(6.64) If $Y_{1}, Y_{2}, \ldots, Y_{n}$ are all independent and identically distributed beta( 2,2 ) random variables, then each has density function

$$
f_{Y}(y)=\frac{\Gamma(4)}{\Gamma(2) \Gamma(2)} y(1-y)=6 y(1-y), \quad 0<y<1
$$

(a) If $Y_{(n)}=\max \left\{Y_{1}, \ldots, Y_{n}\right\}$, then

$$
P\left(Y_{(n)} \leq t\right)=P\left(Y_{1} \leq t, \ldots, Y_{n} \leq t\right)=P\left(Y_{1} \leq t\right) \cdots P\left(Y_{n} \leq t\right)=\left[P\left(Y_{1} \leq t\right)\right]^{n}
$$

since the $Y_{i}$ are independent (the second equality) and identically distributed (the third equality). Now, for any $0<t<1$,
$P\left(Y_{1} \leq t\right)=\int_{0}^{t} f_{Y}(y) d y=\int_{0}^{t} 6 y(1-y) d t=\int_{0}^{t} 6 y d y-\int_{0}^{t} 6 y^{2} d y=3 t^{2}-2 t^{3}=t^{2}(3-2 t)$ so that the distribution function of $Y_{(n)}$ is

$$
F(t)=\left[P\left(Y_{(n)} \leq t\right)\right]^{n}=t^{2 n}(3-2 t)^{n}, \quad 0<t<1
$$

(Of course, $F(t)=0$ for $t \leq 0$, and $F(t)=1$ for $t \geq 1$.
(b) The density function of $Y_{(n)}$ is therefore
$f(t)=\frac{d}{d t} F(t)=\frac{d}{d t} t^{2 n}(3-2 t)^{n}=2 n t^{2 n-1}(3-2 t)^{n}-2 n t^{2 n}(3-2 t)^{n-1}=6 n t^{2 n-1}(3-2 t)^{n-1}(1-t)$
for $0<t<1$ and 0 otherwise.
(c) For $n=2$, the expected value $E\left(Y_{(2)}\right)$ is

$$
E\left(Y_{(2)}\right)=\int_{0}^{1} t f(t) d t=\int_{0}^{1} 12 t^{4}(3-2 t)(1-t) d t=\int_{0}^{1}\left(36 t^{4}-60 t^{5}+24 t^{6}\right) d t=\frac{36}{5}-\frac{60}{6}+\frac{24}{7}=\frac{22}{35}
$$

(6.65) If $Y_{1}, Y_{2}, \ldots, Y_{n}$ are all independent and identically distributed exponential $(\beta)$ random variables, then each has density function

$$
f_{Y}(y)=\frac{1}{\beta} e^{-y / \beta}, \quad 0<y<\infty
$$

(a) If $Y_{(1)}=\min \left\{Y_{1}, \ldots, Y_{n}\right\}$, then

$$
P\left(Y_{(1)}>t\right)=P\left(Y_{1}>t, \ldots, Y_{n}>t\right)=P\left(Y_{1}>t\right) \cdots P\left(Y_{n}>t\right)=\left[P\left(Y_{1}>t\right)\right]^{n}
$$

since the $Y_{i}$ are independent (the second equality) and identically distributed (the third equality). Now, for any $0<t<\infty$,

$$
P\left(Y_{1}>t\right)=\int_{t}^{\infty} f_{Y}(y) d y=\frac{1}{\beta} \int_{t}^{\infty} e^{-y / \beta} d y=e^{-t / \beta}
$$

so that

$$
P\left(Y_{(1)}>t\right)=e^{-t n / \beta}
$$

Thus, the distribution function of $Y_{(n)}$ is

$$
F(t)=P\left(Y_{(1)} \leq t\right)=1-P\left(Y_{(1)}>t\right)=1-e^{-t n / \beta}=1-e^{-t /(\beta / n)}
$$

which is the distribution function of an exponential random variable with mean $\beta / n$.
(b) If $n=5, \beta=2$, then the distribution function of $Y_{(1)}$ is

$$
F(t)=1-e^{-5 t / 2}, \quad 0<t<\infty
$$

so that the corresponding density function is

$$
f(t)=\frac{5}{2} e^{-5 t / 2}, \quad 0<t<\infty
$$

Hence,

$$
P\left(Y_{(1)} \leq 3.6\right)=\frac{5}{2} \int_{0}^{3.6} e^{-5 t / 2} d t=-\left.e^{-5 t / 2}\right|_{0} ^{3.6}=1-e^{-9} .
$$

2. (a) Since $Y_{1} \sim \mathcal{U}(0, \theta)$, we have

$$
f_{Y}(y)= \begin{cases}1 / \theta, & 0 \leq y \leq \theta \\ 0, & \text { otherwise }\end{cases}
$$

(b) If $f(t)$ denotes the density of $\hat{\theta}=\min \left(Y_{1}, \ldots, Y_{n}\right)$, then $f(t)=F^{\prime}(t)$, where

$$
F(t)=P(\hat{\theta} \leq t)=1-P(\hat{\theta}>t)=1-P\left(Y_{1}>t, \ldots, Y_{n}>t\right)=1-\left[P\left(Y_{1}>t\right)\right]^{n} .
$$

Note that in the last step we have used the fact that $Y_{i}$ are iid. Next, for $0 \leq t \leq \theta$, we compute

$$
P\left(Y_{1}>t\right)=\int_{t}^{\infty} f_{Y}(y) d y=\int_{t}^{\theta} \frac{1}{\theta} d y=\frac{\theta-t}{\theta} .
$$

Thus, we conclude

$$
f(t)=\frac{d}{d t}\left(1-\left[\frac{\theta-t}{\theta}\right]^{n}\right)=n \theta^{-n}(\theta-t)^{n-1}, \quad 0 \leq t \leq \theta .
$$

(c) By definition,

$$
E(\hat{\theta})=\int_{-\infty}^{\infty} t f(t) d t=\int_{0}^{\theta} n \theta^{-n} t(\theta-t)^{n-1} d t
$$

This last integral is solved with a simple substitution. Let $u=\theta-t$ so that $d u=-d t$. Thus,

$$
\begin{aligned}
\int_{0}^{\theta} n \theta^{-n} t(\theta-t)^{n-1} d t=-n \theta^{-n} \int_{\theta}^{0}(\theta-u) u^{n-1} d u & =n \theta^{-n} \int_{0}^{\theta} \theta u^{n-1}-u^{n} d u \\
& =n \theta^{-n}\left(\theta \cdot \frac{\theta^{n}}{n}-\frac{\theta^{n+1}}{n+1}\right) \\
& =\frac{\theta}{n+1}
\end{aligned}
$$

(d) From (c), we clearly see that $\hat{\theta}$ is NOT an unbiased estimator of $\theta$. However,

$$
\tilde{\theta}=(n+1) \min \left(Y_{1}, \ldots, Y_{n}\right)
$$

IS an unbiased estimator of $\theta$. (You should check that $2 \bar{Y}$ is also an unbiased estimator of $\theta$. Why?)

