Solutions to Practice Test 2

(1) For any k:

x	$\mathbb{P}(X = x)$	x^k
0	$1-p$	0
1	p	1

So $\mathbb{E}(X_i^k) = (p \times 1) + ((1-p) \times 0) = p$, $\mathbb{E}(X_i^{2k}) = (p \times 1) + ((1-p) \times 0) = p$, $\mathbb{V}(X_i^k) = \mathbb{E}(X_i^{2k}) - (\mathbb{E}(X_i^k))^2 = p - p^2 = p(1-p)$. Thus,

$$\mathbb{E}\left(\frac{1}{n}\sum_{i=1}^n X_i^k\right) = \mathbb{E}(X_i^k) = p$$

and

$$\mathbb{V}\left(\frac{1}{n}\sum_{i=1}^n X_i^k\right) = \frac{\mathbb{V}(X_i^k)}{n} = \frac{p(1-p)}{n}.$$

Since $\mathbb{E}\left(\frac{1}{n}\sum_{i=1}^n X_i^k\right) = p$ and $\mathbb{V}\left(\frac{1}{n}\sum_{i=1}^n X_i^k\right) \to 0$ we have that

$$\frac{1}{n}\sum_{i=1}^n X_i^k \xrightarrow{\text{qm}} p.$$

Since convergence in quadratic mean implies convergence in probability, we also have that

$$\frac{1}{n}\sum_{i=1}^n X_i^k \xrightarrow{\text{P}} p.$$

(2) Let $W = \overline{X} - \overline{Y}$. Then $\mathbb{E}(W) = 68 - 64 = 4$ and

$$\mathbb{V}(W) = \mathbb{V}(\overline{X}) + \mathbb{V}(\overline{Y}) = \frac{4^2}{100} + \frac{3^2}{100} = \frac{25}{100} = \frac{1}{4}.$$

Hence, $rmsd(W) = 1/2$ and by the CLT,

$$W \approx N\left(4, \frac{1}{4}\right).$$

Therefore,

$$\mathbb{P}(\overline{X} > \overline{Y}) = \mathbb{P}(W > 0) = \mathbb{P}\left(\frac{W-4}{\frac{1}{2}} > \frac{-4}{\frac{1}{2}}\right) = \mathbb{P}\left(\frac{W-4}{\frac{1}{2}} > -8\right) \approx \mathbb{P}(Z > -8) \approx 1.$$

(3) By Markov's inequality

$$\mathbb{P}(|X_n| > \epsilon) = \mathbb{P}(X_n > \epsilon) \leq \frac{\mathbb{E}(X_n)}{\epsilon} = \frac{\lambda_n}{\epsilon} = \frac{1}{n\epsilon} \to 0$$

and hence $X_n \xrightarrow{\text{P}} 0$. Now, for any $\epsilon > 0$,

$$\mathbb{P}(|Y_n| \leq \epsilon) \geq \mathbb{P}(Y_n = 0) = \mathbb{P}(X_n = 0) = \frac{e^{-\lambda_n}\lambda_n^0}{0!} = e^{-1/n} \to 1.$$

Hence, $\mathbb{P}(|Y_n| > \epsilon) \to 0$ and so $Y_n \xrightarrow{\text{P}} 0$.

(4a) $f(x;p) = p^x(1-p)^{1-x}$.

$$\mathcal{L}(p) = \prod_i f(X_i;p) = p^S(1-p)^{n-S}$$

where $S = \sum_i X_i$. Hence

$$\ell(p) = S\log(p) + (n-S)\log(1-p)$$

and

$$\ell'(p) = \frac{S}{p} - \frac{n-S}{1-p}.$$

So, $\ell'(\widehat{p}) = 0$ yields $\widehat{p} = S?n$. Now

$$I(p) = -\mathbb{E}\left(\frac{\partial^2 \log f(X:p)}{\partial p^2}\right) = -\mathbb{E}\left(-\frac{X}{p^2} - \frac{1-X}{(1-p)^2}\right) = \frac{1}{p(1-p)}.$$

(4b) $\mathsf{se}(\widehat{p}) = \sqrt{p(1-p)/n}$ and $g(p) = e^p$, $g'(p) = e^p$ so $\mathsf{se}(\widehat{\psi}) = \mathsf{se}(\widehat{p})|g'(\widehat{p})| = \sqrt{p(1-p)/n}e^p$. Now $z_{\alpha/2} = z_{.07} = 1.48$ so the confidence interval is

$$e^{\widehat{p}} \pm 1.48\sqrt{\widehat{p}(1-\widehat{p})/n}e^{\widehat{p}}.$$

(4c)
Step 1: $X_1*, \ldots, X_n^* \sim \text{Bernoulli}(\widehat{p})$.
Step 2: $\widehat{p}^* = n^{-1} \sum_{i=1}^n X_i^*$.
Step 3: Repeat steps 1 and 2 B times to get $\widehat{p}_1^*, \ldots, \widehat{p}_B^*$.
Step 4: $\mathsf{se}_{boot} = \sqrt{B^{-1} \sum_{j=1}^B (\widehat{p}_j^* - \overline{p}^*)^2}$ where $\overline{p}^* = B^{-1} \sum_{j=1}^B p_j^*$.

