

## Formulas For Math 447

### Part A. Fill the blanks of the formulas (30 points)

1. DeMorgan's laws:  $\overline{(A \cap B)} = \overline{A} \cup \overline{B}$ , and  $\overline{(A \cup B)} = \overline{A} \cap \overline{B}$ .
2. Axioms of probability: (1)  $P(A) \geq \underline{0}$ , (2)  $P(S) = \underline{1}$ ,  
(3) if  $A_i$ 's are pairwise disjoint, then  $P(\cup_i A_i) = \sum_i P(A_i)$ .
3. If each sample point in the sample space  $S$  is equally likely to occur,  $P(A) = \frac{N(\underline{\quad})}{N(\underline{\quad})}$  **key:**  
A, S
4. If an experiment can be partitioned into 2 steps, with  $n_i$  choices in the  $i^{th}$  step, then the total # of choices in the experiment is  $n_1 n_2$
5.  $P_r^n = \frac{n!}{(n-r)!}$ ,  $C_r^n = \binom{n}{r} = \frac{n!}{r!(n-r)!}$ ,  
 $\binom{n}{n_1, n_2, n_3} = \frac{n!}{n_1! n_2! n_3!}$ , where  $n_1 + n_2 + n_3 = \underline{n}$
6.  $P(A \cap B) = \underline{P(A|B)P(B)}$ . If  $A$  and  $B$  are independent then  $P(A \cap B) = P(A)P(B)$ .
7.  $P(\overline{A}) = 1 - P(A)$ .  $P(A \cup B) = P(A) + P(B) - \underline{P(A \cap B)}$ ,  
If  $A$  and  $B$  are disjoint then  $P(A \cup B) = P(A) + P(B)$ .
8. Bayes' Rule: If  $\{B_1, \dots, B_k\}$  is a partition of  $S$  and  $P(A), P(B_j) > 0$ , then  
$$P(B_j|A) = \frac{P(A|B_j)P(B_j)}{\sum_{k=1}^k P(A|B_k)P(B_k)}$$
9.  $X \sim \text{bin}(n, p)$ :  $f(i) = \underline{\binom{n}{i} p^i q^{n-i}}$ , if  $i \in \{0, \dots, n\}$ ,  $\mu = \underline{np}$ ,  $\sigma^2 = \underline{npq}$  where  $q = 1 - p$
10.  $X \sim G(p)$ .  $f(i) = q^{i-1} p$  if  $i \geq \underline{1}$ ,  $\mu = \underline{1/p}$ ,  $\sigma^2 = \underline{q/p^2}$
11.  $X \sim N\text{bin}(r, p)$ ,  $f(i) = \underline{\binom{i-1}{r-1} p^r q^{i-r}}$  if  $i \geq \underline{r}$ ,  $\mu = \underline{r/p}$ ,  $\sigma^2 = \underline{rq/p^2}$
12.  $X \sim HG(N, n, r)$ .  $f(i) = \frac{\binom{r}{i} \binom{N-r}{n-i}}{\binom{N}{n}}$ ,  $\mu = \underline{nr/N}$ ,  $\sigma^2 = \underline{\frac{nr(N-r)(N-n)}{N^2(N-1)}}$ .
