

MATH 556 - SOLUTIONS TO THE FINAL EXAM 2011

PROBLEM 1: (17 marks)

(a) Set $g: (0, 1) \rightarrow \mathbb{R}$
 $u \mapsto \mu - \beta \ln(-\ln(u)).$

① $g^{-1}: x \mapsto e^{-e^{-\frac{x-\mu}{\beta}}}$

$(g^{-1})'(x) = \textcircled{1} e^{-e^{-\frac{x-\mu}{\beta}}} \cdot e^{-\frac{x-\mu}{\beta}} \cdot \frac{1}{\beta}$

g is monotone increasing, g^{-1} cont. differentiable } and hence X has a density

$f_X(x) \stackrel{\textcircled{1}}{=} \int_u f(g^{-1}(u)) |(g^{-1})'(u)|$
 $\stackrel{\textcircled{2}}{=} \int_{\left(e^{-e^{-\frac{x-\mu}{\beta}}} \in (0,1) \right)} e^{-e^{-\frac{x-\mu}{\beta}}} \cdot e^{-\frac{x-\mu}{\beta}} \cdot \frac{1}{\beta}$
 $= 1$ because $e^{-\frac{x-\mu}{\beta}} \in (0, \infty).$

① for $x \in \mathbb{R}.$

(b) $M_X(t) \stackrel{\textcircled{1}}{=} E X^{tx} = \int_{-\infty}^{\infty} e^{tx} e^{-e^{-\frac{x-\mu}{\beta}}} e^{-\frac{x-\mu}{\beta}} \cdot \frac{1}{\beta} dx$

Set $y = \bar{e}^{-\frac{x-\mu}{\beta}}$. Then $dy = -\frac{1}{\beta} \bar{e}^{-\frac{x-\mu}{\beta}}$

(2)

and $x = \mu - \beta \ln y$. Thus

$$M_X(t) \stackrel{\textcircled{1}}{=} \int_0^{\infty} e^{t(\mu - \beta \ln y)} e^{-y} dy$$

$$= e^{t\mu} \int_0^{\infty} y^{1-\beta t-1} e^{-y} dy$$

$$\stackrel{\textcircled{1}}{=} e^{t\mu} \Gamma(1-\beta t) \quad \text{for } 1-\beta t > 0 \quad \textcircled{1}$$

$$\Rightarrow t < \frac{1}{\beta}.$$

(c) $E(Y) \stackrel{\textcircled{1}}{=} M'_Y(0)$.

$$S'_Y(t) \stackrel{\textcircled{1}}{=} \frac{M''_Y(t)}{M'_Y(t)} \Rightarrow S'_Y(0) = \frac{EY}{M'_Y(0)} = EY.$$

$$S''_Y(t) \stackrel{\textcircled{1}}{=} \frac{M_Y M''_Y(t) - \{M'_Y(t)\}^2}{M_Y^2(t)} \stackrel{\textcircled{1}}{=} \frac{EY^2 - (EY)^2}{1} = \text{var } Y.$$

(d)

$$S_X(t) = \ln(M_X(t)) = t\mu + \ln \Gamma(1-\beta t)$$

$$S'_X(t) \stackrel{\textcircled{1}}{=} \mu + \frac{\Gamma'(1-\beta t)}{\Gamma(1-\beta t)} (-\beta)$$

$$S'_X(0) \stackrel{\textcircled{1}}{=} \mu + \gamma\beta.$$

$$S''_X(t) \stackrel{\textcircled{1}}{=} (-\beta) \frac{\Gamma''(1-\beta t)(-\beta)\Gamma(1-\beta t) + \beta \{\Gamma'(1-\beta t)\}^2}{\Gamma^2(1-\beta t)}$$

$$S''_X(0) = \frac{(-\beta) \left(\frac{\pi^2}{6} + \beta^2 \right) (-\beta) + \beta \cdot \beta^2}{1} \quad (3)$$

$$\stackrel{(1)}{=} \beta^2 \frac{\pi^2}{6}$$

PROBLEM 2 (16 marks)

(a) The transformation to polar coordinates is

$$T: \mathbb{R}^2 \rightarrow \mathbb{R}^+ \times (0, 2\pi)$$

$$(x, y) \mapsto \left(\sqrt{x^2 + y^2}, \arctan \frac{y}{x} \right)$$

$$T^{-1}: [0, \infty) \times (0, 2\pi) \rightarrow \mathbb{R}^2$$

$$\stackrel{(1)}{(r, \theta)} \mapsto (r \cos \theta, r \sin \theta)$$

$$J \stackrel{(1)}{=} \begin{pmatrix} \cos \theta & \sin \theta \\ -r \sin \theta & r \cos \theta \end{pmatrix} \rightarrow |J| \stackrel{(1)}{=} r$$

