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THE INDIRECT PRACTICAL FUNCTIONS OF EXPLANATIONS

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1. *Introduction*

The view that scientific explanations are instruments by means of which we can achieve (epistemic, causal, etc.) understanding of the phenomena we observe is widely spread. It was held by e.g. Carl Hempel (1965), Michael Friedman (1974), Philip Kitcher (1981) and Wesley Salmon (1984). In this volume, it is adopted by Wesley Salmon and Thomas Grimes.

In my opinion, explaining has a *theoretical* function (creating understanding) but also several *practical* functions. Sometimes we explain in order to make a diagnosis or to assign legal responsibility. In these situations explaining has a *direct practical* use. However, I think that the search for explanations also has *indirect practical* functions. The aim of this paper is to clarify the nature of these indirect practical functions.

In section 2 I describe a specific type of explanatory activity, viz. scientifically epistemically explaining particular events (from now on I will call this activity "SE-explaining"). In section 3 I clarify what the indirect practical function of SE-explaining consists in. In section 4 I present an outline of how similar indirect practical functions can be found for other types of explanatory activity.

My starting-point in section 3 will be the causal decision theory of Brian Skyrms (1984, especially pp. 63-92). Suppose that $a_1,\ldots,a_L$ is a series of mutually exclusive and collectively exhaustive actions. Accor-

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ding to Skyrms we have to make a choice between these actions by means of the following procedure:

(SK) (1) Determine the set $\{k_1,\ldots,k_m\}$ of potential *states of the world* that will be taken into account; determine the set $\{c_1,\ldots,c_n\}$ of potential *consequences* that will be taken into account.
(2) Calculate the *expected utility* (EU) of each potential action by means of the formula
$$EU(a) = \Sigma_i\, b(k_i)\, \Sigma_j\, b(c_j \mid a\&k_i) d(a\&k_i\&c_j)$$
(3) Perform the action which has the highest EU.

Ad 1: the elements of $\{c_1,\ldots,c_n\}$ are potential effects of the actions $a_1, \ldots, a_L$; they are mutually exclusive and collectively exhaustive; the states of the world (which also are mutually exclusive and collectively exhaustive) are factors that determine to which consequence an action leads; so there is a cause-effect relation between the actions and the c_j's and between the k_i's and the c_j's; on the other hand there is no cause-effect relation between actions and states of the world, or vice versa.
Ad 2: $b(k_i)$ is the belief value the decision maker assigns to state k_i; $b(c_j \mid a\&k_i)$ is the belief value the decision maker is prepared to assign to c_j if action a has been performed and he is sure that k_i is the real state of the world. $d(a\&k_i\&c_j)$ is a quantitative measure of the desirability of the state of the world in which a, k_i and c_j occur.

If we apply rule (SK), the amount of utility we really obtain (which may differ from the expected utility of the action we have chosen) is influenced by the belief values we assign: the "better" the belief values are, the better our decisions will be. I will call a set of belief values more rational than another (in some situation S) if and only if in this situation the first set leads to a more rational choice than the second, i.e. to a choice that results in more really obtained utility. In section 3 I will show that SE-explaining sometimes changes our epistemic state in such a way that in subsequent decision processes we assign more rational belief values to states of the world, i.e. more rational $b(k_i)$'s. Because only subsequent decision processes are influenced, this practical function of SE-explaining is an *indirect* one.

2. *SE-explaining*

2.1 SE-explaining is an epistemic activity in which two main phases can be distinguished. In the first phase we construct a *scientific epistemic explanation problem* (SEE-problem); in the second phase we solve the problem. In section 2.3 I will clarify what these phases consist in. In 2.2 I introduce an auxiliary concept, viz. E_α-*scientific argument*.

2.2 We start with a definition of arguments in general. An argument consists of two singular sentences and one probability statement. Singular sentences have the form "Object *a* has property G at time *t*"; their formal representation is G(a,t). Probability statements have the form "In domain D holds: the relative frequency of class G in class F equals *r*" and are written as $P_D(G \mid F)=r$. D is called the domain of the probability statement, G its object class, F its reference class and *r* its frequency number. A probability statement which is necessarily true because of the meaning of the terms occurring in it, is called analytic. Arguments are defined as follows:

(ARG) $<S_1,S_2,W>$ is an argument for the singular sentence G(a,t) if and only if
(1) W is a probability statement with object class G which is not a theorem of the probability calculus and which is not analytical,
(2) S_1 is a singular sentence in which the property D (the property that determines the domain of W) is attributed to (a,t),
(3) S_2 is a singular sentence in which the property F (the property that determines the reference class of W) is attributed to (a,t), and
(4) the frequency number of W is not equal to 0.

