[. (a)
$$P(MM) = P(MM|its identical) + P(MM | its not identical)$$

$$= \pm \times \lambda + \pm \times (1-\lambda) = \pm \lambda + \pm - \pm \lambda$$

$$= \pm + \pm \lambda = \frac{1+\lambda}{4}$$

$$P(FF) = P(FF|its identical) + P(FF|its not identical)$$

$$= \pm \times \lambda + \pm \times (1-\lambda) = \pm \lambda + \pm - \pm \lambda$$

$$= \pm + \pm \lambda = \frac{1+\lambda}{4}$$

$$= \pm + \pm \lambda = \frac{1+\lambda}{4}$$

$$P(MF) = P(MF|its not identical)$$

$$= \pm \times (1-\lambda)$$

$$= \frac{1-\lambda}{2}$$
(b) $L(\lambda) = \int (x_0) \times f(x_0) \times f(x_0)$

$$= \frac{1+\lambda}{4} \times \frac{1+\lambda}{4} \times \frac{1-\lambda}{2} = \frac{(1+2\lambda+\lambda^2)(1-\lambda)}{52}$$

$$= \frac{1-\lambda+2\lambda-2\lambda^2+\lambda^2-\lambda^3}{52} = \frac{1+\lambda-\lambda^2-\lambda^3}{62}$$

$$= \frac{1-\lambda+2\lambda-2\lambda^2+\lambda^2-\lambda^3}{62} = \frac{1+\lambda-\lambda^2-\lambda^3}{62}$$

$$da L(\lambda) = \frac{1-\lambda+2\lambda-2\lambda^2+\lambda^2-\lambda^3}{52} = 0$$

$$3\lambda^2+2\lambda-1=0$$

$$3\lambda^2+2\lambda-$$

2.
$$L(M) = \frac{1}{(2\pi n^2)^{\frac{1}{2}}} e^{-(-\frac{1}{2}\frac{\frac{R}{M}(n_1-n)^2}{n^2})}$$
 $L(M) = -\frac{1}{2}\log(2\pi n^2) - \frac{1}{2}\frac{\Sigma(n_1-M)^2}{n^2}$
 $L(M) = -\frac{1}{2}\log(2\pi n^2) - \frac{1}{2}\frac{\Sigma(n_1-M)^2}{n^2}$
 $\frac{d}{dM}L(M) = -\frac{1}{2n^2}(-2)\Xi(n_1-M) = \frac{\Sigma(n_1-M)^2}{n^2}$
 $\frac{d^2}{dM}((M) = -\frac{1}{2n^2})$
 $L(M) = \frac{n}{n^2}$
 $L(M) = \frac{n}{n^2}$

3. (a)
$$L(\theta) = f_{\theta}(x_{1}) \times f_{\theta}(x_{2}) \times \cdots \times f_{\theta}(x_{n})$$

$$= (\theta+1)x_{1}^{\theta} \times (\theta+1)x_{2}^{\theta} \times \cdots \times (\theta+1)x_{n}^{\theta}$$

$$= (\theta+1)^{n} \int_{i=1}^{n} x_{i}^{\theta}$$

$$= (\theta+1)^{n} \int_{i=1}^{n} (x_{i}^{\theta})$$

$$= (\theta+1)^{n} \int_{i$$

(d) To use the chi-squared distribution, we should satisfy the three conditions in Theorem 2.1 in class. And the null value should be a true value. However, we can see that λ is very close to σ . So chisquare distribution is not a good approximation in this case.

4.
$$f(\theta) = \frac{1}{\theta} e^{-\frac{1}{\theta} x}$$

$$L(\theta_{1}) = \frac{1}{\theta} e^{-\frac{1}{\theta} x_{1}} \times \frac{1}{\theta} e^{\frac{1}{\theta} x_{2}} \times \dots \times \frac{1}{\theta} e^{\frac{1}{\theta} x_{n}}$$

$$= \frac{1}{\theta^{n_{1}}} e^{\frac{1}{\theta} x_{n}} \times \frac{1}{\theta} e^{\frac{1}{\theta} x_{2}} \times \dots \times \frac{1}{\theta} e^{\frac{1}{\theta} x_{n}}$$

