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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 (valuing) 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 mushrooms¹.

Table 1
Formal parameters of the model of cognitive adaptation to ecology

		Ecology								
Perceptual Space	Ω	ω_1	ω_3	\dots	ω_i	\dots	ω_{n-1}	ω_n		
Event X	$P(\Omega)$	p_1	p_2	\dots	p_i	\dots	p_{n-1}	p_n	$U(X)$	$P(X)$
Positive Event (success)	$1 - q$	1	$1 - q_2$		$1 - q_i$		$1 - q_{n-1}$	0	B	$1 - q^*$
Adverse Event (failure)	q	0	q_2	\dots	q_i	\dots	q_{n-1}	1	$-C$	q^*
Attributes	A_1	0	0	\dots	1	\dots	1	1	q_1^*	
	A_2	0	0	\dots	0	\dots	1	1	q_2^*	
	\dots	0	0	\dots	0	\dots	1	1	\dots	
	A_k	0	1	\dots	0	\dots	0	1	q_k^*	
Prospect Value	v	v_1	v_2	\dots	v_i	\dots	v_{n-1}	v_n		
Prospect Expected Value	w	$v_1 p_1$	$v_2 p_2$	\dots	$v_i p_i$	\dots	$v_{n-1} p_{n-1}$	$v_n p_n$		
Decision Rules	R_1	1	0	\dots	0	\dots	0	0		
	R_2	1	1	\dots	0	\dots	0	0		
	\dots	\dots	\dots	\dots	\dots	\dots	\dots	\dots		
	R_n	1	1	\dots	1	\dots	1	1		

Perceptual space Ω

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 $A = \{A_1, A_2, \dots, A_k\}$. 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: $\Omega = A_1 \times A_2 \times \dots \times A_k$. There are $n = 2^k$ of all types of items within perceptual space $\Omega = \{\omega_1, \omega_2, \dots, \omega_n\}$. 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 Ω , 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 ω_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 Ω . 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 (pay-off 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 Ω , 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 Ω is specified by a function $Q(\Omega)$ which ascribes the value of q_i to every item $\omega_i \in \Omega$. As a result, we can ascribe its value: $v_i = B(1 - q_i) - Cq_i$ to every item $\omega \in \Omega$ 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 ω_1 is absolutely safe, with the risk quotient of poisoning $q_1 = 0$. The prospect ω_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: $q_1 = 0 < q_2 < \dots < q_{n-1} < q_n = 1$. As a consequence, the values of the prospects will also be ordered: $v_1 = B > v_2 > \dots > v_{n-1} > v_n = -C$.

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

$$\sum_{i=1}^k q_k^* = 1$$

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

ω	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
A_1	0	0	0	0	0	0	0	0	0,5333	0,5333	0,5333	0,5333	0,5333	0,5333	0,5333	0,5333
A_2	0	0	0	0	0,2667	0,2667	0,2667	0,2667	0	0	0	0	0,2667	0,2667	0,2667	0,2667
A_3	0	0	0,1333	0,1333	0	0	0,1333	0,1333	0	0	0,1333	0,1333	0	0	0,1333	0,1333
A_4	0	0,0667	0	0,0667	0	0,0667	0	0,0667	0	0,0667	0	0,0667	0	0,0667	0	0,0667
q_i	0,000	0,067	0,133	0,200	0,267	0,333	0,400	0,467	0,533	0,600	0,667	0,733	0,800	0,867	0,933	1,000

For item ω_2 highlighted is the variance of risk quotient A_4 , for ω_3 – of the attribute A_3 , for ω_5 – attribute A_2 , and for ω_9 – attribute A_1 . Item ω_1 is absolutely safe $q_1 = 0$, while the item ω_{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 Ω 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 Ω 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 δ 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: $w_i = v_i p_i$. That is why the total attractiveness of all the prospects equates the average value of the prospects:

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

where average risk $q^* = \sum q_i p_i$. 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 Ω . In brief, the number of decision rules equals the number of sub-sets into which the set Ω , that is $|R(\Omega)| = 2^{2^k}$, 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 ecosystem². 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, ω_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 $p_1 \rightarrow 0$, 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, ω_n . Mushrooms ω_n are forbidden, while others are per-

mitted. S/he acts therefore in accordance with the rule: all that is not forbidden 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: $\bar{R}_{n-1} = R_n - Cp_n$. 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, ω_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: $R_0 = \emptyset \subset R_1 \subset \dots \subset R_{n-1} \subset R_n = \Omega$.