Therefore, the joint density of (R, θ) is

$$f_{(R, \theta)}(r, \theta) = \frac{1}{2\pi} e^{-\frac{r^2 \cos^2 \theta}{2}} e^{-\frac{r^2 \sin^2 \theta}{2}} r$$

$$\stackrel{(1)}{=} \frac{1}{2\pi} \cdot e^{-\frac{r^2}{2}} \cdot r, \quad r \in (0, \infty)$$

$$\theta \in (0, 2\pi)$$

(b) This means that $R \perp \theta$ and $R \stackrel{(1)}{\sim} r \cdot e^{-\frac{r^2}{2}} \mathbb{1}_{(0, \infty)}$. (5)

(d) Consider the transformation

$$T: \mathbb{R}^2 \rightarrow \mathbb{R}^2$$

$$(x, y) \rightarrow \left(\frac{x}{y}, y\right)$$

$$T^{-1}(u, v) \mapsto (uv, v) \quad ; \quad J = \begin{pmatrix} v & 0 \\ u & 1 \end{pmatrix}$$

$$\Rightarrow |J| = v.$$

①

The density of $\left(\frac{X}{Y}, Y\right)$ is

$$\textcircled{1} f_{\left(\frac{X}{Y}, Y\right)}(u, v) = \frac{1}{2\pi} e^{-\frac{u^2 v^2}{2}} e^{-\frac{v^2}{2}} |v|, \quad u, v \in \mathbb{R}$$

Therefore, $f_{\frac{X}{Y}}(u) \stackrel{\textcircled{1}}{=} \int_{-\infty}^{\infty} \frac{1}{2\pi} e^{-\frac{v^2(u^2+1)}{2}} |v| dv$

$$= \frac{1}{\pi} \int_0^{\infty} e^{-\frac{v^2(u^2+1)}{2}} \cdot v dv$$

$$\stackrel{\textcircled{1}}{=} \frac{1}{\pi(1+u^2)} \int_0^{\infty} e^{-t} dt$$

$$= \frac{1}{\pi(1+u^2)}$$

Hence, $\frac{X}{Y} \sim \text{Cauchy}(0, 1)$, so MGF does not

② exist because the mean is infinite.

PROBLEM 3

$$f(x|\eta, \psi) = \frac{\exp\sqrt{x\psi}}{\sqrt{2\pi x^2}} \sqrt{x} \cdot e^{-\frac{1}{2}x^{-1}x - \frac{1}{2}\psi x} \mathbb{1}(x > 0)$$

Set

$$h(x) = \mathbb{1}(x > 0) \cdot \frac{1}{\sqrt{2\pi x^2}}$$

$$\textcircled{1} c(x, \psi) = \exp\sqrt{x\psi} \cdot \sqrt{x}$$

$$t_1(x) = -\frac{1}{2x}, \quad t_2(x) = -\frac{1}{2}x$$

$$\textcircled{1} w_1(x, \psi) = x, \quad w_2(x, \psi) = \psi.$$

$$\textcircled{1} \eta_1 = x, \quad \eta_2 = \psi.$$

$$\mathcal{H} = \left\{ (\eta_1, \eta_2) : \int_0^{\infty} \frac{1}{\sqrt{2\pi x^2}} e^{-\eta_1 \frac{1}{2x}} e^{-\eta_2 \frac{1}{2} \cdot x} dx \right\}$$

$$\textcircled{1} = \left\{ (\eta_1, \eta_2) : \eta_1 \in (0, \infty), \eta_2 \in (0, \infty) \right\}.$$

(b) Score function is

$$S_i(x) = \frac{\partial}{\partial \theta_i} \log f(x|\theta)$$

under suitable regularity conditions,

$$E(S_i(x)) = 0$$

This is because

$$\int_{-\infty}^{\infty} \frac{\partial}{\partial \theta_i} \log f(x|\theta) f(x|\theta) dx$$

$$\textcircled{1} = \int_{-\infty}^{\infty} \frac{\partial}{\partial \theta_i} f(x|\theta) dx = \frac{\partial}{\partial \theta_i} \int f(x|\theta) dx = 0.$$