13.  $X \sim \text{Pois}(\lambda)$ .  $f(i) = \frac{e^{-\lambda} \lambda^i}{i!}$ , if  $i \geq 0$ .  $\mu = \underline{\lambda}$ ,  $\sigma^2 = \underline{\lambda}$
14. Tchebysheff's Inequality.  $P(|X - \mu| > k\sigma) \leq \underline{1/k^2}$
15.  $Y = g(X)$ .  $E(g(X)) = \begin{cases} \sum_y y f_Y(y) & \text{dis} \\ \int y f_Y(y) dy & \text{cts} \end{cases} = \begin{cases} \sum_x g(x) f_X(x) & \text{dis} \\ \int g(x) f_X(x) dx & \text{cts} \end{cases}$ ,  $\mu_Y = \underline{E(Y)}$ ,  
$$\sigma_Y^2 = \underline{E(Y^2) - \mu_Y^2}$$
16. The mgf of  $X$  is  $M(t) = \underline{E(e^{Xt})}$ ,  $\frac{d^k M(t)}{dt^k} \Big|_{t=0} = \underline{E(X^k)}$
17. A cdf  $F(t)$  ( $= P(X \leq t)$ ,) satisfying (1)  $F(-\infty) = \underline{0}$ , and  $F(\infty) = \underline{1}$ , (2)  $F(x+) = \underline{F(x)}$ ,  
(3)  $F(x) \uparrow$ . Moreover,  $F(b) - F(a) = \underline{P(a < X \leq b)}$
18.  $F(t) = \begin{cases} \sum_{x \leq t} \underline{f(x)} & \text{dis} \\ \int_{-\infty}^t \underline{f(x)} dx & \text{cts} \end{cases}$ ,  $f(t) = \begin{cases} \underline{F(t) - F(t-)} & \text{dis} \\ \underline{F'(t)} & \text{cts} \end{cases}$
19. For discrete r.v.  $X$ , the p.f.  $f$  satisfies  $f(t) = P(\underline{X = t})$ ,  $f(t) \in [0, 1]$ , and  $\sum_t f(t) = \underline{1}$ ,  
For cts r.v.  $X$ , the d.f.  $f$  satisfies  $f(t) \geq \underline{0}$ , and  $\int f(t) dx = \underline{1}$
20.  $E(aX + b) = \underline{aE(X) + b}$ ,  $\text{Var}(aX + b) = \underline{a^2 \sigma_X^2}$
21.  $X \sim U(a, b)$ .  $f(x) = \frac{1}{b-a}$ , if  $x \in (a, b)$ .  $\mu = \frac{a+b}{2}$ ,  $\sigma^2 = \frac{(b-a)^2}{12}$
22.  $X \sim N(\mu, \sigma^2)$ .  $f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ ,  $\frac{X-\mu}{\sigma} \sim \underline{N(0, 1)}$
23.  $X \sim \mathcal{G}(\alpha, \beta)$ .  $f(x) = \frac{x^{\alpha-1} e^{-x/\beta}}{\Gamma(\alpha)\beta^\alpha}$ , if  $x > \underline{0}$ ,  $\mu = \underline{\alpha\beta}$ ,  $\sigma^2 = \underline{\alpha\beta^2}$ ,  $\Gamma(\alpha + 1) = \underline{\alpha\Gamma(\alpha)}$
24.  $\text{Exp}(\lambda) = \underline{\mathcal{G}(1, \lambda)}$ ,  $\chi^2(\nu) = \underline{\mathcal{G}(\frac{\nu}{2}, 2)}$