(4d) The empirical CDF has $\widehat{F}(0) = \sum_{i=1}^n I(X_i \leq 0)$ on 0 and $\widehat{F}(1) = \sum_{i=1}^n I(X_i \leq 1)$ on 1. So, $\widehat{F}(0) = 1 - \widehat{p}$ and $\widehat{F}(1) = 1$. Thus, the empirical puts mass $1 - \widehat{p}$ on 0 and mass $\widehat{F}(1) - \widehat{F}(0) = \widehat{p}$ on 1. So when we draw X_i^* from $\widehat{F}$, it is the same as drawing from Bernoulli($\widehat{p}$).

(5a) Let X be the number of plants and let Y be the number that flower. Then $X \sim \text{Binomial}(n, p)$ and $Y|X = x \sim \text{Binomial}(x, q)$. Hence

$$f(x, y; , q) = f(x; p) f(y|x; q) = \binom{n}{x} p^x (1-p)^{n-x} \binom{x}{y} q^y (1-q)^{x-y}.$$

So

$$\mathcal{L}(p, q) \propto p^x (1-p)^{n-x} q^y (1-q)^{x-y}.$$

(5b) The log-likelihood is

$$\ell(p, q) x \log(p) + (n - x) \log(1 - p) + y \log(q) + (x - y) \log(1 - q)$$

and

$$\begin{aligned} \frac{\partial \ell}{\partial p} &= \frac{x}{p} - \frac{n - x}{1 - p} \\ \frac{\partial \ell}{\partial q} &= \frac{y}{q} - \frac{x - y}{1 - q}. \end{aligned}$$

Setting these equal to 0 yields

$$\widehat{p} = \frac{X}{n} \quad \text{and} \quad \widehat{q} = \frac{Y}{X}.$$

Now $\mathbb{E}(X) = np$ and $\mathbb{E}(Y) = \mathbb{E}\mathbb{E}(Y|X) = \mathbb{E}(qX) = q\mathbb{E}(X) = qnp$ so we solve

$$\begin{aligned} n\widehat{p} &= X \\ n\widehat{q}\widehat{p} &= Y \end{aligned}$$

which yields the same estimator as the MLE .

(5c) The matrix of second derivatives is

$$H = \begin{pmatrix} -\frac{X}{p^2} - \frac{n-X}{(1-p)^2} & 0 \\ 0 & -\frac{Y}{q^2} - \frac{X-Y}{(1-q)^2} \end{pmatrix}$$

and the Fisher information matrix is

$$I(p,q) = -\mathbb{E}(H) = \begin{pmatrix} \frac{n}{p(1-p)} & 0 \\ 0 & \frac{np}{q(1-q)}. \end{pmatrix}$$

(5d) With $g(p,q) = pq$ we have

$$\nabla g = \begin{pmatrix} q \\ p \end{pmatrix}$$

. So

$$\mathsf{se}\,(\psi) = \sqrt{\nabla^T I^{-1} \nabla} = \sqrt{\frac{pq}{n}\,(1-pq)}.$$

The confidence interval is

$$\widehat{pq} \pm z_{.1}\widehat{\mathsf{se}} = \widehat{pq} \pm 1.28\sqrt{\frac{\widehat{pq}}{n}\,(1-\widehat{pq})}.$$

(6) For any $\epsilon > 0$,

$$P(|X_n| > \epsilon) = P(X_n^2 > \epsilon^2) \leq \frac{\mathbb{E}(X_n^2)}{\epsilon^2} = \frac{\frac{1}{n} + \frac{1}{n^2}}{\epsilon^2} \to 0$$

so $X_n \xrightarrow{\text{P}} 0$.

(7) Proof by contradiction. Assume $X_n \xrightarrow{\text{P}} X$ for some X. Then $X_n \rightsquigarrow X$. Let F_n be the CDF of X_n and let $Z \sim N(0,1)$. Then, for every c,

$$F_n(c) = \mathbb{P}(X_n \leq c) = \mathbb{P}\left(\frac{X_n - (1/n)}{\sqrt{n}} \leq -\frac{(1/n)}{\sqrt{n}}\right) = \mathbb{P}\left(Z \leq -\frac{(1/n)}{\sqrt{n}}\right) \to \mathbb{P}\,(Z \leq 0) = \frac{1}{2}.$$

That is, $F_n(c) \to G(c)$ where $G(c) = 1/2$ for all c. But G is not a CDF which contradicts the fact that X_n converges in distribution.

(8) We've done this before.

