8.4.8 Suppose we have that $\delta(s, \cdot)$ is degenerate at $d(s)$ for each $s$. Then clearly $d: S \rightarrow \mathcal{A}$.

Now suppose we have $d: S \rightarrow \mathcal{A}$ and define

$$
\delta(s, B)= \begin{cases}1 & d(s) \in B \\ 0 & \text { otherwise }\end{cases}
$$

for $B \subset \mathcal{A}$. Then $\delta(s, \mathcal{A})=1$ and, if $B_{1}, B_{2}, \ldots$ are mutually disjoint subsets of $\mathcal{A}$, then $d(s) \in B_{i}$ for one $i$ (and only one) if and only if $d(s) \in \cup_{j=1}^{\infty} B_{j}$, so $\delta\left(s, \cup_{j=1}^{\infty} B_{j}\right)=\sum_{j=1}^{\infty} \delta\left(s, B_{j}\right)$. Therefore, $\delta(s, \cdot)$ is a probability measure for each $s$ and $\delta$ is a decision function.

Now, using the fact that $\delta(s, \cdot)$ is a discrete probability measure degenerate at $d(s)$, we have that $R_{\delta}(\theta)=E_{\theta}\left(E_{\delta(s, \cdot)}(L(\theta, a))\right)=$
$E_{\theta}\left(\delta(s,\{d(s)\})(L(\theta, d(s)))=E_{\theta}(L(\theta, d(s)))\right.$ since $\delta(s,\{d(s)\})=1$.

## 8.4 .9

(a) Consider the decision function $d_{\theta_{0}}(s) \equiv A\left(\theta_{0}\right)$. Then note that $R_{d_{\theta_{0}}}\left(\theta_{0}\right)=0$. Then, if $\delta$ is optimal, we must have that $R_{\delta}\left(\theta_{0}\right) \leq R_{d_{\theta_{0}}}\left(\theta_{0}\right)$ for every $\theta_{0}$, so $R_{\delta}(\theta) \equiv 0$. But this implies that $E_{\delta(s, \cdot)}(L(\theta, a))=0$ at every $s$, where $P_{\theta}(\{s\})>0$. Since $L(\theta, a) \geq 0$, then Challenge 3.3.29 implies that $\delta(s,\{L(\theta, a)=0\})=1$ and, since $L(\theta, a)=0$ if and only if $a=A(\theta)$, this implies that $\delta(s, \cdot)$ is degenerate at $A(\theta)$ for each $s$ for which $P_{\theta}(\{s\})>0$.
(b) Part (a) proved that, for an optimal $\delta, \delta(s, \cdot)$ is degenerate at $A(\theta)$ for each $s$ for which $P_{\theta}(\{s\})>0$. But if there exists $s$ such that $P_{\theta_{1}}(\{s\})>0$ and $P_{\theta_{2}}(\{s\})>0$ and $A\left(\theta_{1}\right) \neq A\left(\theta_{2}\right)$, then this cannot happen and so no optimal $\delta$ can exist.
8.4.10 Suppose $\delta$ is not minimax. Then there exists decision function $\delta^{*}$ such that $\sup _{\theta} R_{\delta^{*}}(\theta)<\sup _{\theta} R_{\delta}(\theta)$. But since $R_{\delta}(\theta)$ is constant in $\theta$ this implies that $R_{\delta^{*}}(\theta)<R_{\delta}(\theta)$ for every $\theta$ and so $\delta$ is not admissible, contradicting the hypothesis. Therefore, $\delta$ must be minimax.