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 $\bar{R}_1 = Bp_1$, 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 $\bar{R}_{n-1} > \bar{R}_{n-2}$ i $\bar{R}_{n-1} > \bar{R}_n$. 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 that 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:

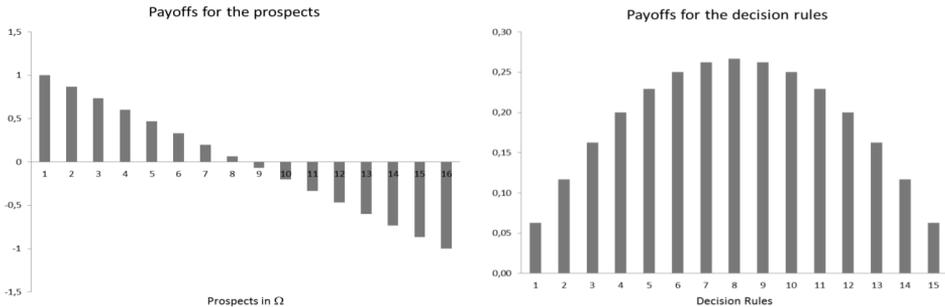
$$B \left(\frac{\sum_{i=2}^{n-1} (1 - q_i) p_i}{\sum_{i=2}^{n-1} q_i p_i} \right) = C$$

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 $\omega = [A_1 A_2 A_3 A_4]$ 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 σ_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 $\hat{R}_i = \bar{R}_i - \bar{R}$ 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 $\Delta_i = 0 \iff \hat{R}_i = \hat{R}$ 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

Standard model and $P^*(\Omega)$ and $Q^*(\Omega)$

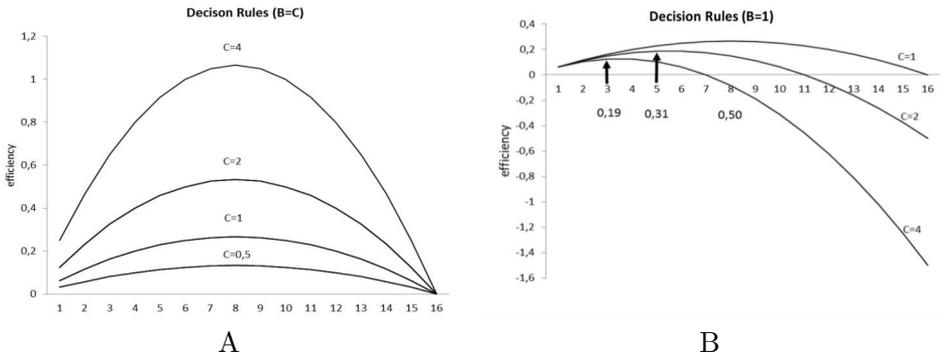


Table 4(A) shows a situation where the strategies of maximum hedging and maximum risk-seeking are equally effective: $\bar{R}_1 = \bar{R}_{n-1}$. Decision rule R_8 is revealed to be the rational strategy R^* (maximizing payoffs in the game). An increasing distance between the potential payoff B and the 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, $Q^*(\Omega)$

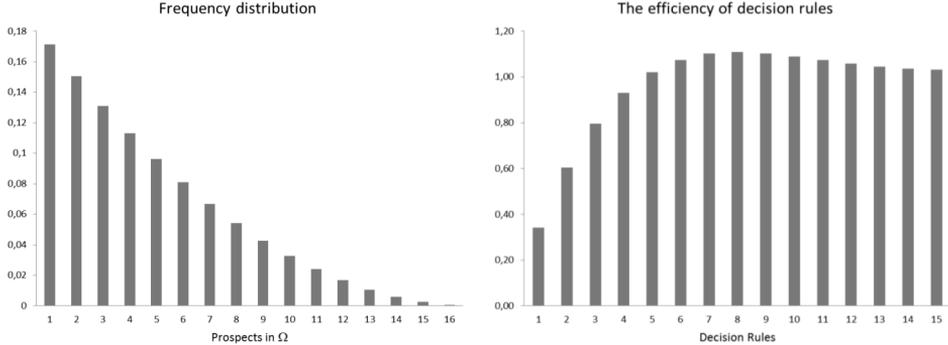


Table 5. presents an ecosystem model which is a modification of the standard model, where it is assumed that the distribution $P(\Omega) = 2^{-k}$ is uniform (the function $Q^*(\Omega)$ is preserved). This is a model of the “friendly ecosystem”, where items characterized as low-risk appear more frequently. 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, $Q^*(\Omega)$

