# COMPARISON OF EXPERIMENTS 

DAVID BLACKWELL<br>HOWARD UNIVERSITY

## 1. Summary

Bohnenblust, Shapley, and Sherman [2] have introduced a method of comparing two sampling procedures or experiments; essentially their concept is that one experiment $a$ is more informative than a second experiment $\beta, \alpha \supset \beta$, if, for every possible risk function, any risk attainable with $\beta$ is also attainable with $\alpha$. If $\alpha$ is a sufficient statistic for a procedure equivalent to $\beta, a>\beta$, it is shown that $\alpha \supset \beta$. In the case of dichotomies, the converse is proved. Whether $>$ and $\supset$ are equivalent in general is not known. Various properties of $\rangle$ and $\supset$ are obtained, such as the following: if $a>\beta$ and $\gamma$ is independent of both, then the combination $(a, \gamma)>(\beta, \gamma)$. An application to a problem in $2 \times 2$ tables is discussed.

## 2. Definitions

An experiment $a$ is a set of $N$ probability measures $u_{1}, \ldots, u_{N}$ on a Borel field B of subsets of a space $X$. The $N$ measures are considered as $N$ possible distributions over $X$, and performing the experiment consists of observing a sample point $x \in X$. A decision problem is a pair ( $a, A$ ), where $A$ is a bounded subset of $N$-space. The points $a \in A$ are considered as the possible actions open to the statistician; the loss from action $a=\left(a_{1}, \ldots, a_{N}\right)$ is $a_{i}$ if the actual distribution of $x$ is $u_{i}$. A decision procedure $f$ for ( $a, A$ ) is a $B$-measurable function from $X$ into $A$, specifying the action $a$ to be taken as a function of the sample point $x$ obtained by the experiment. With every $f=\left[a_{1}(x), \ldots, a_{N}(x)\right]$ is associated a loss vector

$$
v(f)=\left(\int a_{1}(x) d u_{1}, \ldots, \int a_{N}(x) d u_{N}\right)
$$

the $i$-th component of $v(f)$ is the expected loss from $f$ if $x$ has distribution $u_{i}$. The range of $v(f)$ is a subset of $N$-space which we denote by $R_{1}(a, A)$; the convex closure of $R_{1}(a, A)$ will be denoted by $R(a, A)$ and will be called the set of attainable loss vectors in ( $a, A$ ); every vector in $R$ is either attainable or approximable by a randomized mixture of $N+1$ decision procedures.

Theorem 1. $R(a, A)=R\left(a, A_{1}\right)=R_{1}\left(a, A_{1}\right)$, where $A_{1}$ is the convex closure of $A$.
This theorem permits us to restrict attention to closed convex $A$, which we shall do in the following sections. The proof of the theorem will not be given here; it is straightforward except for the fact that $R\left(a, A_{1}\right)=R_{1}\left(a, A_{1}\right)$. This fact follows from the result that whenever $A$ is closed, so is $R_{1}(a, A)$, which has been proved elsewhere by the author [1].

Following Bohnenblust, Shapley and Sherman [2], we shall say that a is more informative than $\beta$, written $a \supset \beta$, if for every $A$ we have $R(a, A) \supset R(\beta, A)$.