In the canonical parametrization,

$$f(x|\eta) = h(x) c(\eta) e^{\sum_{i=1}^k t_i(x) \eta_i}$$

$$\frac{\partial \log f(x|\eta)}{\partial \eta_i} = \frac{\partial}{\partial \eta_i} \left(\log h(x) + \log c(\eta) + \sum_{i=1}^k t_i(x) \eta_i \right)$$

$$= \frac{\partial}{\partial \eta_i} \log c(\eta) + t_i(x).$$

$$\Rightarrow E(t_i(x)) = - \frac{\partial}{\partial \eta_i} \log c(\eta).$$

$$\text{cov}(S_i(x), S_j(x)) = \int_{-\infty}^{\infty} \frac{\partial}{\partial \theta_i} \log f(x|\theta) \frac{\partial}{\partial \theta_j} \log f(x|\theta) f(x|\theta) dx$$

$$= \int_{-\infty}^{\infty} \frac{\partial}{\partial \theta_i} f(x|\theta) \frac{\partial}{\partial \theta_j} f(x|\theta) \frac{1}{f(x|\theta)} dx$$

on the other hand,

$$\int_{-\infty}^{\infty} \frac{\partial^2}{\partial \theta_i \partial \theta_j} \log f(x|\theta) f(x|\theta) dx$$

$$\textcircled{1} = \int_{-\infty}^{\infty} \frac{\frac{\partial^2}{\partial \theta_i \partial \theta_j} f(x|\theta) \cdot f(x|\theta) - \frac{\partial}{\partial \theta_i} f(x|\theta) \frac{\partial}{\partial \theta_j} f(x|\theta)}{f^2(x|\theta)} f(x|\theta) dx$$

$$= \int_{-\infty}^{\infty} \underbrace{\frac{\partial^2}{\partial \theta_i \partial \theta_j} f(x|\theta)}_0 dx - \int_{-\infty}^{\infty} \frac{\partial}{\partial \theta_i} f \frac{\partial}{\partial \theta_j} f \cdot \frac{1}{f} dx$$

$$\Rightarrow \text{cov}(S_i(x), S_j(x)) = - \int_{-\infty}^{\infty} \frac{\partial^2}{\partial \theta_i \partial \theta_j} \log f(x|\theta) \cdot f(x|\theta) dx$$

In the canonical parametrization,

$$\text{cov}(S_i(x), S_j(x)) = \text{cov}(t_i(x), t_j(x))$$

$$\stackrel{\textcircled{1}}{=} - \frac{\partial^2}{\partial \eta_i \partial \eta_j} \log c(\eta)$$

$$(c) \quad E\left(-\frac{1}{2} \frac{1}{X}\right) \stackrel{\textcircled{1}}{=} - \frac{\partial}{\partial \psi} \cdot \log(e^{\sqrt{\psi}} \cdot \sqrt{x})$$

~~$$\stackrel{\textcircled{1}}{=} - \frac{\partial}{\partial \psi} \log(e^{\sqrt{\psi}} \cdot \sqrt{x})$$~~

$$= - \frac{\partial}{\partial x} (\sqrt{\psi} + \frac{1}{2} \log x)$$

~~$$\stackrel{\textcircled{1}}{=} - \frac{\partial}{\partial \psi} (\sqrt{\psi} + \frac{1}{2} \log x)$$~~

$$= - \sqrt{\psi} \cdot \frac{1}{2} \frac{1}{\sqrt{x}} + \frac{1}{2} \frac{1}{x}$$

$$= - \frac{1}{2} \left(\frac{\sqrt{\psi}}{\sqrt{x}} + \frac{1}{x} \right)$$

$$\Rightarrow E\left(\frac{1}{x}\right) \stackrel{\textcircled{1}}{=} \frac{\sqrt{\psi}}{\sqrt{x}} + \frac{1}{x}$$

$$\text{var}\left(-\frac{1}{2} \frac{1}{X}\right) \stackrel{\textcircled{1}}{=} \frac{\partial}{\partial \psi} \left(-\frac{1}{2} \left(\frac{\sqrt{\psi}}{\sqrt{x}} + \frac{1}{x} \right) \right)$$

$$= - \frac{1}{2} \sqrt{\psi} \left(-\frac{1}{2} \cdot \frac{1}{x^{\frac{3}{2}}} + 1 \cdot \frac{1}{x^2} \right)$$

$$= \frac{1}{2} \frac{\sqrt{\psi}}{x^{\frac{3}{2}}} - \frac{1}{2} \frac{1}{x^2}$$

$$\Rightarrow \text{var} \left(\frac{1}{X} \right) \stackrel{\textcircled{1}}{=} \frac{\sqrt{4}}{\sqrt{x}} \cdot x + \frac{2}{x^2}$$