25.  $X \sim \text{beta}(\alpha, \beta)$ .  $f(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)}$ , if  $x \in (0, 1)$ ,  $\mu = \frac{\alpha}{\alpha+\beta}$ , where  $B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$
26. The cdf of  $(X, Y)$  is  $F(x, y) = P(X \leq x, Y \leq y) = \begin{cases} \int_{-\infty}^x \int_{-\infty}^y f(t, s) ds dt & \text{cts} \\ \sum_{t \leq x} \sum_{s \leq y} f(t, s) & \text{dis} \end{cases}$
27. For continuous  $(X, Y)$ , their d.f.  $f(x, y) = \frac{\partial^2 F(x, y)}{\partial x \partial y}$ ,  $f(x, y) \geq 0$ ,  $\int \int f(x, y) dx dy = 1$ ,  
For discrete  $(X, Y)$ , their d.f.  $f(x, y) = P\{X = x, Y = y\}$ ,  $f(x, y) \in [0, 1]$ ,  
 $\sum_x \sum_y f(x, y) = 1$
28.  $P((X, Y) \in A) = \begin{cases} \frac{\int \int_{(x, y) \in A} f(x, y) dx dy}{\sum_{(x, y) \in A} f(x, y)} & \text{cts} \\ \sum_{(x, y) \in A} f(x, y) & \text{dis} \end{cases}$
29.  $f_X(x) = \begin{cases} \int f(x, y) dy & \text{cts} \\ \sum_y f(x, y) & \text{dis} \end{cases}$
30.  $f_{X|Y}(x|y) = \frac{f(x, y)}{f_Y(y)}$ ,  $F_{X|Y}(x|y) = P(X \leq x | Y = y)$
31.  $E(g(X, Y)) = \begin{cases} \int \int g(x, y) f(x, y) dx dy & \text{cts} \\ \sum_x \sum_y g(x, y) f(x, y) & \text{dis} \end{cases}$
32. The cts or discrete  $X$  and  $Y$  are independent iff  $F(x, y) = F_X(x)F_Y(y)$  iff  $f(x, y) = f_X(x)f_Y(y)$
33.  $E(c) = c$ ,  $E(ag(X, Y) + bh(X, Y)) = aE(g(X, Y)) + bE(h(X, Y))$
34.  $Cov(X, Y) = E(XY) - E(X)E(Y)$ ,  $V(aX + bY) = a^2V(X) + b^2V(Y) + 2abCov(X, Y)$ ,  
 $\rho = \frac{Cov(X, Y)}{\sigma_X \sigma_Y}$ ,
35.  $(Y_1, Y_2, \dots, Y_k) \sim M(n, p_1, \dots, p_k)$ .  $f(y_1, \dots, y_k) = \frac{\binom{n}{y_1, \dots, y_k}}{p_1^{y_1} \dots p_k^{y_k}}$ ,  $y_i \in \{0, 1, \dots, n\}$ ,  
 $\sum_i p_i = 1$ , and  $\sum_i y_i = n$ ,  $Cov(Y_i, Y_j) = -np_i p_j$ , if  $i \neq j$ ,  $Y_i \sim \text{bin}(n, p_i)$
36.  $E(X|Y = y) = \begin{cases} \frac{\int x f(x|y) dx}{\sum_x x f(x|y)} & \text{cts} \\ \sum_x x f(x|y) & \text{dis} \end{cases}$ .  $E(E(X|Y)) = E(X)$ ,  
 $E(V(X|Y)) + V(E(X|Y)) = V(X)$
37.  $U = h(Y_1, \dots, Y_n)$ , where  $Y_i$ 's are continuous.  $F_U(t) = \int \dots \int_A f(y_1, \dots, y_n) dy_1 \dots dy_n$ , where  
 $A = \{h(y_1, \dots, y_n) \leq t\}$ ,  $f_U(t) = F'_U(t)$
38.  $U = h(Y)$ , where  $h$  is monotone, and  $Y$  is cts.  $f_U(u) = f_Y(h^{-1}(u)) \cdot \left| \frac{\partial h^{-1}}{\partial u} \right|$
39. If  $X$  and  $Y$  are independent, then  $Cov(X, Y) = 0$ ,  $E(g(X)h(Y)) = E(g(X))E(h(Y))$   
 $M_{X+Y}(t) = M_X(t) \cdot M_Y(t)$
- Hereafter, let  $Y_1, \dots, Y_n$  be a random sample of  $Y$ .**
40. Let  $Y_1, \dots, Y_n$  be a random sample of  $Y$ .  $\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$ ,  $S^2 = S_Y^2 = \frac{1}{n-1} \sum_{i=1}^n (Y_i - \bar{Y})^2$
41. If  $Y \sim N(\mu, \sigma^2)$ ,  $\frac{\bar{Y} - \mu_{\bar{Y}}}{\sigma_{\bar{Y}}} \sim N(0, 1)$ ,  $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2(n-1)$ ,  $\sqrt{n} \frac{\bar{Y} - \mu}{S} \sim t_{n-1}$ , where  $\mu_{\bar{Y}} = \mu$ ,  
 $\sigma_{\bar{Y}}^2 = \sigma^2/n$
42.  $F_{\bar{Y}}(t) \cong \Phi\left(\frac{t - \mu_{\bar{Y}}}{\sigma_{\bar{Y}}}\right)$ , where  $\Phi(t)$  is the cdf of  $N(0, 1)$

