Integrity First, Service Before Self, and Excellence: Core Values of US Air Force Naturally Follow from Decision Theory

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Abstract By analyzing data both from peace time and from war time, the US Air Force came with three principles that determine success: integrity, service before self, and excellent. We show that these three principles naturally follow from decision theory, a theory that describes how a rational person should make decisions.

1 Formulation of the Problem

Empirical fact. Based on its several decades of both peace-time and war-time experience, the US Air Force has come up with the three major principles that determine success (see, e.g., [9]):

- Integrity,
- Service before Self, and
- Success.

Empirically, of these three criteria, integrity is the most important one.

Natural question. How can we explain this empirical observation?

What we do in this paper. In this paper, we show that these three principles naturally follow from decision theory, a theory that describes how a rational person should make decisions.

Structure of the paper. We start, in Section 2, with a brief reminder of decision theory. In Section 3, we show how this leads to the general principles of decision

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making. Finally, in Section 4, we show that these general principles are, in effect, exactly the above three principles of the US Air Force.

2 Decision Making: A Brief Reminder

What we want: a description in commonsense terms. When we make a decision, we want to select the best of all possible decisions.

Let us describe this in precise terms. To describe the above commonsense description in precise terms, we need:

- to describe, in precise terms, which decisions are possible and which are not, and
- to describe, in precise terms, what we mean by "the best".

What we mean by a possible decision: the notion of constraints. To describe which decisions are possible and which are not means to describe the set S of possible decisions. This set is usually described by *constraints* – properties that all possible decisions must satisfy.

For example, if we want to select the best design for a building, the constraints are:

- limits on the cost,
- the requirements that this building should withstand winds (and, if relevant, earthquakes) typical for this area, etc.

What we mean by "the best": optimization. Sometimes, we have a numerical characteristic $f(x)$ that describes the relative quality of different possible decisions x. For example, for a company, this characteristic is the expected profit.

Between any two possible decisions x and x', we should select the one for which the value of the objective function is larger. Corresponding, we say that a possible decision x is *the best* (*optimal*) if the value $f(x)$ is larger than or equal to the value $f(x')$ for any other possible decision x'. The problem of finding such optimal x is known as *optimization*.

What if we do not know the objective function? In some situations, we have an intuitive idea of which decisions are better, but we do not know a function that describes our preferences. Decision theory (see, e.g., [1, 2, 4, 5, 6, 7, 8]) shows that in such situations, we can still describe preferences by an appropriate numerical function. To do that, we need to select two alternatives:

- an alternative A_+ which is better than the consequence of any of the possible decisions, and
- an alternative A_- which is worse than the consequence of any of the possible decisions.

Then, for each value p from the interval $[0,1]$, we can think of a "lottery" $L(p)$ in which:

- we get A_+ with probability p and
- we get A_- with the remaining probability $1-p$.

For each possible decision x, we can ask the user to compare the consequences of this decision with lotteries $L(p)$ corresponding to different values p.

- For small $p \approx 0$, the lottery $L(p)$ is close to A_- and is, thus, worse than the consequences of the decision x: let us denote it by $L(p) < x$.
- For p close to 1, the lottery $L(p)$ is close to A_+ and is, thus, better than the consequences of the decision$x$: $L(p) < x$.

As we continuously change p from 0 to 1, at some point, there should be a switch from $L(p) < x$ to $x < L(p)$. The corresponding threshold point

$$u(x) = \sup\{p : L(p) < x\} = \inf\{p : x < L(p)\}$$

is know as the *utility* of x. In this sense, the consequences of the decision x are equivalent to the lottery $L(u(x))$ in which we get the very good alternative A_+ with the probability $u(x)$ and we get A_- with the remaining probability.

If we compare two lotteries $L(p)$ and $L(p')$, then, of course, the lottery in which the very good alternative A_+ appears with the larger probability is better. Since each alternative x is equivalent to a lottery $L(u(x))$ in which the very good alternative A_+ appears with the probability $u(x)$, we can thus conclude:

- that between any two possible decisions x and x', the decision maker will select the one with the larger value of the utility, and
- that the best decision is the one that has the largest value of the utility.

