Jan Poleszczuk
University of Bialystok

DEcision strategies and cognitive adaptations to ecology

Abstract. In this paper, I discuss the concept of adaptive rationality. I present a simple model of ecology and the set of decision rules. The basic structure of the process of cognitive adaptation to ecology is described as a structure comprising (1) perceptual space, (2) a function valuating perceived items, (3) a set of available decision rules and (4) the adaptation process – identification and selection of the best strategies in given ecological conditions. The presented model of ecosystem allows a conclusion that completely opposite strategies may be compatible with the assumption of adaptive rationality.

Keywords: rationality, ecology, adaptation, decision rule, risk.

Introduction

People’s attitudes to situations of uncertainty (risk) – that is, situations where we can achieve success but are also at risk of failure – are rather varied. Some people, counting on gaining benefits which may enable them to better their circumstances or status, readily engage in risky behaviors – bold, daredevil actions which may seem to outside (uninvolved) observers to be reckless, careless, and unreasonable. Others prefer hedging strategies which, characterized by excessive cautiousness, evidence their fearfulness, pusillanimity, cowardice, timidity, suspiciousness, and tendency toward conformism. Readiness to apply risky strategies seems to be a requirement of achieving success, an inseparable dimension of activity and of an exploratory attitude, while hedging can lead to conservative behaviors, passivity, inability to take advantage of chances, as well as a tendency towards ritualism and adherence to old (tried-and-tested) behavioral models. Everyday observation shows that variations along the continuum between hedging and risk-taking can be related to one’s gender, place within social structures, age, knowledge, and the ability to ascertain the probability of events seen as positive or negative, those which we either strive to achieve or
to avoid; to our competence in predicting and controlling events; and to the factors which specify the availability of alternatives. One may ask whether the polarity of risk-taking and hedging testifies to a departure from the rational model (“cold calculation”), which does not include emotions (bravado or cowardice). Perhaps, though, these are rational action strategies in particular conditions of ecology, the uncertainty of events, and their judgment (valuation). What is needed is a model of decision-making situations which would make it possible to capture the relations between the basic parameters which define the rationality of actions (decisions).

1. The model of cognitive adaptation to ecology

The basic structure of the process of cognitive adaptation to ecology is described as a structure comprising (1) perceptual space, (2) a function estimating (valuating) perceived items, (3) a set of available decision rules, and (4) the learning (adaptation) process – identification and selection of the best strategies in given ecological conditions. I will illustrate the general formal structure of the presented model by referring to an intuitive experience of hunting wild mushrooms.

Table 1

<table>
<thead>
<tr>
<th></th>
<th>Ecology</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceptual Space</td>
<td>$\Omega$ $\omega_1 \omega_3 \ldots \omega_i \ldots \omega_{n-1} \omega_n$</td>
</tr>
<tr>
<td>Event $X$</td>
<td>$P(\Omega)$ $p_1 p_2 \ldots p_i \ldots p_{n-1} p_n$</td>
</tr>
<tr>
<td>Positive Event (success)</td>
<td>$1 - q$ $1 1 - q_2 1 - q_i 1 - q_{n-1} 0$</td>
</tr>
<tr>
<td>Adverse Event (failure)</td>
<td>$q$ $0 q_2 \ldots q_i \ldots q_{n-1} 1$</td>
</tr>
<tr>
<td>Attributes</td>
<td>$A_1$ $0 0 \ldots 1 \ldots 1 1$ $q_1^*$</td>
</tr>
<tr>
<td></td>
<td>$A_2$ $0 0 \ldots 0 \ldots 1 1$ $q_2^*$</td>
</tr>
<tr>
<td></td>
<td>$\ldots$ $0 0 \ldots 0 \ldots 1 1$ $\ldots$</td>
</tr>
<tr>
<td></td>
<td>$A_k$ $0 1 \ldots 0 \ldots 0 1$ $q_k^*$</td>
</tr>
<tr>
<td>Prospect Value</td>
<td>$v$ $v_1 v_2 \ldots v_i \ldots v_{n-1} v_n$</td>
</tr>
<tr>
<td>Prospect Expected Value</td>
<td>$w$ $v_1 p_1 v_2 p_2 \ldots v_i p_i \ldots v_{n-1} p_{n-1} v_n p_n$</td>
</tr>
<tr>
<td>Decision Rules</td>
<td>$R_1$ $1 0 \ldots 0 \ldots 0 0$</td>
</tr>
<tr>
<td></td>
<td>$R_2$ $1 1 \ldots 0 \ldots 0 0$</td>
</tr>
<tr>
<td></td>
<td>$\ldots$ $\ldots$ $\ldots$ $\ldots$ $\ldots$ $\ldots$</td>
</tr>
<tr>
<td></td>
<td>$R_n$ $1 1 \ldots 1 \ldots 1 1$</td>
</tr>
</tbody>
</table>
Perceptual space $\Omega$