**Review formulas for Math 448,**

- Estimator of  $\mu$  is  $\bar{X}$  where  $\bar{X} = \frac{\sum_i X_i}{n}$ , Estimator of  $\sigma^2$  is  $S^2$ , where  $S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$ . **key:**  $\sum_i X_i/n, \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$ .
- An estimator  $\hat{\theta}$  is unbiased if  $E(\hat{\theta}) = \theta$ , bias  $B(\hat{\theta}) = E(\hat{\theta}) - \theta$ , MSE =  $V(\hat{\theta}) + (B(\hat{\theta}))^2$ . **(key:  $E(\hat{\theta}) = \theta, E(\hat{\theta}) - \theta, V(\hat{\theta}) + (B(\hat{\theta}))^2$ ),**
- 100(1 -  $\alpha$ )% CI for  $\theta$ :  $\hat{\theta} \pm z_{\alpha/2} \hat{\sigma}_{\hat{\theta}}$ . **key:  $P(a \leq \theta \leq b), 1 - \alpha$ .**
- 100(1 -  $\alpha$ )% large sample CI for  $\theta$ :  $\hat{\theta} \pm z_{\alpha/2} \hat{\sigma}_{\hat{\theta}}$ . **key:  $\hat{\theta} \pm z_{\alpha/2} \hat{\sigma}_{\hat{\theta}}$ .**
- If (1)  $X_1, \dots, X_n$  are i.i.d. from  $N(\mu_1, \sigma^2)$ , (2)  $Y_1, \dots, Y_m$  are i.i.d. from  $N(\mu_2, \sigma^2)$ , and (3)  $X_i$ 's  $\perp$   $Y_j$ 's, then  $T = \frac{\bar{X} - \mu_o}{S_x/\sqrt{n}} \sim t_{n-1}$ ,  
 $T = \frac{\bar{X} - \bar{Y} - (\mu_x - \mu_y)}{\hat{\sigma}_p \sqrt{1/n_x + 1/n_y}} \sim t_{n-1}$ , where  $\hat{\sigma} = \sqrt{\frac{(n-1)S_x^2 + (m-1)S_y^2}{n+m-2}}$ ,  $F = S_x^2/S_y^2 \sim F_{n-1, m-1}$ ,  
**key:  $\sigma^2, \sigma^2, \perp, t_{n-1}, t_{n+m-2}, \sqrt{\frac{(n-1)S_x^2 + (m-1)S_y^2}{n+m-2}}, \chi_{n-1}^2, F_{n-1, m-1}$ ,**
- $f_{Y(j)}(t) = \binom{n}{j-1, 1, n-j} (F(t))^{j-1} (f(t)) (1 - F(t))^{n-j}$ . **key:  $(F(t))^{j-1} (f(t)) (1 - F(t))^{n-j}$ .**
- Given two unbiased estimators  $\hat{\theta}_1$  and  $\hat{\theta}_2$ ,  $\text{eff}(\hat{\theta}_1, \hat{\theta}_2) = \frac{V(\hat{\theta}_2)}{V(\hat{\theta}_1)}$ . **key: unbiased,  $\frac{V(\hat{\theta}_2)}{V(\hat{\theta}_1)}$ ,**
- $\hat{\theta}$  is consistent or  $\hat{\theta} \xrightarrow{P} \theta$  if  $P(|\hat{\theta} - \theta| > \epsilon) \rightarrow 0$ ,  $\forall \epsilon > 0$ . **key: 0,  $\forall \epsilon$ ,**
- If (1)  $E(\hat{\theta}) = \theta$  and (2)  $V(\hat{\theta}) \rightarrow 0$ , as  $n \rightarrow \infty$ , then  $\hat{\theta}$  is consistent. **key:  $\theta, \rightarrow 0$ ,**