$$(n L(\theta_{1}) = (n \frac{1}{\theta^{n_{1}}} + (-\frac{1}{\theta} \frac{x_{n}^{2}}{x_{n}^{2}})) (n e)$$

$$\frac{1}{\theta^{1}} = -\frac{n}{\theta} + \frac{1}{\theta^{2}} \frac{x_{n}^{2}}{\theta^{2}} = 0$$

$$n_{1}\theta = \frac{n}{\theta^{2}} \frac{x_{n}^{2}}{x_{n}^{2}} = 0$$

$$n_{1}\theta = \frac{n}{\theta^{2}} \frac{x_{n}^{2}}{x_{n}^{2}} \times \dots \times \frac{1}{\theta^{2}} e^{\frac{1}{\theta} x_{n}^{2}} \times \dots \times \frac{1}{\theta^$$

$$Vor(\bar{p}) = Var(\frac{1}{n}, \frac{2}{n!} p_i) = \frac{1}{n^2} (p^2 + p^2 + \dots + p^2) = \frac{np^2}{n_1^2} = \frac{p^2}{n_1}$$

$$Vor(\bar{y}) = Var(\frac{1}{n^2}, \frac{2}{n!} y_i) = \frac{1}{n^2n^2} (k^2p^2 + k^2p^2 + \dots + k^2p^2) = \frac{nk^2p^2}{k^2n_2^2} = \frac{p^2}{n_2}$$

$$Var(a \bar{b} + (1-a)\bar{y}) = a^2 Var(\bar{k}) + (1-a)^2 Var(\bar{y}) = a^2 \frac{p^2}{n_1} + (1-a)^2 \frac{p^2}{n_2}$$

$$\frac{d}{da} Var = 2n \cdot \frac{p^2}{n_1} - 2(1-a) \frac{p^2}{n_2} = 0.$$

$$2n \cdot \frac{p^2}{n_1} - 2 \cdot \frac{p^2}{n_2} + 2n \cdot \frac{p^2}{n_2} = 0.$$

$$2n \cdot (\frac{p^2}{n_1} + \frac{p^2}{n_2}) = 2 \cdot \frac{p^2}{n_2}$$

$$a = \frac{p^2}{n_1 p^2 + n_1 p^2} = \frac{p^2}{n_2} \times \frac{n_1 p_2}{n_2 p^2 + n_1 p^2} = \frac{n_1}{n_2 + n_1}$$

$$a \cdot p^2 + (1-a) \cdot p^2 = \frac{n_1}{n_2 + n_1} = \frac{p^2}{n_2 + n_1 p^2} = \frac{n_1 \bar{k} + n_2 \bar{y}}{k(n_1 + n_2)} = \frac{k^2 \bar{k} + n_2 \bar{y}}{k(n_1 + n_2)}$$

$$L(\theta) = \frac{1}{\theta} e^{\frac{1}{\theta} p_1} \times \frac{1}{\theta} e^{\frac{1}{\theta} p_2} \times \dots \times \frac{1}{\theta} e^{\frac{1}{\theta} p_{n_1}} \times \frac{1}{k^n \theta^{n_1}} \times \frac{1}{k^n \theta^{n_2}} \times \dots \times \frac{1}{k^n \theta^{n_k}} \times e^{\frac{1}{\theta} \theta^{n_k$$

$$(n L(\theta) = -n_1 (n(\theta) - n_2 ln(k\theta) - \frac{1}{\theta} Z \kappa_i - \frac{1}{R\theta} Z y_i)$$

$$\frac{d}{d\theta} \left(\Lambda L(\theta) = -\frac{\theta}{\Lambda^2} - \frac{\theta}{\Lambda^2} + \frac{\theta}{\Lambda^2} \frac{\partial}{\partial \rho} (1 + \frac{1}{16} \frac{\partial}{\partial \rho} \frac{\partial}{\partial \gamma}) \right) = 0$$

$$\frac{n_1}{\Theta} + \frac{n_2}{\Theta} = \frac{1}{\Theta^2} \sum_{i} p_i + \frac{1}{k \Theta^2} \sum_{i} y_i$$

$$\Theta = \frac{k \sum x_i + \sum y_i}{k \sum x_i + \sum y_i}$$

$$\Theta = \frac{k \sum x_i + \sum y_i}{k(x_i + x_i)}$$