

# SOME REMARKS ON THE TWO-ARMED BANDIT 

## by

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## 1 INTRODUCTION

In this paper we consider the following situation: An experimenter has to perform a total of $N$ trials on two Bernoulli-type experiments $E_{1}$ and $E_{2}$ with success probabilities $\alpha$ and $\beta$ respectively, where both $\alpha$ and $\beta$ are unknown to him. The trials are to be carried out sequentially and independently, except that for each trial the experimenter may choose between $E_{1}$ and $E_{2}$, using the information obtained in all previous trials. The decisions on the part of the experimenter to use $E_{1}$ or $E_{2}$ in the successive trials may be randomized, i.e. for any trial he may use a chance mechanism in order to choose $\mathrm{E}_{1}$ or $\mathrm{E}_{2}$ with probabilities $\delta$ and $1-\delta$ respectively, where $\delta$ may depend on the decisions taken and the results obtained in the previous trials. A strategy $\Delta$ will be a set of such $\delta$ 's, completely describing the experimenters behaviour in every conceivable situation.

[^0]We assume the experimenter wants to maximize the number of successes. More precisely, we assume that he incurs a loss

$$
\begin{equation*}
L(\alpha, \beta, s)=N \max (\alpha, \beta)-s \tag{1.1}
\end{equation*}
$$

if he scores a total of $s$ successes. If he uses a strategy $\Delta$, his expected loss is then given by the risk function

$$
\begin{equation*}
R(\alpha, \beta, \Delta)=N \max (\alpha, \beta)-E(S \mid \alpha, \beta, \Delta), \tag{1.2}
\end{equation*}
$$

where $S$ denotes the random number of successes obtained. Thus the risk of a strategy $\Delta$ equals the expected amount by which the number of successes the experimenter will obtain using $\Delta$ falls short of the number of successes he would score if he were clairvoyant and would use the more favourable experiment throughout the $N$ trials.

We say that state $(m, k ; n, l)$ is reached during the series of trials if in the first $m+n$ trials $E_{1}$ is used $m$ times, yielding $k$ successes, and $E_{2}$ is used $n$ times, yielding 1 successes. Clearly, under a strategy $\Delta$, the probability that this will happen is of the form

$$
\begin{equation*}
\pi_{\alpha, \beta, \Delta}(m, k ; n, l)=p_{\Delta}(m, k ; n, 1) \alpha^{k}(1-\alpha)^{m-k} \beta^{l}(1-\beta)^{n-1}, \tag{1.3}
\end{equation*}
$$

where $p_{\Delta}(m, k ; n, l)$ depends on the state $(m, k ; n, l)$ and the strategy $\Delta$, but not on $\alpha$ and $\beta$. It is easy to show (e.g. by induction on $N$ ) that the class of all strategies is convex in the sense that there exists, for every pair of strategies $\Delta_{1}$ and $\Delta_{2}$ and for every $\lambda \varepsilon[0,1]$, a strategy $\Delta$ such that

$$
\begin{equation*}
p_{\Delta}(m, k ; n, l)=\lambda p_{\Delta}(m, k ; n, l)+(1-\lambda) p_{\Delta}(m, k ; n, l) \tag{1.4}
\end{equation*}
$$

for every state ( $m, k ; n, l$ ).

Moreover, this strategy $\Delta$ can always be taken to be such, that according to it the experimenter should base all his decisions exclusively on the numbers of successes and failures observed with $E_{1}$ and $E_{2}$, irrespective of the order in which these data became available. Denoting the class of all such strategies by $D$ and remarking that $R(\alpha, \beta, \Delta)$ can be expressed in terms of the $\pi_{\alpha, B, \Delta}(m, k ; n, l)$, we may conclude that $D$ is an essentially complete class of strategies. We denote the probabilities $\delta$ constituting any strategy in $\mathscr{D}$ by $\delta(m, k ; n, l)$ : the probability with which the experimenter, having completed the first $m+n$ trials and thereby having reached state $(m, k ; n, l)$, chooses $E_{1}$ for the next trial.

We note that if $p_{\Delta}(m, k ; n, l)=0$ for a state $(m, k ; n, l)$, then $\delta(m, k ; n, l)$ does not play any role in the description of $\Delta$ and may be assigned an arbitrary value without affecting the strategy. We shall say that any strategy $\Delta^{\prime}$ such that $p_{\Delta^{\prime}}(m, k ; n, l)=p_{\Delta}(m, k ; n, l)$ for all states ( $m, k ; n, l$ ) constitutes a version of $\Delta$.

