{1} - \overline{z})^{2} \right) \\ & = \frac{1}{8} \left(\frac{z}{z} (\chi_{1} - \overline{\chi} + \overline{\chi} - \overline{z})^{2} + z (y_{1} - \overline{y} + \overline{y} - \overline{z})^{2} \right) = \frac{1}{8} \left(\frac{z}{z} (\chi_{1} - \overline{\chi})^{2} + 2 \underbrace{(\chi_{2} - \overline{z})^{2} (\chi_{1} - \overline{\chi})^{2} + 4 (\overline{\chi} - \overline{z})^{2} + 71 - \frac{1}{8} (3 S_{x}^{2} + 4 (\overline{\chi} - \overline{z})^{2} + 4 S_{y}^{2} + 5 (9 - \overline{z})^{2} \right) \end{array}$$

 $=\frac{1}{8}\left(0,1656+0,64+0,3168+0,512\right)=$

 $=\frac{1}{8}\cdot 1,6349=0,2043$

$$= 2(x-\overline{2})(2xi - 4\overline{X}) = 2(x-\overline{2})(2xi - \overline{4})$$

$$= 0$$

$$= 2(x-\overline{2})(2xi - 4\overline{X}) = 2(x-\overline{2})(2xi - 4\overline{X}) = 2(x-\overline{2})(2xi - 4\overline{X}) = 0$$

$$= \frac{1}{8}(3S^{2}x + 4(x-\overline{2})^{2} + 4S^{2}y + 5(5-\overline{2})^{2}) = \frac{1}{8}(3\cdot0,0552 + 4(1.38-1.78)^{2} + 4\cdot0,0792 + 5(2.1-1.78)^{2} = \frac{1}{8}(3\cdot0,0552 + 4(1.38-1.78)^{2} + 4\cdot0,0792 + 5(2.1-1.78)^{2} = 0$$

 $X \sim Bin(M,p) = {\binom{M}{X}} p^{X} (I-p)^{M-X}$ EX=Mp VX=mpq=mp(1-P) Find an unbiased estimate for Var X We have to estimate P with p We can estimate $\hat{p} = \frac{x}{m}$ estimate $\hat{p} = \frac{x}{m}$ of heads $E\left[V_{ar}X\right] - E\left[m\hat{p}\left(3-\hat{p}\right)\right] =$ 2 m(Ep-Ep2)=m(Ex-(Varp+(Ep)2)= = $m\left(p-\left(\frac{1}{m^2}VarX + \frac{1}{m^2}(EX)^2\right) =$ $= m(p - \frac{1}{m^2}(mp(1-p)+(mp)^2) =$ $= mp - p(1-p) - mp^2 - mp(1-p) - p(1-p)$ = p(+p) (m-1)

$$Var(X)_{orr} = \frac{m}{m-1} Var(X) = mp(1-p)$$

$$69$$
 $6 = \frac{26}{M} = \frac{16}{25}$

$$Var X = \frac{m}{m-1} Var(X) = 25 \cdot \frac{16}{25} \cdot (1 - \frac{16}{25}) =$$

$$-16.\frac{9}{25} = 5,76$$