Each item (entity) within perceptual space can be represented as a configuration of binary attributes which describe it. We have, therefore, a set $k$ of attributes $A = \{A_1, A_2, \ldots, A_k\}$. For example, the attribute $A_1$ can stand for the “color of the mushroom’s cap” (1 – “red”, 0 – any other color). An “attribute” is therefore a certain feature, that is, a property of the item, and the value of 1 is its highlighted “variant” to which we pay attention. All forest mushrooms can be described as types characterized by a configuration of attributes: $\Omega = A_1 \times A_2 \times \ldots \times A_k$. There are $n = 2^k$ of all types of items within perceptual space $\Omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$. In the model of perception adopted here we assume that each item can be assigned a “quality”, and one can easily and simultaneously identify all values of its attributes. Perceptual space is a rational classification of all mushroom specimens: none belongs to two different types and there is no specimen which belongs to no type. In the space $\Omega$, the function $P(\Omega)$, which ascribes to each type of item $\omega \in \Omega$ the number $p$ designating the frequency with which the type appears in the ecosystem is specified. We assume that for each type $\omega_1$ the number $p_1 \in (0, 1)$ and $\sum p_i = 1$. The function $P(\Omega)$ can be specified by the covariance matrix of attributes $Cov(A)$. In particular, when diagonal elements $Cov(A) = 1/4$, that is, variances of attributes reach maximum values, and the covariances equal zero for all pairs of attributes, the matrix $Cov(A)$ generates the function $P^*(\Omega)$, which ascribes to each item an equal frequency, $p(\omega) = 2^{-k}$. This is a case of equal distribution in space $\Omega$. The space is characterized by maximum entropy: the probability of an item having a variant of a given attribute equals 1/2 for each variant, and attributes are independent. Perceptual space, the ecosystem $E$, is specified by a pair $E = \{\Omega, P(\Omega)\}$.

The space of item valuation

Items present in perceptual space are estimated in a particular way. Each item $\omega \in \Omega$ is linked to two kinds of consequences: positive (payoff $B$ acquired as a result of consuming mushrooms) and negative (cost $C$, if it turns out that the mushroom was poisonous). The item (mushroom) is not merely something one perceives within the space of attributes $\Omega$, but also something which either prognosticates positive consequences or constitutes a threat. Consuming mushrooms carries a risk: if it turns out that the mushroom was edible, one can consider this a success; if not, poisoning will certainly incur costs (failure). Each item is not only a perceived object, but also a prospect which may bring positive consequences $B(1 - q)$ or negative results (losses) $-Cq$. The value of $q \in [0, 1]$ is the probability of failure (poi-
soning) and the measure of risk factor (threat). From a psychological point of view, \( B(1 - q) \) is something we desire, while \(-Cq\) constitutes a threat, a loss which we would like to avoid, something the anticipation (imagining, expecting) of which can arouse fear. While perception concerns attributes, the prospect refers to future (anticipated) states. It is linked to uncertainty “perceived” as risk. Each item \( \omega \in \Omega \) will carry a certain risk comprising two elements: an estimate of the weight of loss \( C \) and the probability of its occurrence. The set \( \Omega \) is specified by a function \( Q(\Omega) \) which ascribes the value of \( q \) to every item \( \omega_i \in \Omega \). As a result, we can ascribe its value:

\[
v_i = B(1 - q_i) - Cq_i\]

for every item \( \omega_i \in \Omega \) as a prospect.