Whether an argument is E_α-scientific depends on the epistemic status of W, S_1 and S_2. In general, the *epistemic status(es)* a person assigns to a sentence reflect(s) the reasons why he accepts it as true. Two epistemic statuses are important here: "empirically founded" and "scientifically founded". The content of these statuses is clarified in the subsequent paragraphs.

A person has to give the status *empirically founded* to a singular sentence if and only if his own observations contain sufficient evidence for it or he has good reasons to believe that someone else has gathered sufficient observational evidence for it.

A person has to give the status *scientifically founded* to a probability statement if and only if he knows a proof that this statement is derivable from his primary scientific knowledge. The primary scientific knowledge of individual X at time t_β consists of all theories, phenomenological laws, distribution functions etc. that X regards as empirically adequate at t_β. A scientific entity (theory, law, etc.) is regarded as *empirically adequate* if and only if it has passed some empirical tests; since we do not need a precise concept of empirical adequacy in this article, I do not discuss the nature of these tests.

The *knowledge situation* of an individual X at t_β is the set of all sentences X consciously accepts as true at time t_β. Knowledge situations are finite and not deductively closed. A description of the *epistemic state* of X at t_β consists of (i) a description of the knowledge situation of X at t_β, and (ii) a survey of the epistemic statuses which X at t_β assigns to the sentences he consciously accepts as true. The epistemic state of X at t_β will be formally represented by $E_{X,\beta}$. Arbitrary epistemic states will be written as E_α.

We now have all the elements we need to define the concept *E_α-scientific argument*:

(SA) If $<S_1,S_2,W>$ is an argument for the singular sentence S_E, then it is E_α-scientific if and only if
(1) E_α is an epistemic state in which S_1 and S_2 have the status "empirically founded", and
(2) E_α is an epistemic state in which W has the status "scientifically founded".

2.3 Consider an individual X and a sentence S_E to which X at time t_β assigns the status "empirically founded". If X compiles a list of all arguments for S_E which are $E_{X,\beta}$-scientific, and subsequently gives himself the task of changing his epistemic state to the effect that at t_γ ($t_\beta < t_\gamma$) an additional scientific argument for S_E emerges (i.e. to the effect that a particular argument which did not meet the criteria of (SA) with respect to the initial epistemic state $E_{X,\beta}$, and therefore is not on the list, does meet the criteria with respect to the new state $E_{X,\gamma}$), then X has constructed a *scientific epistemic explanation problem*.

Every SEE-problem can be represented by means of a scheme of the following form:

S_E
$<S_1,S_2,W>$
$<S_1',S_2',W'>$
$<S_1'',S_2'',W''>$, etc.

S_E is the sentence for which an additional scientific argument has to be found, and is called the *object sentence* of the SEE-problem. The arguments listed in the scheme are the $E_{X,\beta}$-scientific arguments. They constitute the *reference list* of the SEE-problem (which may be empty).

SE-explaining the particular event described by sentence S_E amounts to (i) constructing a SEE-problem in which S_E is the object sentence, and (ii) solving this problem. Solving a SEE-problem amounts to appropriately modifying one's epistemic state and constructing an additional scientific argument. I will not discuss the exact procedures by means of which SEE-problems can be solved[1].

3. *The indirect practical function of SE-explaining*

3.1 In this section I will show that SE-explaining sometimes changes the individual's epistemic state in such a way that in subsequent decision processes he assigns more rational belief values to states of the world. My argument consists of three lemmas. In each of the sections 3.2-3.4 I discuss one of these lemmas. In 3.5 I summarize the argument. In 3.6 I compare the indirect practical function I assign to SE-explaining to the function Wesley Salmon attributes to explanations in his statistical relevance model.

3.2 A person assigns the status "scientifically founded" to a probability statement if and only if he knows a proof that it is derivable from his primary scientific knowledge; the primary scientific knowledge of X at time t_β consists of all the scientific entities that X regards as empirically adequate at t_β (cf. the definitions in section 2.2). Before I can formulate my first lemma, some clarifications about the status "empirically adequate" and about "derivability" have to be made.

Assigning the status "empirically adequate" to a scientific entity is sufficient but not necessary for accepting it. If we accept a scientific entity (because we regard it as empirically adequate, or for some other reason), we enter into an epistemic commitment: we agree to accept all probability statements for which we know a proof that they are derivable from the entity. By assigning the status "empirically adequate" to a scientific entity, we enter into an additional, more specific epistemic commitment:

(COM) By giving a scientific entity A the status "empirically adequate", one agrees to give the status "scientifically founded" to every probability statement for which one knows a proof that it is derivable from A.

Assigning the status "scientifically founded" to a probability statement is a sufficient reason (but not a necessary one) for accepting it.