(9) Suppose that $X_n \xrightarrow{d} X$. Let F_n denote the cdf of X_n and let F denote the cdf of X. Every non-integer x is a point of continuity of F. So, for every integer k, $F_n(k+\epsilon) \to F(k+\epsilon)$ for any $0 < \epsilon < 1$. Now,

$$\begin{aligned} P(X_n = k) &= F_n(k+\epsilon) - F_n(k-\epsilon) \\ &\to F(k+\epsilon) - F(k-\epsilon) \\ &= P(X = k). \end{aligned}$$

Now suppose that $P(X_n = k) \to P(X = k)$. Let x be a point of continuity of F. Then x is not an integer, so $x = k + \epsilon$ for some integer k and some $0 < \epsilon < 1$.

$$F_n(x) = P(X_n \le x) = \sum_{j=1}^{k} P(X_n = j) \to \sum_{j=1}^{k} P(X = j) = P(X \le k) = P(X \le x) = F(x).$$

Thus, $X_n \xrightarrow{d} X$.

(10) $p(x) = 0$ for all x so p is not a probability function. But $X_n \rightsquigarrow 0$.

(11) The plug-in estimator is

$$\widehat{\psi} = \frac{\left(\frac{1}{n}\sum_{i=1}^n X_i^5\right)\left(\frac{1}{n}\sum_{i=1}^n X_i^4\right)}{\left(\frac{1}{n}\sum_{i=1}^n X_i^3\right)}.$$

Step 1: Sample $X_1^*, \ldots, X_n^* \sim \widehat{F}_n$.
Step 2. Compute $\widehat{\psi}^*(X_1^*, \ldots, X_n^*)$.
Step 3. Repeat 1 and 2 B times to get: $\widehat{\psi}_1^*, \ldots, \widehat{\psi}_B^*$.

Step 4:

$$\widehat{\mathsf{se}} = \sqrt{\frac{1}{B}\sum_{j=1}^{B}(\widehat{\psi}_j - \overline{\psi}^*)^2}.$$

(12) Note that

$$F(x) = \begin{cases} 0 & x < 0 \\ 1-p & 0 \le x < 1 \\ 1 & x > 1 \end{cases}$$

and

$$\widehat{F}(x) = \begin{cases} 0 & x < 0 \\ 1-\widehat{p} & 0 \le x < 1 \\ 1 & x > 1 \end{cases}$$

where $\widehat{p} = n^{-1}\sum_{i=1}^{n} X_i$. Therefore,

$$\max_x |\widehat{F}(x) - F(x)| = |(1-p) - (1-\widehat{p})| = |\widehat{p} - p| \xrightarrow{\text{P}} 0.$$

(13) Let $p = (p_1, \ldots, p_k)$. The likelihood is

$$\mathcal{L}(p) \propto \prod_{j=1}^{k} p_j^{X_j}$$

and the log-likelihood is

$$\ell(p) = \sum_{j=1}^{k} X_j \log p_j.$$

To maximize this we need to take into account the constraint that $\sum_{j=1}^{k} p_j = 1$ so we use the method of Lagrange multipliers. We maximize

$$A(p) = \sum_{j=1}^{k} X_j \log p_j - \lambda(\sum_{j=1}^{k} p_j - 1).$$

Taking

$$\frac{\partial A(p)}{\partial p_j} = 0$$

gives

$$\widehat{p}_j = \frac{X_j}{\lambda}.$$

Now, the constraint implies that

$$\sum_{j=1}^{n} \widehat{p}_j = \frac{\sum_{j=1}^{k} X_j}{\lambda}$$

hence $\lambda = n$ and hence

$$\widehat{p}_j = \frac{X_j}{n}.$$

To compute the Fisher information matrix, we ned to remember that there are only $k-1$ free parameters so the matix is $(k-1) \times (k-1)$. Keep in mmind that $p_k = 1 - p_1 - p_2 - \cdots - p_{k-1}$. Hence, for $j = 1, \ldots, k-1$,

$$\frac{\partial \log f(X;p)}{\partial p_j} = \frac{X_j}{p_j} - \frac{X_k}{p_k}$$

and hence

$$\frac{\partial^2 \log f(X;p)}{\partial p_j^2} = -\frac{X_j}{p_j^2} - \frac{X_k}{p_k^2}$$

and

$$\frac{\partial^2 \log f(X;p)}{\partial p_j \partial p_r} = -\frac{X_k}{p_k^2}.$$

The Fisher information matrix is

$$n \begin{pmatrix} \frac{1}{p_1} + \frac{1}{p_k} & \frac{1}{p_k} & \cdots & \frac{1}{p_k} \\ \frac{1}{p_k} & \frac{1}{p_2} + \frac{1}{p_k} & \cdots & \frac{1}{p_k} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{1}{p_k} & \frac{1}{p_k} & \cdots & \frac{1}{p_{k-1}} + \frac{1}{p_k} \end{pmatrix}.$$