Since we are considering a symmetric problem in the sense that it remains invariant when $\alpha$ and $\beta$ are interchanged, it seems reasonable to consider strategies with a similar symmetry. Thus we are led to define the class $\boldsymbol{\mathscr { S }}$ of all symmetric strategies:
$\Delta \varepsilon \mathcal{J}$ iff $\Delta \varepsilon \mathscr{D}$ and $\delta(m, k ; n, l)=1-\delta(n, l ; m, k)$ for all states $(m, k ; n, l)$ with $p_{\Delta}(m, k ; n, l) \neq 0$. Clearly, for $\Delta \varepsilon \boldsymbol{\mathscr { J }}$,

$$
\begin{align*}
\delta(m, k ; m, k) & =\frac{1}{2} \text { if } p_{\Delta}(m, k ; m, k) \neq 0 \text {, and }  \tag{1.5}\\
p_{\Delta}(m, k ; n, l) & =p_{\Delta}(n, l ; m, k) \text { for all states }(m, k ; n, l) \tag{1.6}
\end{align*}
$$

It follows that, for $\Delta \varepsilon \mathscr{\mathscr { V }}$ and all $(\alpha, \beta)$,

$$
\begin{equation*}
R(\alpha, \beta, \Delta)=R(6, \alpha, \Delta) \tag{1.7}
\end{equation*}
$$

Another argument in favour of considering $\mathcal{f}$ is the following result.

## THEOREM 1

There is a strategy $\Delta \varepsilon \boldsymbol{\mathscr { C }}$ with minimax risk.

## PROOF

The existence of a minimax-risk strategy $\Delta_{1} \varepsilon \mathcal{D}$ is well known for this type of problem. Let $\Delta_{2} \varepsilon \mathscr{D}$ be defined by

$$
\delta_{2}(m, k ; n, l)=1-\delta_{1}(n, l ; m, k) \quad \text { for all states }(m, k ; n, l)
$$

Then

$$
\begin{array}{ll}
p_{\Delta_{2}}(m, k ; n, 1)=p_{\Delta_{1}}(n, l ; m, k) & \text { for all states, hence } \\
R\left(\alpha, \beta, \Delta_{2}\right)=R\left(\beta, \alpha, \Delta_{1}\right) & \text { for all }(\alpha, \beta) \text { so that } \Delta_{2} \text { has }
\end{array}
$$

minimax risk. By convexity we may construct a strategy $\Delta \varepsilon \mathbb{D}$ satisfying (1.4) with $\lambda=\frac{1}{2}$. We have

$$
\begin{array}{ll}
p_{\Delta}(m, k ; n, l)=p_{\Delta}(n, l ; m, k) & \text { for all states, and }  \tag{1.8}\\
R(\alpha, \beta, \Delta)=\frac{1}{2} R\left(\alpha, \beta, \Delta_{1}\right)+\frac{1}{2} R\left(\alpha, \beta, \Delta_{2}\right) & \text { for all }(\alpha, \beta), \text { which }
\end{array}
$$

implies that $\Delta$ too has minimax risk. Finally, if $\Delta \notin \mathscr{\mathscr { J }}$, we define $\Delta^{\star} \varepsilon \boldsymbol{f} \quad$ by

$$
\delta^{\star}(m, k ; n, 1)=\frac{1}{2} \delta(m, k ; n, 1)+\frac{1}{2}[1-\delta(n, 1 ; m, k)] \text { for all states. }
$$

One easily verifies that (1.8) implies

$$
p_{\Delta t}(m, k ; n, l)=p_{\Delta}(m, k ; n, l) \quad \text { for all states, and as a result }
$$

$\Delta^{\star} \varepsilon \mathscr{\mathcal { U }} \quad$ has minimax risk.
$\qquad$


#### Abstract

-5- In section 2 we derive a recurrence relation, which we then use in section 3 to study the structure of admissible strategies in $\mathcal{D}$. For these strategies we prove certain monotonicity properties of $\delta(m, k ; n, l)$. Though these results may seem intuitively evident, one does well to remember that the two-armed bandit problem has been shown to defy intuition in many aspects (cf. [1]). Section 4 indicates how our results to some degree facilitate the search for minimax-risk strategies. Even so, the algebra involved is extremely tedious for $N$ as small as 4. Already for slightly larger values of $N$ it remains prohibitive.

Among the contributions to the two-armed bandit problem the work of W. Vogel, who considered the same set-up we do, deserves special mention. In [2] he discussed a certain subclass of the class $\mathcal{E}$, and in [3] he obtained asymptotic bounds for the minimax risk for $N \rightarrow \infty$. Since we shall not be concerned with asymptotics in this paper we state the following result without a formal proof: The lower bound for the asymptotic minimax risk for $N \rightarrow \infty$ that was obtained by Vogel in [3] may be raised by a factor $\sqrt{2}$. The result is proved by applying the same method that was used in [3] to the optimal symmetric strategy for $\alpha+\beta=1$ that was discussed in [2]. Combining this lower bound with the upper bound given in [3] we find that the asymptotic minimax risk must be between $0.265 \mathrm{~N}^{\frac{1}{2}}$ and $0.376 \mathrm{~N}^{\frac{1}{2}}$.