In this model we assume that all items (prospects) share the values of \( B \) and \( C \), and the only differentiating parameter is the risk factor \( q_i \). Let us note that the prospect \( \omega_1 \) is absolutely safe, with the risk quotient of poisoning \( q_1 = 0 \). The prospect \( \omega_n \), on the other hand, is extremely harmful, with the risk quotient \( q_n = 1 \). If the level of risk quotient between the prospects differs, they can be ordered: \( q_1 = 0 < q_2 < \ldots < q_{n-1} < q_n = 1 \). As a consequence, the values of the prospects will also be ordered:

\[
v_1 = B > v_2 > \ldots > v_{n-1} > v_n = -C.
\]

We can connect the function specifying the values of risk quotients to the space of attributes. Let us use \( q^*_k \) to signify the probability that an item characterized by one highlighted variant of the \( k \)-th attribute shows itself to be harmful (poisonous). If the conditions below are fulfilled:

\[
\sum_{i=1}^{l-1} q^*_i < q^*_l
\]

that is, the attributes can be ordered in accordance with their power to anticipate negative consequences, and each subsequent attribute (beginning with the weakest) has a higher power than the sum of those which precede it, and

\[
\sum_{i=1}^{k} q^*_i = 1
\]

the value of \( q_i \) for an item is the sum of risk quotients connected to the attributes which describe it. In other words, all classes of items are differentiable according to their risk quotient \( q_i \). Such an additive model of generating function \( Q^*(\Omega) \) can be obtained from:

\[
q^*_i = \frac{2^{k-i}}{2^k - 1}
\]
Risk quotient is then a function of the index $i$ for items $\omega \in \Omega$

$$q_i = \frac{i - 1}{2^k - 1}$$

Table 2  
Space for $k = 4$ and function

<table>
<thead>
<tr>
<th>$\omega$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_1$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.5333</td>
<td>0.5333</td>
<td>0.5333</td>
<td>0.5333</td>
<td>0.5333</td>
<td>0.5333</td>
<td></td>
</tr>
<tr>
<td>$A_2$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.2667</td>
<td>0.2667</td>
<td>0.2667</td>
<td>0.2667</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.2667</td>
<td>0.2667</td>
<td>0.2667</td>
<td>0.2667</td>
</tr>
<tr>
<td>$A_3$</td>
<td>0</td>
<td>0</td>
<td>0.1333</td>
<td>0.1333</td>
<td>0</td>
<td>0</td>
<td>0.1333</td>
<td>0.1333</td>
<td>0</td>
<td>0</td>
<td>0.1333</td>
<td>0.1333</td>
<td>0</td>
<td>0</td>
<td>0.1333</td>
<td>0.1333</td>
</tr>
<tr>
<td>$A_4$</td>
<td>0</td>
<td>0</td>
<td>0.0667</td>
<td>0</td>
<td>0</td>
<td>0.0667</td>
<td>0</td>
<td>0.0667</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0667</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

For item $\omega_2$ highlighted is the variance of risk quotient $A_4$, for $\omega_3 - \omega$ of the attribute $A_3$, for $\omega_5 - \omega$ attribute $A_2$, and for $\omega_9 - \omega$ attribute $A_1$. Item $\omega_1$ is absolutely safe $q_1 = 0$, while the item $\omega_{16}$ is deadly, $q_{16} = 1$. The values of $q_i$ differ by a constant interval of $2^{-k-1}$ and constitute an example of a perfect ordering of $\Omega$ as concerns the dominance (significance) of attributes specified by the risk of poisoning: $A_1$ is characterized by the highest risk, $A_4$ – the lowest. The first line shows the items of $\Omega$ as ordered according to attribute $A_1$, followed by $A_2$ etc. The function $Q^*(\Omega)$, generating risk factors for particular items in perceptual space, can take a shape which differs from the additive model, which may mean that the risk quotients expressed by attributes can enter various (intensifying or reducing) interactions. In other words, the function ordering the attributes presented here is characterized by the fact that there are no interactions between attributes (no rearrangements disturb the order of dominance).

An ecological model $E = \{\Omega, P(\Omega), Q(\Omega)\}$, where the function $P^*(\Omega) = 2^{-k}$ generates continuous uniform distribution (maximum entropy), and the function $Q^*(\Omega)$ which generates maximum order of attribute dominance will be called the standard model.

