# A COMMENT ON AN EXAMPLE BY MACHINA 

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#### Abstract

: Machina (2007) demonstrates an example where the Choquet utility maximization theory is inconsistent with a natural symmetry requirement. The comment shows that this requirement is consistent with two models: expected utility maximization w.r.t. the concave integral (Lehrer, 2005) and utility maximization w.r.t. a partially-specified probability (Lehrer, 2007).


Keywords: Choquet utility maximization, partially-specified probability, concave integral for capacities

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## 1. The example

In a recent paper Machina (2007, Table 2, p. 11) introduced the following example. An urn contains twenty balls of four different colors a,b,c, and d. Ten balls are either a or b and the other ten are either c or d . A decision maker (DM) chooses an act, then a ball is randomly drawn and a reward is given to DM according to the color of the ball and the chosen act. The following table summarizes the rewards related to four acts. We will later discuss two decision problems: $f_{1}$ vs. $f_{2}$ and $f_{3}$ vs. $f_{4}$.

|  | a | b | c | d |
| :---: | :---: | :---: | :---: | :---: |
| $f_{1}$ | 0 | 200 | 100 | 100 |
| $f_{2}$ | 0 | 100 | 200 | 100 |
| $f_{3}$ | 100 | 200 | 100 | 0 |
| $f_{4}$ | 100 | 100 | 200 | 0 |

One can see that $f_{4}$ is a mirror image of $f_{1}$ and $f_{3}$ is a mirror image of $f_{2}$. Thus, if DM strictly prefers $f_{2}$ to $f_{1}$ (i.e. $f_{2} \succ f_{1}$ ) we would expect that he should strictly prefers $f_{3}$ to $f_{4}$ (i.e. $f_{3} \succ f_{4}$ ). This is inconsistent with Choquet expected utility maximization (Schmeidler, 1989), as explained in Machina (2007). This explanation is replicated in the next section.

The aim of this comment is to show that ' $f_{2} \succ f_{1}$ and $f_{3} \succ f_{4}$ ' is consistent with two models. The first is that of expected utility maximization w.r.t the concave integral for capacities (Lehrer, 2005). The second model is that of expected utility maximization w.r.t partially-specified probabilities (Lehrer, 2007).

## 2. Why Choquet expected utility maximization does not work here?

Let $\Omega$ be a finite state space. A capacity (or a non-additive probability) is a function $v: \Omega \rightarrow[0,1]$ such that $v(\emptyset)=0, v(\Omega)=1$ and is monotonic w.r.t. inclusion.

An act is a function defined over $\Omega$ and ranged to the set of rewards, say $W$. Suppose that the preference order on $W$ is represented by a (non-negative) utility function $U$.

We denote by $\mathbb{1}_{E}$ the indicator of a subset $E$ of $\Omega$. Let $f$ be an act and $v$ be a capacity. A decomposition of $U \circ f$ is a positive combination of indicators that equals $U \circ f$. Formally, a decomposition of $U \circ f$ is $\sum_{i=1}^{k} \alpha_{i} \mathbb{1}_{E_{i}}$ that is equal to $U \circ f$ and $\alpha_{i} \geq 0$, $i=1, \ldots, k$. The Choquet decomposition is the one that satisfies $\Omega=E_{1} \supsetneqq E_{2} \supsetneqq \ldots \supsetneqq E_{k}$.

The capacity $v$ and the utility function $U$ induce an order over the set of acts as follows. Suppose that $e$ and $g$ are acts, then

$$
e \succ_{C h o} g \text { if and only if } \sum_{i=1}^{k} \alpha_{i} v\left(E_{i}\right)>\sum_{i=1}^{\ell} \beta_{i} v\left(G_{i}\right),
$$

where $\sum_{i=1}^{k} \alpha_{i} \mathbb{1}_{E_{i}}$ and $\sum_{i=1}^{\ell} \beta_{i} \mathbb{1}_{G_{i}}$ are the Choquet decompositions of $U \circ e$ and $U \circ g$, respectively.