## 2 A RECURRENCE RELATION

For $\Delta \varepsilon \mathbb{D}$ we consider the expected number of successes
$E(S \mid \alpha, \beta, \Delta)$ as a function of the $\delta(m, k ; n, l)$. Clearly, the dependence on each $\delta(m, k ; n, l)$ is linear.

We denote the coefficient of $\delta(m, k ; n, l)$ in $\mathbb{E}(S \mid \alpha, \beta, \Delta)$ (and hence also in $-R(\alpha, \beta, \Delta))$ by $p_{\Delta}(m, k ; n, l) c_{\alpha, \beta, \Delta}(m, k ; n, l)$. If all $\delta(m, k ; n, l)$ are strictly between 0 and 1 , then all $p_{\Delta}(m, k ; n, l)$ are positive and as a result all $c_{\alpha, \beta, \Delta}(m, k ; n, l)$ are uniquely determined. Otherwise the $c_{\alpha, \beta, \Delta}(m, k ; n, l)$ are defined by continuity.

## THEOREM 2

For any strategy $\Delta$ in $D$ the functions $c_{\alpha, \beta, \Delta}(m, k ; n, l)$ satisfy the following relations.

$$
\begin{align*}
& \text { (2.1) } c_{\alpha, \beta, \Delta}(m, k ; n, 1)=(\alpha-\beta) \alpha^{k}(1-\alpha)^{m-k} \beta^{l}(1-\beta)^{n-1} \\
& \text { if } m+n=N-1 \text {, } \\
& c_{\alpha, \beta, \Delta}(m, k ; n, l)=\delta(m+1, k+1 ; n, l) c_{\alpha, \beta, \Delta}(m+1, k+1 ; n, l)+  \tag{2.2}\\
& +\delta(m+1, k ; n, 1) c_{\alpha, B, \Delta}(m+1, k ; n, 1)+ \\
& +[1-\delta(m, k ; n+1,1+1)]_{\alpha, \beta, \Delta}(m, k ; n+1,1+1)+ \\
& +[1-\delta(m, k ; n+1, I)] c_{\alpha, \beta, \Delta}(m, k ; n+1,1) \\
& \text { if } m+n \leq N-2 \text {. }
\end{align*}
$$

## PROOF

By continuity it is obviously sufficient to consider the case where all $\delta(m, k ; n, l)$ as well as $\alpha$ and $\beta$ are strictly between 0 and 1. This ensures that expression (1.3) is positive for all states ( $m, k ; n, 1$ ). Hence the conditional expectation $e_{\alpha, B, \Delta}(m, k ; n, l)$ of the total number of successes $S$ under $\alpha, \beta$ and $\Delta$ given that the state ( $m, k ; n, 1$ ) is reached, exists.

It is clearly a linear function of $\delta(m, k ; n, l)$ and may thus be written in the form
(2.3) $e_{\alpha, \beta, \Delta}(m, k ; n, 1)=a_{\alpha, \beta, \Delta}(m, k ; n, 1) \delta(m, k ; n, 1)+b_{\alpha, \beta, \Delta}(m, k ; n, 1)$.

It follows that
(2.4) $\quad c_{\alpha, \beta, \Delta}(m, k ; n, l)=a_{\alpha, \beta, \Delta}(m, k ; n, 1) \alpha^{k}(1-\alpha)^{m-k} \beta^{l}(1-\beta)^{n-1}$.

Dropping the subscripts $\alpha, \beta$ and $\Delta$, we obtain, from the definition of $e(m, k ; n, 1)$,

$$
\begin{aligned}
e(m, k ; n, l) & =\delta(m, k ; n, l)[\alpha e(m+1, k+1 ; n, l)+(1-\alpha) e(m+1, k ; n, l)]+ \\
+ & {[1-\delta(m, k ; n, l)][\beta e(m, k ; n+1,1+1)+(1-\beta) e(m, k ; n+1, l)] }
\end{aligned}
$$

and consequently
(2.5) $a(m, k ; n, I)=\alpha e(m+1, k+1 ; n, I)+(1-\alpha) e(m+1, k ; n, I)+$
$-\beta e(m, k ; n+1,1+1)-(1-\beta) e(m, k ; n+1,1)$,
(2.6) $b(m, k ; n, l)=\beta e(m, k ; n+1, l+1)+(1-\beta) e(m, k ; n+1, l)$.