The function specifying the value of the prospect $v_i = B(1 - q_i) - Cq_i$ shows that the prospect’s value is nonnegative, $v_i \geq 0$, if the condition below is fulfilled:

$$B \left( \frac{1 - q_i}{q_i} \right) \geq C$$

If $q_i > 0.5$, the coefficient $\delta = (1 - q_i)/q_i \in [0, 1]$, and we encounter a typical risk situation: the payoffs $B$ must be significantly higher than the potential costs $C$, and the coefficient $\delta$ discounts $B$ vis-a-vis $C$. If $q_i < 0.5$,
the prospect can also have a positive value when the cost $C$ is exceptionally high and the payoffs $B$ are low $B < C$. In the above case we are dealing with more than a risk – it is gambling.

A prospect’s attractiveness (its “utility”, when we consider the prospective outcome of mushroom-hunting) $w_i$ depends on its value but also on how often it appears in the ecosystem: $w_i = v_ip_i$. That is why the total attractiveness of all the prospects equates the average value of the prospects:

$$\sum_{i=1}^{n} w_i = \sum_{i=1}^{n} v_ip_i = B(1 - q^*) - Cq^*$$

where average risk $q^* = \sum q_ip_i$. This measures an overall yield of the ecosystem when we assume a particular model of behavior: the mushroom hunter picks all mushrooms. S/he has no knowledge about mushrooms and pays no attention to their attributes. No features of these items inform him/her of danger. One can surmise s/he behaves totally irrationally or else is utterly ignorant.

**Decision rules**

It seems reasonable that a rational mushroom-hunter will pick them with care: he will accept some items (prospects) and reject, ignore – others. The decision rule specifies the set of acceptable items and the set of unacceptable items. It is therefore a function which ascribes to each item $\omega \in \Omega$ the number 0 – “a rejected item”, 1 – “an accepted item”, $R_i(\Omega) \rightarrow \{0, 1\}$. A set of decision rules $R(\Omega)$ is a power set of the space $\Omega$. In brief, the number of decision rules equals the number of sub-sets into which the set $\Omega$, that is $|R(\Omega)| = 2^k$, can be divided. Decisions taken by the decision-maker are “deterministic” in character: if an item fulfills the demands of the rule, it is accepted, if not – it is rejected. This is a special case of a more general model where decisions can be probabilistic in character; that is, the function $R_i(\Omega) : \omega \in \Omega \rightarrow [0, 1]$ would ascribe to items belonging to its domain (rule) only the probability of choice (rejection).

Decision rules allow a characterization of various “modes of operation”. The rule $R_0 = \{\emptyset\}$ is a rule, whose domain is an empty set – the rule accepts no items (that is, the mushroom hunter does not pick mushrooms, s/he does not like mushrooms). Its opposite, the rule $R_n = \{\Omega\}$, accepts each prospect – that is, the mushroom hunter picks (accepts) all mushrooms s/he sees in the forests. In fact, the mushroom hunter does not need to know anything about mushrooms (s/he does not need to distinguish between them; only a minimal competence of differentiating mushrooms from stones and other...
items is required). That means that s/he gathers all mushrooms, both edible and poisonous. All types of mushrooms find their way to his/her basket, proportionally to the frequency with which they appear in the ecosystem. In between these extreme “rules” there are others. It is worth noticing that ordering items according to their value, $v_i$, makes it possible to radically narrow down the set of rules. Let us imagine that our mushroom hunter equips him/herself with a mushroom guidebook which describes mushrooms and informs the reader what risk there is of encountering poisonous types. The book symbolizes the knowledge which can come from the mushroom hunter’s own experience or be part of common knowledge in his/her society (culture). The rules $R_0$ and $R_n$ can also constitute knowledge (convention) – the first being a categorical prohibition on consuming mushrooms, the last – a general consent to it or a feature characteristic for the beginning phase of learning.

Hedging Strategy

The rule $R_1 = \{\omega_1\}$, whose domain comprises one item, $\omega_1$, may be called an extreme hedge strategy – the mushroom hunter accepts only the mushrooms which are absolutely safe, where the risk of being poisoned equals zero ($q_1 = 0$), and so the value of the prospect is highest and amounts to $B$. The mushroom hunter chooses the mushrooms which are no doubt edible, there is no risk of being poisoned. These mushrooms $\{\omega_1\}$ are permitted (commanded), the rest – forbidden. Therefore, s/he acts in accordance with the rule: all that is not permitted is forbidden [Lewicka 1993: 139]. S/he keeps to what s/he knows. His/her strategy is exploitative in character. S/he is risk averse, since accepting other mushrooms equals accepting the risk of poisoning. As a consequence s/he does not learn (does not come to know new mushrooms). S/he is monophagous. The hedging strategy guarantees s/he will not be poisoned. Adhering to the hedging strategy, s/he can count on (expect) an average “payoff” $\bar{R}_1 = v_1 p_1 = B p_1$, which benchmarks the attractiveness of the prospect which confirms to rule $R_1$. The value of $\bar{R}_1$ is a measure of effectiveness of the strategy (decision rule $R_1$). When $p_1 \to 0$, the effectiveness of strategy $R_1$ falls, yet the conclusion that the mushroom hunter must change it does not follow: s/he would have to have a better (more effective) alternative!