- If  $g(\cdot)$  is continuous,  $\hat{\theta}_1 \xrightarrow{P} \theta_1$  and  $\hat{\theta}_2 \xrightarrow{P} \theta_2$ , then  $\hat{\theta}_1 \pm \hat{\theta}_2 \xrightarrow{P} \theta_1 \pm \theta_2$ ,  $\hat{\theta}_1 \hat{\theta}_2 \xrightarrow{P} \theta_1 \theta_2$ ,  $g(\hat{\theta}_1) \xrightarrow{P} g(\theta_1)$ . **key: cts,  $\theta_1 \pm \theta_2, \theta_1 \theta_2, g(\theta_1)$ ,**
- If  $X_1, \dots, X_n$  are i.i.d. from  $f(x; \theta) = \exp\{T(x)\psi(\theta) + g(\theta) + h(x)\}$ ,  $\hat{\gamma} = G(\sum_i T(X_i))$  and  $\psi(\theta) = \gamma(\theta)$ , then  $\hat{\gamma}$  is the MVUE of  $\gamma$ . **key:  $T(x)\psi(\theta), \sum_i T(X_i), E(\hat{\gamma})$ ,**
- An MME of  $\theta$ , is the solution of  $\theta$  to  $\mu'_i(\theta) = \bar{X}^i$  for  $k$  i's, where  $\mu'_i(\theta) = E(X^i)$ , and  $k$  is the dimension of  $\theta$ . **key:  $\bar{X}^i, E(X^i)$ ,**
- Given a random sample  $X_1, \dots, X_n$  from  $f(x; \theta)$ , their likelihood is  $L(\theta) = \prod_i f(X_i; \theta)$ , the MLE  $\hat{\theta}$  of  $\theta$  maximizes  $L(\theta)$ . If  $g(\theta)$  is a concave function of  $\theta$ , the MLE of  $g(\theta)$  is  $g(\hat{\theta})$ . **key:  $\prod_i f(X_i; \theta), L(\theta), 1 - 1, g(\hat{\theta})$ ,**
- Given a random sample from  $f(x; \theta)$ , and a function  $g(\theta)$ , under certain conditions,  $P(g(\hat{\theta}) \leq t) \approx \Phi\left(\frac{t - g(\hat{\theta})}{\hat{\sigma}_{g(\hat{\theta})}}\right)$ , where  $\hat{\theta}$  is the MLE of  $\theta$ ,  $\hat{\sigma}_{g(\hat{\theta})} = \sqrt{\left\{ \left( \frac{\partial g}{\partial \theta} \right)^2 / \left( -n E \left( \frac{\partial^2 \log f(X; \theta)}{\partial \theta^2} \right) \right) \right\} \Big|_{\theta = \hat{\theta}}}$ . **key:  $\approx, MLE, \sqrt{\left\{ \left( \frac{\partial g}{\partial \theta} \right)^2 / \left( -n E \left( \frac{\partial^2 \log f(X; \theta)}{\partial \theta^2} \right) \right) \right\} \Big|_{\theta = \hat{\theta}}$ ,**
- The 5 elements of a test are (1)  $H_o$ , (2)  $H_a$ , (3) test statistics (4)  $\alpha$ , (5)  $\beta$ . **key:  $H_o, H_a, RR, Conclusion$ ,**
- Probability of type I error is  $\alpha$ , Probability of type II error is  $\beta$ . **key:  $P(H_a|H_o), P(H_o|H_a)$ ,**
- For a large sample test for  $H_o: \theta = \theta_o$ , a test statistic is  $Z = \frac{\hat{\theta} - \theta_o}{\hat{\sigma}_{\hat{\theta}}}$ , a RR is  $Z > z_{\alpha/2}$  if  $\theta > \theta_o$ ; and a RR is  $Z < -z_{\alpha/2}$  if  $\theta < \theta_o$ ; **key:  $\frac{\hat{\theta} - \theta_o}{\hat{\sigma}_{\hat{\theta}}}, > z_{\alpha/2}, |Z| > z_{\alpha/2}$ ,**