If $m+n=N-1$, then (2.5) becomes $a(m, k ; n, 1)=\alpha-\beta$, and hence (2.1) follows from (2.4). On the other hand, rewriting (2.5) by means of (2.3) leads to

$$
\begin{aligned}
(2.7) \quad a(m, k ; n, l) & =\alpha \delta(m+1, k+1 ; n, 1) a(m+1, k+1 ; n, 1)+ \\
& +(1-\alpha) \delta(m+1, k ; n, l) a(m+1, k ; n, 1)+ \\
& +\beta[1-\delta(m, k ; n+1,1+1)] a(m, k ; n+1,1+1)+ \\
& +(1-\beta)[1-\delta(m, k ; n+1,1)] a(m, k ; n+1,1)+ \\
& +[\alpha b(m+1, k+1 ; n, 1)+(1-\alpha) b(m+1, k ; n, 1)+ \\
& -\beta b(m, k ; n+1,1+1)+ \\
& -(1-\beta) b(m, k ; n+1,1)-\beta a(m, k ; n+1,1+1)+ \\
& -(1-\beta) a(m, k ; n+1,1)],
\end{aligned}
$$

where for $m+n \leqq N-2$ the last expression between square brackets vanishes as one easily verifies using (2.5) and (2.6). This result, combined with (2.4), gives (2.2).

Let $\mu$ be a prior distribution on the closed unit square. For a strategy $\Delta \varepsilon$,

$$
\begin{equation*}
\rho(\mu, \Delta)=\int R(\alpha, \beta, \Delta) d \mu(\alpha, \beta) \text { denotes the average risk of } \tag{2.8}
\end{equation*}
$$

$\Delta$ against $\mu$. If we define

$$
\begin{equation*}
\gamma_{\mu, \Delta}(m, k ; n, l)=\int c_{\alpha, \beta, \Delta}(m, k ; n, l) d \mu(\alpha, \beta) \text {, then } \tag{2.9}
\end{equation*}
$$

$-p_{\Delta}(m, k ; n, l) \gamma_{\mu, \Delta}(m, k ; n, l)$ is the coefficient of $\delta(m, k ; n, l)$ in $\rho(\mu, \Delta)$. It follows that any strategy $\Delta$ that has $\delta(m, k ; n, l)=1$ whenever $\gamma_{\mu, \Delta}(m, k ; n, l)>0$ and $\delta(m, k ; n, l)=0$ whenever $\gamma_{\mu, \Delta}(m, k ; n, l)<0$, minimizes $\rho(\mu, \Delta)$ for fixed $\mu$ and is therefore a Bayes strategy against $\mu$. This may be seen by successively finding the optimal $\delta(m, k ; n, l)$ for $m+n=N-1, N-2, \ldots, 0$, and noting that for $m+n=v$ these optimal values do not depend on the values of $\delta(m, k ; n, l)$ for $m+n<v .$. Conversely, every Bayes strategy against $\mu$ has a version with $\delta(m, k ; n, I)=1 \quad($ or 0$)$ whenever $\gamma_{\mu, \Delta}(m, k ; n, l)>0 \quad($ or $<0)$.

## THEOREM 3

Let $\mu$ be a prior distribution on the closed unit square and let $\gamma_{\mu}(m, k ; n, l)$ be defined by

$$
\begin{align*}
& \gamma_{\mu}(m, k ; n, I)=\int(\alpha-\beta) \alpha^{k}(1-\alpha)^{m-k} \beta^{\perp}(1-\beta)^{n-I} d \mu(\alpha, \beta)  \tag{2.10}\\
& \text { if } m+n=N-1,
\end{align*}
$$

$$
\begin{align*}
\gamma_{\mu}(m, k ; n, l) & =\gamma_{\mu}^{+}(m+1, k+1 ; n, 1)+\gamma_{\mu}^{+}(m+1, k ; n, 1)+  \tag{2.11}\\
& -\gamma_{\mu}^{-}(m, k ; n+1,1+1)-\gamma_{\mu}^{-}(m, k ; n+1,1)
\end{align*}
$$

for $m+n \leq N-2$, where $x^{+}$and $x^{-}$denote $\max (0, x)$ and $\max (0,-x)$ respectively: Then $\Delta \varepsilon \mathcal{D}$ is a Bayes strategy against $\mu$ if and only if it has a version with $\delta(m, k ; n, l)=1$ whenever $\gamma_{\mu}(m, k ; n, l)>0$ and $\delta(m, k ; n, l)=0$ whenever $\gamma_{\mu}(m, k ; n, l)<0$.

PROOF
According to the remarks preceding the theore $m$, $\Delta$ is Bayes against $\mu$ iff it has a version for which $\delta(m, k ; n, l)=1$ (or 0 ) if $\gamma_{\mu, \Delta}(m, k ; n, l)>0$ (or $<0$ ). Integrating (2.1) and (2.2) with respect to $\mu$ and substituting the values of the $\delta(m, k ; n, 1)$ we find that for this version of $\Delta$, $\gamma_{\mu, \Delta}(m, k ; n, 1)$ equals $\gamma_{\mu}(m, k ; n, l)$ as defined by (2.10) and (2.11) for all states.