⑧

$$(d) \text{cov} \left(-\frac{1}{2} X, -\frac{1}{2} \frac{1}{X} \right) \stackrel{\textcircled{1}}{=} \frac{1}{4} \text{cov} \left(X, \frac{1}{X} \right)$$

$$\stackrel{\textcircled{1}}{=} \frac{\partial}{\partial \psi} \left(-\frac{1}{2} \frac{\sqrt{4}}{\sqrt{x}} - \frac{1}{2} \frac{1}{x} \right)$$

$$\stackrel{\textcircled{1}}{=} -\frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{\sqrt{x\psi}}$$

$$\Rightarrow \text{cov} \left(X, \frac{1}{X} \right) \stackrel{\textcircled{1}}{=} -\frac{1}{\sqrt{x\psi}}$$

(e) • not always well defined ^①

• $\text{cov}(X, Y) = 0 \not\Rightarrow X \perp Y$ ^①

• may not attain the bounds ± 1 . ^①

PROBLEM 4

$$f_X(x) = \int_{-\infty}^{\infty} f_{X|M=m}(x) \cdot f_M(m) dm$$

$$\stackrel{\textcircled{1}}{=} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma} e^{-\frac{(x-m)^2}{2\sigma^2}} \frac{1}{\tau} e^{-\frac{(m-\mu)^2}{2\tau^2}} dm$$

$$e^{-\frac{(x-m)^2}{2\sigma^2}} \cdot e^{-\frac{(m-\mu)^2}{2\tau^2}} =$$

~~$$e^{-\frac{x^2 - 2xm + m^2}{2\sigma^2} - \frac{m^2 - 2m\mu + \mu^2}{2\tau^2}} = e^{-\frac{x^2}{2\sigma^2} + \frac{2xm}{2\sigma^2} - \frac{m^2}{2\sigma^2} - \frac{m^2}{2\tau^2} + \frac{2m\mu}{2\tau^2} - \frac{\mu^2}{2\tau^2}}$$~~

(9)

$$= e^{-\frac{m^2(\tau^2 + \sigma^2) - 2m(\tau^2 x + \mu\sigma^2) + \tau^2 x^2 + \sigma^2 \mu^2}{2\sigma^2 \tau^2}}$$

$$\stackrel{\textcircled{1}}{=} e^{-\frac{\left(m - \frac{\tau^2 x + \mu\sigma^2}{\tau^2 + \sigma^2}\right)^2}{2\sigma^2 \tau^2 / (\tau^2 + \sigma^2)}} e^{-\frac{\left(\frac{\tau^2 x + \mu\sigma^2}{\tau^2 + \sigma^2}\right)^2 - \frac{\tau^2 x^2 + \sigma^2 \mu^2}{2\sigma^2 \tau^2}}{2\sigma^2 \tau^2 / (\tau^2 + \sigma^2)}}$$

Hence,

$$f_X(x) = \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{\tau^2 + \sigma^2}} e^{-\frac{\tau^4 x^2 + \mu^2 \sigma^4 + 2 \times \mu \sigma^2 \sigma^2 - \tau^4 x^2 - \tau^2 \sigma^2 x - \sigma^4 \mu^2}{2\tau^2 \sigma^2 (\tau^2 + \sigma^2)}}$$

$$\times \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \sqrt{\frac{\tau^2 + \sigma^2}{1}} \frac{1}{\tau\sigma} e^{-\frac{\left(m - \frac{\tau^2 x + \mu\sigma^2}{\tau^2 + \sigma^2}\right)^2}{2\tau^2 \sigma^2 / (\tau^2 + \sigma^2)}} dm$$

$$= \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{\tau^2 + \sigma^2}} e^{-\frac{(x - \mu)^2}{2(\tau^2 + \sigma^2)}}$$