Back to Machina's example. The Choquet decomposition of $U \circ f_{1}$ is $U(0) \mathbb{1}_{\Omega}+$ $U(100) \mathbb{1}_{\{b c d\}}+(U(200)-U(100)) \mathbb{1}_{\{b\}}$ and that of $U \circ f_{2}$ is $U(0) \mathbb{1}_{\Omega}+U(100) \mathbb{1}_{\{b c d\}}+$ $(U(200)-U(100)) \mathbb{1}_{\{c\}}$. Suppose that $f_{2} \succ_{C h o} f_{1}$ as induced by some capacity $v$ defined over $\Omega=\{a, b, c, d\}$ and a utility function $U$ defined over $W=\{0,100,200\}$ (without loss of generality $U(0)=0$ ). It implies that $U(100) v(b c d)+(U(200)-U(100)) v(b)<$ $U(100) v(b c d)+(U(200)-U(100)) v(c)$, which implies that $v(b)<v(c)$. However, the fact that $v(b)<v(c)$ implies, by a similar calculation, that $f_{4} \succ_{C h o} f_{3}$.

In short, $f_{2} \succ_{\text {Cho }} f_{1}$ implies $f_{4} \succ_{\text {Cho }} f_{3}$. In other words, $f_{2} \succ_{C h o} f_{1}$ and $f_{3} \succ_{C h o} f_{4}$ together, are inconsistent with Choquet utility maximization theory.

## 3. Explanation with the concave integral for capacities

Lehrer (2005) proposed and axiomatized a different integral for capacities than the Choquet integral. This is the concave integral, which in turn induces another order over acts.

As before, suppose that $e$ and $g$ are acts. Define an order $\succ_{\text {cav }}$ as follows:

$$
\begin{equation*}
e \succ_{\text {cav }} g \text { if and only if } \max \sum_{i=1}^{k} \alpha_{i} v\left(E_{i}\right)>\max \sum_{j=1}^{\ell} \beta_{j} v\left(G_{j}\right), \tag{1}
\end{equation*}
$$

where the maxima are taken over all decompositions $\sum_{i=1}^{k} \alpha_{i} \mathbb{1}_{E_{i}}$ of $e$ and $\sum_{j=1}^{\ell} \beta_{j} \mathbb{1}_{G_{j}}$ of $g$.

As for the example above, suppose that DM believes that at least one of the balls must be $b$ or $c$. The minimal estimation of the probability of the event $\{b c\}$ is therefore $\frac{1}{20}$. Let $v$ represent the minimal estimation of each event. It implies that $v(a)=v(b)=$ $v(c)=v(d)=0, v(b c)=\frac{1}{20}$ and $v(a b)=v(c d)=\frac{1}{2}$. The rest can be completed in a monotonic manner.

The best decomposition (i.e. the one that maximizes the right-hand side of eq. (1)) of $U \circ f_{1}$ is the Choquet decomposition, $U(0) \mathbb{1}_{\Omega}+U(100) \mathbb{1}_{\{b c d\}}+(U(200)-U(100)) \mathbb{1}_{\{b\}}$.

However the best decomposition of $U \circ f_{2}$ is no long the Choquet one. The best decomposition is $U(100) \mathbb{1}_{\{c d\}}+(U(200)-U(100)) \mathbb{1}_{\{b c\}}+(2 U(100)-U(200)) \mathbb{1}_{\{b\}}$.

It turns out that due to eq. (1), $f_{2} \succ_{\text {cav }} f_{1}$. The reason is that $U(0) v(\Omega)+U(100) v(b c d)+$ $(U(200)-U(100)) v(b)=\frac{U(100)}{2}<\frac{U(100)}{2}+\frac{U(200)-U(100)}{20}=U(100) v(c d)+(U(200)-$ $U(100)) v(b c)+(2 U(100)-U(200)) v(b)$.

For a similar calculation $f_{3} \succ_{\text {cav }} f_{4}$.

## 4. Explanation with partially-specified probabilities

Here the model used is that of partially-specified probabilities (Lehrer, 2007). It is known that ${ }^{1} \mathbb{P}(a, b)=\mathbb{P}(c, d)=\frac{1}{2}$. Equivalently, there are two non-trivial random variables with known expectation: $X_{1}=[1,1,0,0]$ whose expectation is $\frac{1}{2}$, and $X_{2}=$ $[0,0,1,1]$ whose expectation is $\frac{1}{2}$.