## 3 ADMISSIBLE STRATEGIES

For the type of problem considered in this paper every admissible strategy is also a Bayes strategy. In the sequel we shall, however, need a slightly stronger result. We shall say that a prior distribution is nonmarginal if, for some $\varepsilon>0$, it assigns probability 1 to the set

$$
\begin{equation*}
Q_{\varepsilon}=\{(\alpha, \beta)| | \alpha-\beta \mid \alpha(1-\alpha) \beta(1-\beta) \geq \varepsilon, 0<\alpha<1,0<\beta<1\} . \tag{3.1}
\end{equation*}
$$

THEOREM 4
Every admissible strategy $\Delta \varepsilon D$ is Bayes against a nonmarginal prior distribution.

PROOF
Let $\Delta$ be a Bayes strategy against a prior distribution $\mu$ on the closed unit square and suppose that $\Delta$ is not Bayes against any nonmarginal prior. It is sufficient to show that $\Delta$ is not admissible.

For any sufficiently small $\varepsilon_{i}>0$, consider the restricted problem where the parameter space is reduced to the set $A_{i}=Q_{\varepsilon_{i}}$ as defined by (3.1). Since $A_{i}$ is compact, the assertion that every admissible strategy is Bayes remains true for the restricted problem. By our assumption $\Delta$ is not Bayes, and therefore not admissible in the new problem. It follows that there exists a strategy $\Delta_{i}$ that is Bayes against a prior distribution $\mu_{i}$ on $A_{i}$ and for which

$$
R\left(\alpha, \beta, \Delta_{i}\right) \leqq R(\alpha, \beta, \Delta) \quad \text { for all } \quad(\alpha, \beta) \varepsilon A_{i}
$$

By a standard prodedure we may select a sequence $\varepsilon_{i}>0$ and corresponding $\mu_{i}$ and $\Delta_{i}$ such that the strategies $\Delta_{i}$ converge to a strategy $\Delta_{0}$ in the sense that $\delta_{i}(m, k ; n, l)$ converges to $\delta_{0}(m, k ; n, l)$ for every state $(m, k ; n, l)$. Obviously

$$
R\left(\alpha, \beta, \Delta_{0}\right) \leq R(\alpha, \beta, \Delta) \quad \text { for all } \alpha, \beta \varepsilon[0,1],
$$

since the inequality must hold on every $A_{i}$ and both functions are continuous.

Since $\Delta_{i}$ converges to $\Delta_{o}$ there exists a positive integer $\mathfrak{j}$ for which $\Delta_{j}$ has the following properties:
(a) For all states with $\delta_{0}(m, k ; n, l)=0 \quad, \delta_{j}(m, k ; n, l) \neq 1$;
(b) For all states with $\delta_{0}(m, k ; n, l)=1 \quad, \delta_{j}(m, k ; n, l) \neq 0$;
(c) For all states with $0<\delta_{0}(m, k ; n, l)<1,0<\delta_{j}(m, k ; n, l)<1$. This implies that $\delta_{0}(m, k ; n, l)=\delta_{j}(m, k ; n, l)$ for every state with $\delta_{j}(m, k ; n, l)=0$ or 1 .

Recalling that $\Delta_{j}$ is Bayes against $\mu_{j}$ and noting that this property can not be destroyed by changing only those $\delta_{j}(m, k ; n, l)$ that are strictly between 0 and 1 , we find that $\Delta_{o}$ is Bayes against the prior distribution $\mu_{j}$ on $A_{j}$. As $\Delta$ is not Bayes against $\mu_{j}$ by our assumption, the inequality $R\left(\alpha, \beta, \Delta_{0}\right) \leq R(\alpha, \beta, \Delta)$ on the closed unit square must be strict for at least one point $(\alpha, \beta)$ and the inadmissibility of $\Delta$ follows.

We are now in a position to prove a theorem that provides some insight in the structure of admissible strategies.

## THEOREM 5

If $\mu$ is a nonmarginal prior distribution and $m+n \leq N-2$, then

$$
\begin{equation*}
\gamma_{\mu}(m, k ; n+1,1+1)<\gamma_{\mu}(m+1, k+1 ; n, l) \tag{3.2}
\end{equation*}
$$

$$
\begin{equation*}
\gamma_{\mu}(m+1, k ; n, l)<\gamma_{\mu}(m, k ; n+1, l) \tag{3.3}
\end{equation*}
$$

PROOF

$$
\begin{aligned}
\text { For } m+n=N & -2,(2.10) \text { yields } \\
\gamma_{\mu}(m+1, k+1 ; n, l) & =\gamma_{\mu}(m, k ; n+1, l+1)= \\
& =\int(\alpha-\beta)^{2} \alpha^{k}(1-\alpha)^{m-k} \beta^{l}(1-\beta)^{n-1} d \mu(\alpha, \beta),
\end{aligned}
$$

which is strictly positive since $\mu$ is nonmarginal. In the same way one shows that (3.3) is satisfied for $m+n=N-2$.