\textcircled{1}

$$\Rightarrow X \sim N(\mu, \tau^2 + \sigma^2).$$

(b) RIGHT-HAND side is

$$E\left(E(XY|Z) - E(X|Z)E(Y|Z)\right)$$

$$+ E\left(E(X|Z)E(Y|Z)\right) - E\left(E(X|Z)\right)E\left(E(Y|Z)\right)$$

$$\stackrel{\textcircled{1}}{=} E(XY) - EX EY \stackrel{\textcircled{1}}{=} \text{cov}(X, Y).$$

$$(c) \text{cov}(X_1, X_2) \stackrel{\textcircled{1}}{=} E(\text{cov}(X_1, X_2 | M)) + \text{cov}(E(X_1 | M), E(X_2 | M))$$

$$\stackrel{\textcircled{1}}{=} 0 + \text{cov}(M, M) = \text{var}(M) \stackrel{\textcircled{1}}{=} \tau^2.$$

$$\text{var}(X_1) \stackrel{\textcircled{1}}{=} \tau^2 + \sigma^2 = \text{var}(X_2).$$

$$\Rightarrow \text{corr}(X_1, X_2) = \frac{\tau^2}{\tau^2 + \sigma^2} > 0.$$

(d) no, because $\text{corr} > 0$. $\textcircled{4}$

PROBLEM 5

a) MGF of \bar{X}_n :

$$E\left(e^{\frac{t}{n}X_1 + \dots + \frac{t}{n}X_n}\right) \stackrel{\textcircled{1}}{=} \prod_{i=1}^n M_{X_i}\left(\frac{t}{n}\right)$$

$$\stackrel{\textcircled{1}}{=} e^{\lambda(e^t - 1) \cdot n} \quad \sim \quad X_1 + \dots + X_n \sim \text{Poi}(n \cdot \lambda).$$

Hence, \bar{X}_n has support $\{0, \frac{1}{n}, \frac{2}{n}, \dots\}$ and

$$P(\bar{X}_n = \frac{k}{n}) = P(X_1 + \dots + X_n = k) \stackrel{\textcircled{1}}{=} \frac{(n\lambda)^k}{k!} e^{-n\lambda}.$$

(b)

$$\text{var}(X_1(X_1 - 1)) = E(X_1^2(X_1 - 1)^2) - \{E(X_1(X_1 - 1))\}^2$$

$$= E(X_1^4 - 2X_1^3 + X_1^2) - \{E(X_1^2) - E(X_1)\}^2$$

$$\stackrel{\textcircled{1}}{=} EX_1^4 - 2EX_1^3 + EX_1^2 - \{E(X_1^2) - E(X_1)\}^2$$

$$M_{X_1}(t) = e^{\lambda(e^t - 1)} \quad (11)$$

$$\textcircled{1} \begin{cases} M'_{X_1}(t) = e^{\lambda(e^t - 1)} \cdot \lambda e^t \rightsquigarrow EX_1 = \lambda \\ M''_{X_1}(t) = e^{\lambda(e^t - 1)} (\lambda^2 e^{2t} + \lambda e^t) \rightsquigarrow EX_1^2 = \lambda^2 + \lambda \end{cases}$$

$$\textcircled{1} \begin{cases} M'''_{X_1}(t) = e^{\lambda(e^t - 1)} (\lambda^3 e^{3t} + \lambda^2 e^{2t} + 2\lambda^2 e^{2t} + \lambda e^t) \\ \rightsquigarrow EX_1^3 = \lambda^3 + 3\lambda^2 + \lambda \end{cases}$$

$$M^{IV}_{X_1}(t) = e^{\lambda(e^t - 1)} (\lambda^4 e^{4t} + 3\lambda^3 e^{3t} + \cancel{\lambda^2} \lambda^2 e^{2t} + 3\lambda^3 e^{3t} + 6\lambda^2 e^{2t} + \lambda e^t)$$

$$\rightsquigarrow EX_1^4 = \lambda^4 + 3\lambda^3 + \lambda^2 + 3\lambda^3 + 6\lambda^2 + \lambda = \lambda^4 + 6\lambda^3 + 7\lambda^2 + \lambda$$

$$\text{var}(X_1, (X_1, -1)) = \lambda^4 + \underbrace{6\lambda^3} + \underbrace{7\lambda^2} + \underbrace{\lambda} - \underbrace{(2\lambda^3)} - \underbrace{6\lambda^2} - \underbrace{2\lambda} + \underbrace{\lambda^2} + \underbrace{\lambda} = (\lambda^2 + \lambda - \lambda)^2$$

$$\textcircled{1} = 4\lambda^3 + 2\lambda^2$$

(c) $g(x) = \sqrt{x}$ is concave

$-g(x)$ is convex.