In other words, decisions are equivalent to optimizing the utility function $u(x)$.

Comments.

- We can get the value $u(x)$ by bisection: first we compare x with the lottery $L(0.5)$ and thus find out whether $u(x) \in [0, 0.5]$ or $u(x) \in [0.5, 1]$; then, we compare x with the lottery corresponding to the midpoint of the resulting interval, etc. At any given moment, we only have an interval containing $u(x)$ – i.e., we only know $u(x)$ with some uncertainty. This way, after k steps, we determine $u(x)$ with accuracy $2^{-(k+1)}$. Thus, for each desired accuracy $\varepsilon > 0$, after a few iterations $k = \lceil |\log_2(\varepsilon)| \rceil - 1$, we will find the value $u(x)$ with the desired accuracy.
- Of course, decision theory described the ideal solution, when the decision maker is perfectly rational: e.g., if the decision maker prefers A to B and B to C, he/she should also prefer A to C. It should be mentioned that decisions of actual decision makers are not always rational in this sense; see, e.g., [3].

Summarizing: resulting description of the decision making problem.

- *What we have:* we have a set S, and we have a function $f(x)$ that maps elements of this set to real numbers.
- *What we want:* we want to find the element $x \in S$ for which the value of the function $f(x)$ is the largest possible, i.e., for which $f(x) \geq f(x')$ for all $x' \in S$.

3 Resulting General Principles of Decision Making

Ideal problem and realistic solutions. In some cases, we have:

- the exact description of the set S,
- the exact description of the objective function $f(x)$, and
- the exact description of the possible decision x which is optimal with respect to the given objective function.

However, such situations are rare.

In practice:

- we may only have an approximate description of the set S of possible solutions,
- we may only have an approximate description of the objective function $f(x)$ – since this function, as we have mentioned, often needs to be elicited from the decision maker, and at each stage of this elicitation, we only get an approximate value of utility, and
- optimization algorithms may only provide an approximate solution to the optimization problem.

How the difference between ideal and realistic solution affects the quality of the decision. Let us analyze how the above difference between the ideal and the realistic solution to the corresponding optimization problem affects the quality of the resulting decision.

- If the generated solution is not actually possible, this "solution" is useless. From this viewpoint, satisfying constraints is the most important thing.
- Once we make sure that we limit ourselves to possible solutions, we need to make sure that the optimized function should be correct. This is more important than having an effective optimization technique – since even if we perform perfect optimization with respect to this wrong objective function, the resulting decision will not be optimal with respect to the *desired* objective function.
- Finally, the optimization technique should be effective – otherwise, the selected decision will not be as good as it could be.

4 The General Principles of Decision Making Are, in Effect, Exactly the Three Principles of the US Air Force

Let us show that the above general principles of decision making indeed correspond to the above three principles of the US Force: integrity, service (before self), and excellence.

Constraint satisfaction means integrity. As we have mentioned, the most important principle of decision making is that all constraints should be satisfied. This is exactly what is usually mean by integrity: according to Wikipedia, it means "a consistent and uncompromising adherence to strong moral and ethical principles and values".

This principle is, as we have mentioned, the most important in decision making – and it is indeed listed first in the usual description of the three principles of the UA Air Force.

Correctness of objective function means service (before self). For decisions involving a group of people, correctness of the objective function means that this objective function should perfectly reflect the needs of this group – and it should reflect the needs of the decision maker only to the extent that these needs are consistent with the group needs. This is what is meant by service: when the interests of other are valued before one's own interests.

This principle is second in importance in decision making – and it is indeed listed second in the usual description of the three principles of the UA Air Force.

Effectiveness of solving the corresponding optimization problem means excellence. Excellence (but not perfection) means that we need to try to our best to find solutions that are as good as possible, and that we must be good at this task.

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