18. Sample size for an upper-tail  $\alpha$ -level test is  $n = (\text{_____})^2$  **key:**  $\frac{(z_\alpha + z_\beta)\sigma}{\mu_a - \mu_o}$ ,

19. The P-value is  $\begin{cases} P(W \text{_____} w) | H_o \text{ is correct} & \text{if } H_a : \theta > \theta_o \\ P(W \text{_____} w) | H_o \text{ is correct} & \text{if } H_a : \theta < \theta_o \\ \text{_____} P(W \text{_____} |w|) | H_o \text{ is correct} & \text{if } H_a : \theta \neq \theta_o \end{cases}$  where  $W$  is the ( $Z$  or  $T$ ) test statistic and  $w$  is the observed value of  $W$ . **key:**  $\geq, \leq, \underline{2}, \geq$ ,

20. Suppose that  $Z \sim N(0, 1)$ ,  $X \sim \chi^2(u)$ ,  $Y \sim \chi^2(v)$ . If  $Z \text{_____} X$ ,  $T = \text{_____}$ , then  $T \sim t_u$ ; If  $X \text{_____} Y$ ,  $F = \text{_____}$ , then  $F \sim F_{u,v}$  and  $X + Y \sim \text{_____}$ . **key:**  $\underline{1}$ ,  $\underline{Z/\sqrt{X/u}}$ ,  $\underline{1}$ ,  $\underline{X/u}$ ,  $\underline{Y/v}$ ,  $\underline{\chi^2(u+v)}$ ,

21. The MP test for  $H_o: \theta = \theta_o$  v.s.  $H_a: \theta = \theta_a$ , the MP test has the RR satisfying:  $\frac{L(\theta_o)}{L(\theta_a)} \text{_____} k$  and  $P_\theta(RR) = \alpha$  if  $\theta = \text{_____}$ . **key:**  $\leq, \underline{\theta_o}$ ,

22. The Likelihood ratio test for  $H_o: \theta \in \Theta_o$  v.s.  $H_a: \theta \notin \Theta_o$  has a RR:  $\{\lambda \text{_____} k\}$ , where

$\lambda = \text{_____}$ ;  $\hat{\theta}_o$  is the MLE under  $\text{_____}$ ;  $\hat{\theta}$  is the MLE under  $\text{_____}$ ;

$k$  satisfies  $\max\{P(RR) : \theta \in \Theta_o\} = \text{_____}$ ; if  $n$  is large, then  $-2\ln\lambda$  is approximated  $\text{_____}$ ; where  $v = \text{_____}$ ;  $r$  and  $r_o = \#$  of free parameters in  $\Theta$  and in  $\Theta_o$ , respectively.

**key:**  $\leq, \underline{\frac{L(\hat{\theta}_o)}{L(\hat{\theta})}}$ ,  $\underline{\Theta_o}$ ,  $\underline{\Theta}$ ,  $\underline{\alpha}$ ,  $\underline{\chi^2(v)}$ ,  $\underline{r - r_o}$

23. Suppose  $(x_i, Y_i)$ 's are independent,  $\mu_{x_i}(\theta) = E(Y_i)$ , the LSE of  $\theta$ , denoted by  $\hat{\theta}$ , minimizes  $\text{_____}$ .

If  $\mu_{x_i}(\theta) = \beta_0 + \beta_1 x_i$  and  $V(Y_i) = \sigma^2$ , the LSE  $\hat{\beta}_0 = \text{_____}$ ,

$\hat{\beta}_1 = \text{_____}$ ,  $S_{xy} = \text{_____}$ ,  $E(\hat{\beta}_0) = \text{_____}$ ,  $E(\hat{\beta}_1) = \text{_____}$ ,

$\sigma_{\hat{\beta}_0}^2 = \text{_____}$ ,  $\sigma_{\hat{\beta}_1}^2 = \text{_____}$ , an unbiased estimator of  $\sigma^2$  is  $\hat{\sigma}^2 = \text{_____}$ ,

**key:**  $\underline{\sum_{i=1}^n [Y_i - \mu_{x_i}(\theta)]^2}$ ,  $\underline{\bar{Y} - \hat{\beta}_1 \bar{x}}$ ,  $\underline{S_{xy}/S_{xx}}$ ,  $\underline{n(\bar{xY} - \bar{x}\bar{Y})}$ ,  $\underline{\beta_0}$ ,  $\underline{\beta_1}$ ,

$\underline{\sigma^2 \bar{x}^2 / S_{xx}}$ ,  $\underline{\sigma^2 / S_{xx}}$ ,  $\underline{\frac{1}{n-2}(S_{yy} - \hat{\beta}_1 S_{xy})}$ ,

If  $Y_i \sim \text{_____}$ , then  $\hat{\beta}_j \sim \text{_____}$ ,  $\frac{n-2}{\sigma^2} \hat{\sigma}^2 \sim \text{_____}$ ,  $\hat{\sigma}^2, \hat{\beta}_0, \hat{\beta}_1$  are  $\text{_____}$ ,  $\text{_____} \sim t_{n-2}$ ,