It will be shown that ' $f_{2}$ preferred to $f_{1}$ ' is supported by the belief that $\mathbb{P}(b, c)$ is positive, which implies that $\mathbb{P}(b, c) \geq \frac{1}{20}$. Indeed, suppose that the expectation of the random variable $[0(a), 1(b), 1(c), 0(d)]$ (i.e the random variable that takes the value 0 on $a, 1$ on $b, 1$ on $c, 0$ on $d$ ) is at least $\frac{1}{20}$. Denote this random variable by $X_{3}=[0,1,1,0]$. So, $\mathbb{E}\left(X_{3}\right) \geq \frac{1}{20}$. In order to simplify the explanation assume that expectation of $X_{3}$ is known to be precisely $\frac{1}{20}$.

The probability $\mathbb{P}$ is only partially known. For instance, the probability $\mathbb{P}(a)$ is unknown. However, the expectation of some, but not all, random variables is known. Here, the expectation of any linear combination of $X_{1}, X_{2}$ and $X_{3}$ is known. Denote by $\mathcal{Y}$ the set of random variables whose expectation is known. In other words, DM knows $\mathbb{E}(X)$ for every $X \in \mathcal{Y}$. The pair $(\mathbb{P}, \mathcal{Y})$ is a partially-specified probability, which induces an order over acts. ${ }^{2}$

Suppose that $e$ and $g$ are acts. Define an order $\succ_{P S P}$ as follows:

$$
\begin{equation*}
e \succ_{P S P} g \text { if and only if } \max \sum_{i=1}^{k} \alpha_{i} \mathbb{E}\left(X_{i}\right)>\max \sum_{j=1}^{\ell} \beta_{j} \mathbb{E}\left(X_{j}^{\prime}\right), \tag{2}
\end{equation*}
$$

[^1]where the left-hand side maximum is taken over all linear combinations $\sum_{i=1}^{k} \alpha_{i} X_{i}$ that are less than or equal to $e$ with $X_{i} \in \mathcal{Y}$, and the right-hand side maximum is taken over all linear combinations $\sum_{j=1}^{\ell} \beta_{j} X_{j}^{\prime}$ that are less than or equal to $g$ with $X_{i}^{\prime} \in \mathcal{Y}$.

Note that $U \circ f_{1}$ corresponds to the random variable $Y=[0, U(200), U(100), U(100)]$ and $U \circ f_{2}$ corresponds to the random variable $Z=[0, U(100), U(200), U(100)]$. Denote, $m=\min (U(100), U(200)-U(100))$. Since, $Z \geq m X_{3}+[0,0, U(100), U(100)], \mathbb{E}(Z) \geq$ $m \mathbb{E}\left(X_{3}\right)+U(100) \mathbb{E}\left(X_{2}\right)=\frac{m}{20}+\frac{U(100)}{2}$.

The best approximation from below (in the sense of eq. (2)) to $Y$ with linear combinations of $X_{1}, X_{2}$ and $X_{3}$ is $U(100) X_{2}$, whose expectation is $\frac{U(100)}{2}$. Thus, according to eq. (2)), $f_{2}$ is preferred to $f_{1}$ (because $\frac{m}{20}+\frac{U(100)}{2}>\frac{U(100)}{2}$ ).

From similar arguments, $f_{3}$ is preferred to $f_{4}$ (in this calculation $X_{1}$ and $X_{3}$ are used). Thus, $f_{2} \succ_{P S P} f_{1}$ and at the same time $f_{3} \succ_{P S P} f_{4}$.

## 5. References

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[^1]:    ${ }^{1} \mathbb{P}$ denotes the probability function and $\mathbf{E}$ stands for expectation w.r.t $\mathbb{P}$.
    ${ }^{2}$ Lehrer (2007) provides an axiomatization and introduces the corresponding solution concepts for strategic models (Nash-like and correlated-like).