Risk-seeking strategy

Unlike when applying hedging strategy, here the mushroom hunter rejects only those mushrooms which are certainly inedible, that is, those which guarantee poisoning, $\omega_n$. Mushrooms $\omega_n$ are forbidden, while others are per-
omitted. S/he acts therefore in accordance with the rule: all that is not for-
bidden is permitted. Strategy $R_n$ accepted all types of mushrooms, strategy $R_{n-1}$ excludes only those mushrooms which are no doubt poisonous but does not exclude those for which the risk of poisoning is $q_{n-1} < 1$. The risk-seeking strategy is exploratory in character. The area of acceptance includes items $\{\Omega - \omega_n\}$. The mushroom hunter is not risk-averse. S/he is learning (coming to know new mushrooms). S/he is not monophagous: except for the most poisonous mushrooms, s/he eats all kinds. Risk-seeking strategy does not guarantee that s/he will not be poisoned. But it gives the mushroom hunter hope s/he will eat his/her full. Adhering to strategy $R_{n-1}$ s/he can count on (expect) an average payoff: $\bar{R}_{n-1} = R_n - C p_n$. All in all, if strategy $R_1$ is a strategy of maximum hedging (of minimal risk), strategy $R_2$ is less a hedging strategy, because it accepts prospects which may carry a risk, $\omega_2$. Each consecutive decision strategy broadens its range of acceptance by another high-risk prospect. To sum up, one can order the rules according to an increasing range of accepted risk: $R_0 = \emptyset \subset R_1 \subset \ldots \subset R_{n-1} \subset R_n = \Omega$.

Each decision rule is linked to a measure of its efficacy, which is a sum of attractiveness of the prospects comprising the domain of the rule:

$$\bar{R}_h = \sum_{i=1}^{h} v_i p_i$$

If decision rules differ in their efficacy, the question arises as to what rule should a decision-maker adopt? Let us assume that we are dealing with a rational (in its economic sense) mushroom hunter, who wants to gain maximum payoffs. A rational “player” (mushroom hunter) should choose the decision rule $R^*$, which ensures for him maximum payoffs in this “game with nature”. Can the rule of maximum hedging be rational (maximize payoffs?) The ordering of prospects according to their value enables one to specify what condition determines whether extreme hedging is rational. The value of the rule $R_1$ equals $\bar{R}_1 = B p_1$, but the value of the rule that follows is a value of a more general rule $R_1 \subset R_2$, that is $\bar{R}_2 = \bar{R}_1 + v_2 p_2$. The rule $R_1 = R^* \iff \bar{R}_1 > \bar{R}_2$; that is, when $v_2 p_2 < 0$. Because $p_2 > 0$, the condition is $v_2 < 0$; that is, the second prospect must be negative. That happens when the condition: $B (1 - q_2) / q_2 < C$ is fulfilled. In brief: when payoffs $B$ are small, costs $C$ are high, and the risk of poisoning is high enough, the strategy of maximum caution is a rational strategy, maximizing the payoffs in the game. If the condition is not fulfilled, the strategy of maximum hedging is not rational; strategy $R_2$ is better. That
does not mean that $R_2$ is the best $R^*$. Can the strategy of maximum risk-taking $R_{n-1}$ be rational? This would mean that $R_{n-1} > R_{n-2}$ and $R_{n-1} > R_n$. For $p_n > 0$, and for large payoffs $B$ and small costs $C$, the condition can be fulfilled. If rationality conditions for the strategy of maximum hedging and the strategy of maximum risk-taking are not fulfilled, the strategy $R^*$ may be a broader $R_1$ than a narrower $R_{n-1}$ which, as concerns efficacy, means that the efficacy of strategy $R^*$ is always higher than the efficacy of $R_1$ and $R_{n-1}$. In particular, it is possible that extreme hedging and extreme risk-seeking can be equally effective: $\bar{R}_1 = \bar{R}_{n-1}$. This will happen when:

$$B \left( \sum_{i=2}^{n-1} (1 - q_i)p_i \right) = C$$

The standard model

An example illustrating presented formalism.