Next we suppose that the theorem is valid for $m+n=v$, where $0<v \leq N-2$, and we assume $m+n=v-1$.

By (2.11) we have then

$$
\begin{aligned}
\gamma_{\mu}(m+1, k & +1 ; n, 1)-\gamma_{\mu}(m, k ; n+1,1+1)= \\
& =\left[\gamma_{\mu}^{+}(m+2, k+2 ; n, 1)-\gamma_{\mu}^{+}(m+1, k+1 ; n+1,1+1)\right]+ \\
+ & {\left[\gamma_{\mu}^{+}(m+2, k+1 ; n, 1)-\gamma_{\mu}^{+}(m+1, k ; n+1,1+1)\right]+} \\
& +\left[\gamma_{\mu}^{-}(m, k ; n+2,1+2)-\gamma_{\mu}^{-}(m+1, k+1 ; n+1,1+1)\right]+ \\
& +\left[\gamma_{\mu}^{-}(m, k ; n+2,1+1)-\gamma_{\mu}^{-}(m+1, k+1 ; n+1,1)\right] \geq 0,
\end{aligned}
$$

since by hypothesis each of the four expressions is nonnegative. Equality can occur only if all four expressions vanish. However, the first and the third one can vanish only if $\gamma_{\mu}(m+1, k+1 ; n+1,1+1)<0$ and $\geq 0$ respectively, and hence inequality (3.2) is strict.

Similarly (3.3) follows from

$$
\begin{aligned}
\gamma_{\mu}(m, k ; n & +1,1)-\gamma_{\mu}(m+1, k ; n, 1)= \\
& =\left[\gamma_{\mu}^{+}(m+1, k+1 ; n+1,1)-\gamma_{\mu}^{+}(m+2, k+1 ; n, 1)\right]+ \\
& +\left[\gamma_{\mu}^{+}(m+1, k ; n+1,1)-\gamma_{\mu}^{+}(m+2, k ; n, 1)\right]+ \\
& +\left[\gamma_{\mu}^{-}(m+1, k ; n+1,1+1)-\gamma_{\mu}^{-}(m, k ; n+2,1+1)\right]+ \\
& +\left[\gamma_{\mu}^{-}(m+1, k ; n+1,1)-\gamma_{\mu}^{-}(m, k ; n+2,1)\right] \geq 0,
\end{aligned}
$$

and the fact that the first expression in square brackets can vanish only if $\gamma_{\mu}(m+2, k+1 ; n, 1)<0$ and the third one only if $\gamma_{\mu}(m+1, k ; n+1,1+1) \geq 0$, which would imply $\gamma_{\mu}(m+2, k+1 ; n, 1)>0$.

Every admissible strategy $\Delta \varepsilon \mathscr{D}$ has a version for which

$$
\begin{equation*}
\delta(m, k ; n+1, l+1) \leq \delta(m+1, k+1 ; n, l) \tag{3.4}
\end{equation*}
$$

$$
\begin{equation*}
\delta(m+1, k ; n, l) \leq \delta(m, k ; n+1, l) \tag{3.5}
\end{equation*}
$$

for all $m+n \leq N-2$, where in each of these inequalities at least one member equals 0 or 1.

PROOF
By theorem 4, $\Delta$ is Bayes against a nonmarginal prior $\mu$, and as a result the theorem is proved by applying theorems 5 and 3.

COROLLARY 2
Every admissible strategy $\Delta \varepsilon \mathcal{D}$ has a version for which

$$
\begin{align*}
& \delta(m, k ; n, 1)[1-\delta(m+1, k+1 ; n, 1)][1-\delta(m+1, k ; n, 1)]=0  \tag{3.6}\\
& {[1-\delta(m, k ; n, 1)] \delta(m, k ; n+1,1+1) \delta(m, k ; n+1,1)=0}
\end{align*}
$$

for all $m+n \leq N-2$.

PROOF
As before, we let $\mu$ denote the nonmarginal prior of theorem 4 and consider the version of $\Delta$ having $\delta(m, k ; n, l)=1$ (or 0 ) whenever $\gamma_{\mu}(m, k ; n, 1)>0(o r<0)$. If $(3.6)$ were false for this version, then $\gamma_{\mu}(m, k ; n, l) \geq 0, \quad \gamma_{\mu}(m+1, k+1 ; n, I) \leq 0$ and $\gamma_{\mu}(m+1, k ; n, l) \leq 0$, The second of these inequalities implies $\gamma_{\mu}(m, k ; n+1,1+1)<0$ by theorem 5, and hence (2.11) shows that $\gamma_{\mu}(m, k ; n, l)<0$, which contradicts the first inequality.

Similarly, if (3.7) were false, then $\gamma_{\mu}(m, k ; n, 1) \leqq 0$, $\gamma_{\mu}(m, k ; n+1, l+1) \geq 0$ and $\gamma_{\mu}(m, k ; n+1, l)>0$.