Jensen's inequality: $-g(EX) \stackrel{\textcircled{2}}{\leq} E(-g(X))$

$$E\left(-\sqrt{\frac{1}{n} \sum X_i (X_i - 1)}\right) \geq -\sqrt{E\left(\frac{1}{n} \sum X_i (X_i - 1)\right)}$$

$$E\left(\sqrt{\dots}\right) \stackrel{\textcircled{1}}{\leq} \sqrt{E(X_1 (X_1 - 1))} \stackrel{\textcircled{1}}{=} \sqrt{\lambda^2} = \lambda.$$

(d) $Z_i = X_i (X_i - 1)$ are iid with $E Z_i = \lambda^2$ and $\text{var}(Z_i) < \infty$. (2)

WLLN: $\frac{1}{n} \sum_{i=1}^n Z_i \xrightarrow{P} \lambda^2$ (1)

LMT: $\sqrt{\frac{1}{n} \sum_{i=1}^n Z_i} \xrightarrow{P} \lambda$ (1)

(e) For $y < 0$, $P(Y_n \leq y) = 0$.

For $y \geq 0$, $P(Y_n \leq y) = P\left(\frac{1}{n} \sum_{i=1}^n (X_i)(X_i - 1) \leq y^2\right)$

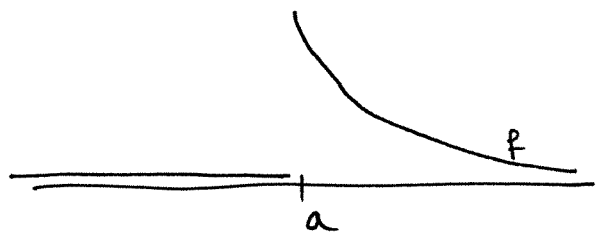
By the CLT, $\frac{\bar{Z}_n - \lambda^2}{\sqrt{4\lambda^3 + 2\lambda^2}} \cdot \frac{1}{\sqrt{n}} \rightsquigarrow N(0, 1)$. Hence,

$P(\bar{Z}_n \leq y^2) \approx P\left(\frac{\bar{Z}_n - \lambda^2}{\sqrt{4\lambda^3 + 2\lambda^2}} \cdot \sqrt{n} \leq \frac{y^2 - \lambda^2}{\sqrt{4\lambda^3 + 2\lambda^2}}\right)$
 $\approx \Phi\left(\frac{y^2 - \lambda^2}{\sqrt{4\lambda^3 + 2\lambda^2}} \cdot \sqrt{n}\right)$

PROBLEM 6

$\Rightarrow P(Y_n \leq y) = 1 - P(Y_n > y)$
 $\stackrel{(1)}{=} 1 - P(X_1 > y, \dots, X_n > y)$
 $\stackrel{(1)}{=} 1 - \prod_{i=1}^n P(X_i > y)$
 $\stackrel{(1)}{=} 1 - (1 - F(y))^n$

(b)



$$P(n(Y_n - a) \leq y) \stackrel{\textcircled{1}}{=} P(Y_n \leq \frac{y}{n} + a)$$

$$\stackrel{\textcircled{1}}{=} 1 - \left(1 - F\left(\frac{y}{n} + a\right)\right)^n$$

$$\stackrel{\textcircled{1}}{=} 1 - \left(1 - \frac{F\left(\frac{y}{n} + a\right) - F(a)}{\frac{y}{n}} \cdot n\right)^n$$

$$n \cdot \frac{F\left(\frac{y}{n} + a\right) - F(a)}{\frac{y}{n}} = \frac{F\left(\frac{y}{n} + a\right) - F(a)}{\frac{y}{n}} \cdot y$$

$$\stackrel{\textcircled{1}}{\rightarrow} f(a) \cdot y$$

Hence, $P(n(Y_n - a) \leq y) \stackrel{\textcircled{1}}{\rightarrow} \begin{cases} 1 - e^{-f(a) \cdot y}, & y > 0 \\ 0, & y < 0 \end{cases}$

(c) $\underbrace{n \cdot (Y_n - a)}_{\rightsquigarrow \text{Exp}(f(a))} \cdot \underbrace{\frac{1}{n}}_{\rightarrow 0} \xrightarrow{P} 0$ by Slutsky's Lemma. $\textcircled{4}$