**key:**  $\underline{N(\beta_0 + \beta_1 x_i, \sigma^2)}$ ,  $\underline{N(\beta_j, \sigma_{\hat{\beta}_j}^2)}$ ,  $\underline{\chi^2(n-2)}$ ,  $\underline{\text{independent}}$ ,  $\underline{\frac{\hat{\beta}_j - \beta_j}{\hat{\sigma}_{\hat{\beta}_j}}}$ ,

24. Under the Bayes model, conditional on  $\theta$ ,  $Y_1, \dots, Y_n$  are i.i.d. with  $f(y|\theta)$ , and  $\theta \sim g(\theta)$ . The posterior df is  $g(\theta|\underline{y}) = \underline{\hspace{10em}}$ , where  $\underline{y} = (y_1, \dots, y_n)$  the Bayes estimator of  $h(\theta)$  is  $\hat{h} = \underline{\hspace{10em}}$

**key:**  $\frac{\prod_{i=1}^n f(y_i|\theta)g(\theta)}{f_Y(\underline{y})}, E(h(\theta)|\underline{y})$ ,

**Formulas for 447:**

23.  $X \sim \mathcal{G}(\alpha, \beta)$ .  $f(x) = \underline{\hspace{10em}}$  if  $x > \underline{\hspace{2em}}$ ,  $\mu = \underline{\hspace{2em}}$ ,  $\sigma^2 = \underline{\hspace{2em}}$ ,  $\Gamma(\alpha + 1) = \underline{\hspace{2em}}$ , **key:**  $\frac{x^{\alpha-1}e^{-x/\beta}}{\Gamma(\alpha)\beta^\alpha}, 0, \alpha\beta, \alpha\beta^2, \alpha\Gamma(\alpha)$

24.  $Exp(\lambda) = \underline{\hspace{10em}}$ ,  $\chi^2(\nu) = \underline{\hspace{10em}}$ , **key:**  $\mathcal{G}(1, \lambda), \mathcal{G}(\frac{\nu}{2}, 2)$

25.  $X \sim beta(\alpha, \beta)$ .  $f(x) = \underline{\hspace{10em}}$  if  $x \underline{\hspace{2em}}$ ,  $\mu = \underline{\hspace{2em}}$ , where  $B(\alpha, \beta) = \underline{\hspace{2em}}$ , **key:**  $\frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)}, \in (0, 1), \frac{\alpha}{\alpha+\beta}, \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$

41. If  $Y_i$ 's are i.i.d. with  $N(\mu, \sigma^2)$ , then  $\frac{\bar{Y} - \mu_{\bar{Y}}}{\sigma_{\bar{Y}}} \sim \underline{\hspace{2em}}$ ,  $\frac{(n-1)S^2}{\sigma^2} \sim \underline{\hspace{2em}}$ ,  $S^2 \underline{\hspace{2em}} \bar{Y}$ , where  $\mu_{\bar{Y}} = \underline{\hspace{2em}}$ ,  $\sigma_{\bar{Y}}^2 = \underline{\hspace{2em}}$  **key:**  $N(0, 1), \chi^2(n-1), \perp, \underline{\mu}, \underline{\sigma^2/n}$

	$X_i$ 's $\sim$ :	$X_1 + X_2 \sim$ :	
	$\mathcal{G}(\alpha_i, \beta)$	$\underline{\hspace{2em}}$	$\frac{\mathcal{G}(\alpha_1 + \alpha_2, \beta)}{\chi^2(v_1 + v_2)}$
	$\chi^2(v_i)$	$\underline{\hspace{2em}}$	$\frac{Pois(\lambda_1 + \lambda_2)}{N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)}$
44. If $X_1 \underline{\hspace{2em}} X_2$ .	$Pois(\lambda_i)$	$\underline{\hspace{2em}}$	$\frac{bin(n_1 + n_2, p)}{bin(n_1 + n_2, p)}$
	$N(\mu_i, \sigma_i^2)$	$\underline{\hspace{2em}}$	
	$bin(n_i, p)$	$\underline{\hspace{2em}}$	