The second inequality implies $\gamma_{\mu}(m+1, k+1 ; n, 1)>0$ by theorem 5 , and hence $\gamma_{\mu}(m, k ; n, 1)>0$ by (2.11), which contradicts the first inequality. This completes the proof.

For symmetric strategies a more explicit result may be obtained.

## COROLLARY 3

Every admissible strategy $\Delta \varepsilon \boldsymbol{\mathcal { y }}$ has a version for which

$$
\begin{equation*}
\delta(m, k ; n, l)=1, \quad \delta(n, l ; m, k)=0 \tag{3.8}
\end{equation*}
$$

whenever $m+n \leq N-1, k \geqq 1, m-k \leq n-1$ and $(m, k ; n, l) \neq(n, l ; m, k)$.

## PROOF

For the version of $\Delta$ that satisfies corollary 1 we find by repeated application of (3.4) and (3.5)

$$
\delta(m, k ; n, 1) \geqq \delta(m-k+1,1 ; n+k-1, k) \geqq \delta(n, 1 ; m, k)
$$

where at least one of the extreme members must be 0 or 1 . Since their sum equals 1 if $p_{\Delta}(m, k ; n, l) \neq 0$, (3.8) will hold in this case. If $p_{\Delta}(m, k ; n, l)=0$, then by (1.6) we also have $p_{\Delta}(n, l ; m, k)=0$ and choosing $\delta(m, k ; n, l)=1$ and $\delta(n, l ; m, k)=0$ merely leads to another version of $\Delta$.

We conclude this section by remarking that corollaries 1,2 and 3 obviously continue to hold if, instead of admissibility, we require that $\Delta$ be Bayes against a nonmarginal prior.

In section 1 we have shown that there exists a symmetric minimaxrisk strategy. For the type of problem considered in this paper there exists a least favourable prior distribution and any minimax-risk strategy is Bayes against any least favourable prior. These assertions continue to hold if the parameter space is reduced to a compact subset of the closed unit square.

## THEOREM 6

There exists a minimax-risk strategy $\Delta \varepsilon \mathscr{\mathcal { J }}$ which obeys (3.4) through (3.8).

PROOF
By the remark at the end of section 3 , it is sufficient to demonstrate the existence of a symmetric minimax-risk strategy that is Bayes against a nonmarginal prior.

For sufficiently small $\varepsilon_{i}>0$ let $A_{i}=Q_{\varepsilon_{i}}$ as defined by (3.1) and let $\mu_{i}$ and $\Delta_{i}$ denote a least favourable prior and a symmetric minimax-risk strategy for the restricted problem where the parameter space is reduced to the compact set $A_{i}$. Repeating the proof of theorem 4 we may select a sequence $\varepsilon_{i} \searrow 0$ and corresponding $\mu_{i}$ and $\Delta_{i}$ such that the strategies $\Delta_{i}$ converge to a strategy $\Delta_{o}$ that is Bayes against a nonmarginal prior $\mu_{j}$ on $A_{j}$. Since the convergence is defined as convergence of the $\delta_{i}(m, k ; n, l)$ to the $\delta_{0}(m, k ; n, l), \Delta_{0}$ is symmetric. As the maximum risk of $\Delta_{i}$ on $A_{i}$ does not exceed the minimax risk on the entire closed unit square and $R\left(\alpha, \beta, \Delta_{0}\right)$ is continuous, the convergence
of $\Delta_{i}$ to $\Delta_{0}$ implies that $\Delta_{0}$ has minimax risk.

For $N=1$ or $2,(1.5)$ and (3.8) uniquely determine a symmetric strategy. It follows from theorem 6 and corollary 3 that this strategy has minimax risk and is in fact the only admissible strategy in $\mathscr{J}$. For $N \geq 3$ the situation rapidly becomes more complicated. In order to find a symmetric minimax-risk strategy $\Delta_{0}$ satisfying (3.4) through (3.8) one first has to find a general expression for the risk function $R(\alpha, \beta, \Delta)$ of an arbitrary symmetric strategy $\Delta$ satisfying (3.8). Then, with the aid of (3.4) through (3.7), one has to solve the remaining $\delta(m, k ; n, 1)$ directly using the minimax property.