Table 3

| Standard model of the ecosystem: $k = 4$, $P^*(\Omega) = 2^{-k}$, $Q^*(\Omega) = (i - 1)/(2^{-k} - 1)$, $B = C = 1$ |

Assumptions adopted regarding risk $q_i$ linked to prospects $\omega \in \Omega$ order these prospects according to their value, $v_i$. The rules of maximum hedging and maximum risk-taking are equally effective: $\bar{R}_1 = \bar{R}_{n-1}$. The $R^*$ (maximally effective) rule is the rule $R_8 = \{\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6, \omega_7, \omega_8\}$. The model shows an interesting quality linked to the cognitive dimension of the decision-making process. Each item can be described as a vector $\omega = [A_1A_2A_3A_4]$ of the values (codes) of variants of attributes. The rule of maximum hedging $R_1$ requires that the decision-maker has information...
about the state of each attribute – s/he accepts only items $\omega_1 = [0000]$. In order to reject an item it is enough that one of its attributes not be 0, but it also means that s/he must consider the full range of qualities exhibited by items. The rule of maximum risk-seeking $R_{n-1}$ is also cognitively demanding – the mushroom hunter rejects items $\omega_n = [1111]$. In this case also the whole range of values of attributes must be noted. The rule $R^*$ is maximally efficient, but it is also one which requires minimal cognitive information. This is because the rule $R_8$ equals the directive of: note attribute $A_1$ and if $A_1 = 0$, accept the item, if $A_1 = 1$, reject (ignore) it. For rule $R_8$, the range of acceptance is designated by a blueprint: $\omega = [0****]$. The only significant information is that which regards the state of attribute $A_1$.

2. Decision strategies and the dynamics of learning (adaptation)

Decision rules are pure strategies in the “game with nature”. Let us say that $s_i$ stands for the probability that the mushroom hunter chooses the rule $R_i$. Strategy $\sigma_h$ will stand for probability distribution on the set of all decision rules $R$. Learning consists in changing one’s strategy, therefore, in changing the value of $s_i$ (the probability of choosing rule $R_i$). A simple model showing a change in strategy makes the direction and scale of the change $s_i$ conditional on the effectiveness of decision rules. It requires that the values of decision rules are not negative. This is ensured by the normalization $\hat{R}_i = \tilde{R}_i - \bar{R}$ as concerns the rule $R_n = \bar{R}$ (an average effectiveness of the ecosystem). An average value of normalized efficiency is:

$$\hat{R} = \sum_{i=1}^{n} \hat{R}_i s_i$$

The rule governing this change (in discrete time) can take a simple form of proportional reinforcement:

$$s_{i}^{t+1} = \frac{\hat{R}_i}{\hat{R}} s_{i}^{t}$$

If we mark changes $s_{i}^{t+1} - s_{i}^{t} = \Delta_i$, the learning process is normalized $\sum \Delta_i = 0$, and if $\Delta_i < 0$, the rule $R_i$ is chosen more and more infrequently, $\Delta_i > 0$, is chosen more often. Evolution halts in a stationary state (state of balance) when $\Delta_i = 0$; that is, when the condition $\Delta_i = 0 \iff \tilde{R}_i = \hat{R}$ is fulfilled. The learning (adaptation) process ends with the selection of decision rule $R^*$, which is the one best adapted to the ecosystem.
Ecological adaptations

The ecosystem model \( E = \{\Omega, P(\Omega), Q(\Omega), R(\Omega), B, C\} \) presented here contains complete information about perceptual space, the frequency with which items appear in a given the ecosystem, the distribution of risk, effectiveness of decision rules, and the value of payoffs \( B \) and costs \( C \). We can analyze the dynamics of a particular model by changing the value of the parameters which specify it.