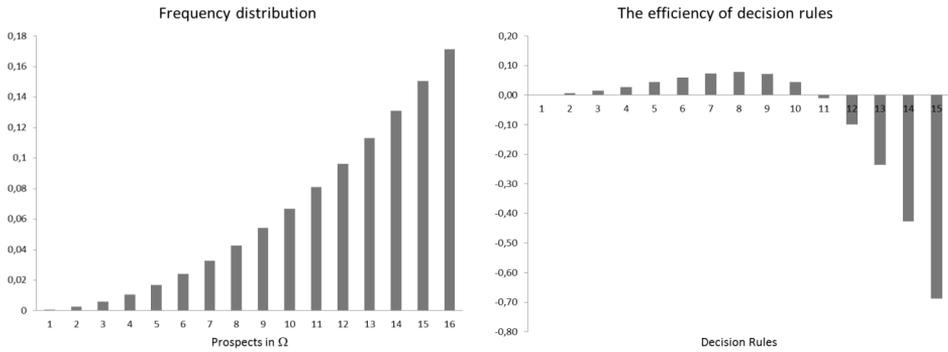


Table 7

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

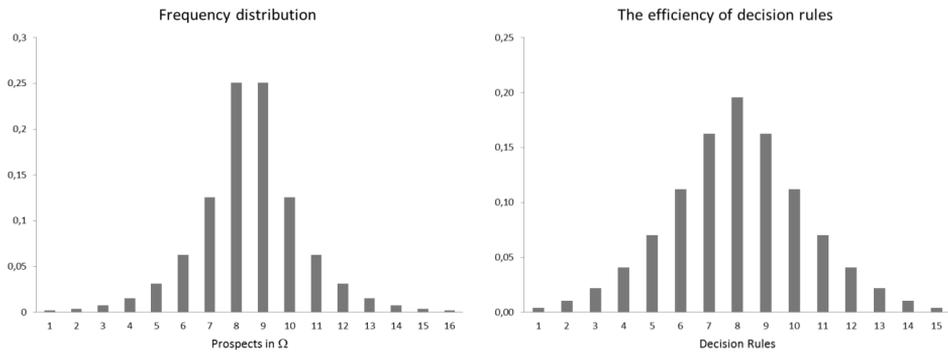
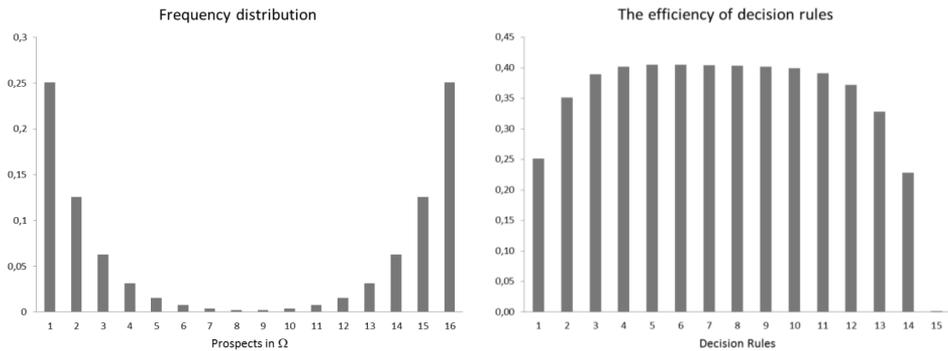


Table 8

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 $P^*(\Omega)$

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

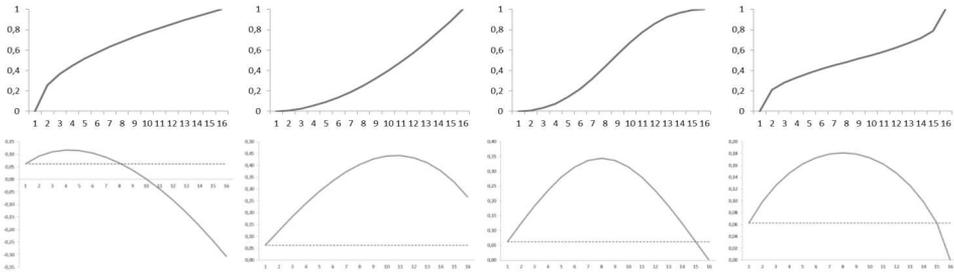


Table 9. presents ecosystems which differ by function $Q(\Omega)$ – they do not differ in the C/B ratio, the value of maximum hedging strategy is identical for all types. In type I ecosystem all items carry more risk. In effect, a narrowing down $R^* = R_4$ has taken place, and the ecosystem comprises 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

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.

N O T E S

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.

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² 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.

R E F E R E N C E S

Lewicka M. *Aktor czy obserwator. Psychologiczne mechanizmy odchyień od racjonalności w myśleniu potocznym*, Warszawa–Olsztyn 1993.