To accomplish the first step of computing $R(\alpha, \beta, \Delta)$ for an arbitrary symmetric strategy, one may proceed recursively. This is especially useful if one wants to find $R(\alpha, \beta, \Delta)$ for a number of values of $N$. If $X_{v}=1-Y_{v}=1$ or 0 according to whether $E_{1}$ or $E_{2}$ is carried out on the $v=$ th trial $(v=1,2, \ldots, N)$, then $R(\alpha, \beta, \Delta)$, being equal to $|\alpha-\beta| \quad$ multiplied by the expected number of times the experimenter uses the less favourable experiment, is given by
(4.1) $\quad R(\alpha, \beta, \Delta)=\frac{1}{2} N|\alpha-\beta|-\frac{1}{2}(\alpha-\beta) \sum_{v=1}^{N} E\left(X_{v}-Y_{v} \mid \alpha, \beta, \Delta\right)$. Remembering the definition of $\pi_{\alpha, \beta, \Delta}(m, k ; n, l)$, we have

$$
\begin{equation*}
E\left(X_{v}-Y_{v} \mid \alpha, \beta, \Delta\right)=\sum \pi_{\alpha, \beta, \Delta}(m, k ; n, 1)[2 \delta(m, k ; n, 1)-1], \tag{4.2}
\end{equation*}
$$

where the summation is extended over all states ( $m, k ; n, l$ ) with $m+n=v-1$, and where the $\pi_{\alpha, \beta, \Delta}(m, k ; n, l)$ can be computed recursively by means of

$$
\begin{align*}
\pi_{\alpha, \beta, \Delta}(m, k ; n, 1) & =\alpha \delta(m-1, k-1 ; n, 1) \pi_{\alpha, \beta, \Delta}(m-1, k-1 ; n, 1)+ \\
& +(1-\alpha) \delta(m-1, k ; n, 1) \pi_{\alpha, \beta, \Delta}(m-1, k ; n, 1)+  \tag{4.3}\\
& +\beta[1-\delta(m, k ; n-1,1-1)] \pi_{\alpha, \beta, \Delta}(m, k ; n-1,1-1)+ \\
& +(1-\beta)[1-\delta(m, k ; n-1,1)] \pi_{\alpha, \beta, \Delta}(m, k ; n-1,1)
\end{align*}
$$

starting from

$$
\pi_{\alpha, \beta, \Delta}(0, k ; 0,1)= \begin{cases}1 & \text { if } k=1=0,  \tag{4.4}\\ 0 & \text { otherwise } .\end{cases}
$$

The work involved may be reduced somewhat by means of the relation

$$
\begin{equation*}
\pi_{\alpha, \beta, \Delta}(m, k ; n, l)=\pi_{\beta, \alpha, \Delta}(n, l ; m, k), \tag{4.5}
\end{equation*}
$$

which is a consequence of (1.3) and (1.6).
For $N=3$, only $\delta(2,1 ; 0,0)$ remains undetermined by the requirement that $\Delta$ be symmetric and must satisfy (3.8), and one finds $R(\alpha, \beta, \Delta)=\frac{3}{2}|\alpha-\beta|-\frac{1}{2}(\alpha-\beta)^{2}\{1+\delta(2 ; 1 ; 0,0)+[1-\delta(2,1 ; 0,0)](\alpha+\beta)\}$. After a little algebra one sees that $\Delta_{0}$ must have $\delta(2,1 ; 0,0)=1$ and that $R\left(\alpha, \beta, \Delta_{0}\right)$ attains its maximum $M\left(\Delta_{0}\right)=9 / 16$ when $|\alpha-\beta|=3 / 4$. For $N=4$ only $\delta(2,1 ; 0,0), \delta(3,1 ; 0,0)$ and $\delta(3,2 ; 0,0))$ are to be determined and

$$
\begin{aligned}
R(\alpha, \beta, \Delta) & =2|\alpha-\beta|-\frac{1}{2}(\alpha-\beta)^{2}\left\{\left(\alpha^{2}+\beta^{2}+3 \alpha \beta-\alpha-\beta+3\right)-\delta(2,1 ; 0,0) \alpha \beta+\right. \\
& -\delta(3,2 ; 0,0)[1+\delta(2,1 ; 0,0)]\left(\alpha^{2}+\beta^{2}+\alpha \beta-\alpha-\beta\right)+ \\
& \left.+\delta(3,1 ; 0,0) \delta(2,1 ; 0.0)\left(\alpha^{2}+\beta^{2}+\alpha \beta-2 \alpha-2 \beta+1\right)\right\} .
\end{aligned}
$$

Using (3.6), one finds after lengthy calculations that $\Delta_{0}$ must have $\delta(2,1 ; 0,0)=4 / 5, \delta(3,1 ; 0,0)=1 / 2$ and $\delta(3,2 ; 0,0)=1$, so that the riskfunction of $\Delta_{0}$ is given by

$$
R\left(\alpha, \beta, \Delta_{0}\right)=2|\alpha-\beta|-\frac{17}{10}(\alpha-\beta)^{2}+\frac{1}{5}(\alpha-\beta)^{4}
$$

and attains its maximum $M\left(\Delta_{0}\right)=.617$ when $|\alpha-\beta|=.654$. For larger values of i the number of $\delta(\mathrm{m}, \mathrm{k} ; \mathrm{n}, \mathrm{l})$ that have to be determined increases rapidly, and consequently the algebra involved becomes distressingly complicated.

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