Table 4

<table>
<thead>
<tr>
<th>( A )</th>
<th>( B )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard model and ( P^<em>(\Omega) ) and ( Q^</em>(\Omega) )</td>
<td></td>
</tr>
<tr>
<td><img src="image1" alt="Decision Rules (B=1)" /></td>
<td><img src="image2" alt="Decision Rules (B=1)" /></td>
</tr>
</tbody>
</table>

Table 4(A) shows a situation where the strategies of maximum hedging and maximum risk-seeking are equally effective: \( \bar{R}_1 = \bar{R}_{n-1} \). Decision rule \( R_8 \) is revealed to be the rational strategy \( R^* \) (maximizing payoffs in the game). An increasing distance between the potential payoff \( B \) and the potential loss \( C \) does not influence the choice of decision strategy. An increasing distance (between payoffs and losses) causes departure from strategy \( R^* \) to result in higher losses in adaptive efficiency. One may think that when the “desire” for \( B \) and the “fear” of \( C \) grow, the decision-maker will show more sensitivity. When \( B \) and \( C \) are small (low payoffs and small losses), the difference between \( R^* \) and \( R_7 \) or \( R_9 \) is negligible!

Table 4(B) shows quite another situation: \( B = 1 \), but the cost \( C \) (the cost of mushroom poisoning) increases. It is the decision rule \( R_5 \) (a narrower rule, demanding, therefore, more information about other attributes!) that constitutes strategy \( R^* \) for \( C = 2 \); for \( C = 4 \), the rule \( R_3 \) (cognitive requirements increase!) is the strategy \( R^* \). The range of acceptable mushrooms falls: from 50% to 31% and to 19%. With increasing costs \( C \) a risk becomes a gamble, and preference is given to decision rules providing a higher level of hedging against the rapidly declining efficacy of rules more general than \( R^* \). A distinct asymmetry appears: while movement from the rule of
maximum hedging $R_1$ towards $R^*$ moderately improves the effectiveness of decision rules, stepping outside the range of $R^*$ causes a sharp decline in effectiveness.

Table 5

Model of type I ecosystem – a friendly ecosystem, $Q^*(\Omega)$

Table 5. presents an ecosystem model which is a modification of the standard model, where it is assumed that the distribution $P(\Omega) = 2^{-k}$ is uniform (the function $Q^*(\Omega)$ is preserved). This is a model of the “friendly ecosystem”, where items characterized as low-risk appear more frequently. In brief, a “blind” mushroom hunter’s chance of happening upon a less harmful mushroom is higher. As shown, the shift from the rule of maximum hedging to a rule that is more risky significantly increases effectiveness, and expanding the rule beyond its optimal range ($R^* = R_8$) does not pose a threat of increased loss in effectiveness. The difference between effectiveness $R^* = R_8$ and the rule of complete ignorance $R_n$ is small, and one can expect that when cost perception (the cost of acquiring information about the state of attributes – for example when looking for mushrooms at dusk!) in this ecosystem is high, a rational decision-maker will gather anything s/he sees. Let us notice that, due to a different type of distribution $P(\Omega)$, the rule $R_8$ will include a range of specimens which exceeds 50%.

Table 6. presents the model of an unfriendly ecosystem, where high-risk items (prospects) appear more often. Here, also, the rule $R_8$ is the best $R^*$. However, shifting from the rule of maximum hedging does not significantly increase effectiveness, and stepping outside the generality range of the rule $R^*$ can result in significant losses in effectiveness. One can suspect that a decision-maker would have to have deep trust in the working order of his/her perceptual mechanism to form his/her decisions based on observing the state of attribute $A_1$ (which is required by the decision rule $R_8$).
Table 6
Model of type II ecosystem – an unfriendly ecosystem, $Q^*(\Omega)$

Table 7
Model of type III ecosystem, $Q^*(\Omega)$

Table 8
Model of type IV ecosystem, $Q^*(\Omega)$
In the case of a type III ecosystem both the items which are dangerous and those which are absolutely safe appear rarely. One can see that the efficacy $R^* = R_8$ clearly dominates the efficacy of other decision rules. A departure from $R^*$ results in a significant decrease in efficacy.

Type IV ecosystem is dominated by either beneficial or harmful prospects. Here, also, rule $R_8$ is the best one $R^*$. It is not, however, a strongly dominant rule as concerns its effectiveness: broader and narrower rules are equally effective, with more distinct differences appearing at extreme values of generality of decision rules.

Not only function $P(\Omega)$, but also function $Q(\Omega)$ can undergo changes.

Table 9
Models of ecosystems with a variable function $Q(\Omega)$ and function $P^*(\Omega)$

<table>
<thead>
<tr>
<th>Ecology</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C/B = 1$</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>$[\alpha]R_1$</td>
<td>0.0625</td>
<td>0.0625</td>
<td>0.0625</td>
<td>0.0625</td>
</tr>
<tr>
<td>$R^*$</td>
<td>0.1162</td>
<td>0.4413</td>
<td>0.3443</td>
<td>0.1814</td>
</tr>
<tr>
<td>$[r]R_{n-1}$</td>
<td>-0.2436</td>
<td>0.3291</td>
<td>0.0625</td>
<td>0.0625</td>
</tr>
<tr>
<td>$R_n$</td>
<td>-0.3061</td>
<td>0.2666</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$ExtR^*$</td>
<td>0.25</td>
<td>0.69</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>$R^*/R_1$</td>
<td>1.9</td>
<td>7.1</td>
<td>5.5</td>
<td>2.9</td>
</tr>
<tr>
<td>$R^*$</td>
<td>$R_4$</td>
<td>$R_{11}$</td>
<td>$R_8$</td>
<td>$R_8$</td>
</tr>
</tbody>
</table>

Table 9. presents ecosystems which differ by function $Q(\Omega)$ – they do not differ in the $C/B$ ratio, the value of maximum hedging strategy is identical for all types. In type I ecosystem all items carry more risk. In effect, a narrowing down $R^* = R_4$ has taken place, and the ecosystem comprises fewer specimens $ExtR^* = 0.25$. The dominance of effectiveness $R^*$ over the rule of maximum hedging equals 1.9. When a general decrease in risk levels takes place (type II ecosystem), the maximum rule $R^* = R_{11}$ becomes
Decision Strategies and Cognitive Adaptations to Ecology
generalized, and includes more specimens $ExtR^* = 0.69$. The dominance of efficiency $R^*$ over the efficiency of the rule of maximum hedging has also risen – 7.1. In type III (IV) ecosystems a symmetrical rise (fall) in risk diversity $q_i$, can be observed, whose sole effect is the dominance of efficiency $R^*$ with a larger variability of risk (in this case, deviating from $R^*$ is more costly).

Conclusion

The model of ecosystem presented here allows a conclusion that none of the strategies highlighted (hedging – $R_1$ and risk-seeking – $R_{n-1}$) must be incompatible with the assumption of adaptive rationality. Our mushroom-hunter may face negative (being poisoned) and non-negative (not being poisoned) events. While picking mushrooms, s/he actions a certain function of his/her objective – s/he aims to eat his/her full (gain payoffs $B$) and avoids poisoning (cost $C$). Risk-seeking strategy works to achieve the objective of eating one’s fill while accepting a certain risk of poisoning; hedging strategy works to achieve the same objective while observing higher safety standards (is risk-averse). The ecological model shows that the strategy which maximizes “payoffs” $R^*$ can be located between those extreme behavior rules. The model shows that if the ecosystem is characterized by appropriate functions $P(\Omega)$ and $Q(\Omega)$ and values $B$ (value of success) and $C$ (cost of failure), the choice of either one of these extreme strategies is perfectly comprehensible as a rational choice, that is, as a choice which maximizes the average payoff in the “game with nature”. If “poisoning” is a danger and a loss $C$, and eating “a tasty mushroom” is a positive event and a reward $B$, the choice of hedging or risk-seeking strategy does not in any way contradict the rational model which assumes a maximization of expected value (utility). Aiming to eat one’s fill (a positive state) and aiming to avoid poisoning (a negative state) are intertwined, and without knowing the values of an environment’s parameters we cannot declare which action (strategy) is a rational adaptation to it.

NOTES

1 Obviously, it is not a model of “mushroom hunting”, but intuitions connected to picking mushrooms allow one to notice the sense of parameters of the model: as is commonly known, mushrooms have low nutritional value (B) and can be detrimental to health (poisonous) incurring a cost (loss C). In its most general sense, mushroom hunting is a risky game with nature.
This is of course an idealized assumption: we assume that the mushroom hunter picks “a lot of” mushrooms, that they are randomly and independently distributed (not clumped), and the mushroom hunter picks mushrooms all alone as s/he meanders at random through the ecosystem etc.

REFERENCES