There is no general definition of derivability of probability statements from scientific entities: the meaning of derivability depends on the type of entity involved or on the entity itself. So we have some type-specific definitions of derivability and some entity-specific definitions. To illustrate this, we consider the law of the pendulum, $P = 2\pi\sqrt{l/g}$. The (type-specific) definition of derivability for phenomenological laws will tell us (i) that from this law we can derive statements of the types $P(P_{a,b} \mid L_{c,d}) = r$ and $P(L_{c,d} \mid P_{a,b}) = r$ (where $P_{a,b}$ is a time interval and $L_{c,d}$ a length interval) and (ii) that the value of r (which is 0 or 1) depends on the relation between [a,b] and $[2\pi\sqrt{c/g}, 2\pi\sqrt{d/g}]$ (for statements of the first type) or on the relation between [c,d] and $[2\pi\sqrt{a/g}, 2\pi\sqrt{b/g}]$ (for statements of the second type).[2]

From most entities of our primary scientific knowledge, a large (sometimes infinite) number of probability statements is derivable; the law of the pendulum illustrates this. But for each entity, each individual is acquainted with only a small number of statements for which he knows a proof of derivability. So situations in which and individual knows a scientific entity (and knows how to derive probability statements from it) but is not allowed to assign the status "scientifically founded" to all the probability statements that are derivable from it, occur very frequently.

Let's call the set of all probability statements to which X at t_β assigns the status "scientifically founded", the *effective explanatory knowledge* of

X at time $t_ß$. Furthermore, let a person's *potential explanatory knowledge* consists of all the probability statements that are derivable from elements of his primary scientific knowledge (the exact meaning of derivability depending on the [type of] entity). These concepts can be used to reformulate the conclusion of the previous paragraph as follows: there is always a discrepancy between a person's effective explanatory knowledge and his potential explanatory knowledge; the former is only a small fraction of the latter.

A SEE-problem has been solved if and only if our epistemic state is appropriately modified and an additional scientific argument has been constructed. Let the *empirical knowledge* of an individual consist of the singular sentences to which he has given the status "empirically founded". Then the definition of solved SEE-problems entails that an enlargement of our empirical knowledge and/or our effective explanatory knowledge is necessary in order to solve such problem. Because of the discrepancy between potential and effective explanatory knowledge, enlarging the latter is often possible without enlarging the former. But on the other hand, an appropriate enlargement of the effective explanatory knowledge is sometimes impossible within the limits of the current potential explanatory knowledge of X. So there are SEE-problems which can only be solved if X's potential explanatory knowledge enlarged. This brings us to the first lemma:

(L_1) SE-explaining sometimes leads to an enlargement of the primary scientific knowledge of the person who is involved.

3.3 My second lemma is an answer to the question "what happens when a person's primary scientific knowledge grows?". To answer this question, I introduce some new concepts. An *object-moment* is a couple of an object and a point of time. A *family of properties* (or *family* for short) is a series of properties which are defined so that an object-moment cannot posses more than one of the properties. When D is a set of object-moments, the family $G_1,\ldots,G_n$ is called *characteristic of domain D* if and only if each element of D necessarily possesses one of the properties of the family. *Probability models* are defined as follows:

(PM) Consider the set D (consisting of all object-moments (x,t) such that object *x* at time *t* has property D) and two families characteristic of D, $F_1,\ldots,F_m$ and $G_1,\ldots,G_n$. A series of $m \times n$ probability statements

$$
\begin{aligned}
&P_D(G_1 \mid F_1)=p_{11}\\
&P_D(G_1 \mid F_2)=p_{12}\\
&\qquad\quad |\\
&P_D(G_1 \mid F_m)=p_{1m}\\
&P_D(G_2 \mid F_1)=p_{21}\\
&\qquad\quad |\\
&P_D(G_n \mid F_m)=p_{nm}
\end{aligned}
$$

is called a *probability model for family $G_1,\ldots,G_n$ in domain D* if and only if for every F_i holds: $\sum_j p_{ji} = 1$

$F_1,\ldots,F_m$ is the *antecedent family* of the model, $G_1,\ldots,G_n$ its *consequens family*. Finally, X is allowed to call a probability model *scientifically founded* if and only if he has given each of its elements the status "scientifically founded".

The probability statements that are derivable from a scientific entity can be grouped into probability models. For instance, from the law of the pendulum we can derive an infinite number of probability models in which the antecedent family is a set of length intervals and the consequens family a set of time intervals. We can also derive an infinite number of probability models in which the consequens family consists of length intervals and the antecedent family of time intervals. Because of the relation between scientific entities and probability models, a number of probability models is automatically added to a person's potential explanatory knowledge if an empirically adequate scientific entity is added to his primary scientific knowledge.

On the other hand, every probability statement that is part of the potential explanatory knowledge of a person X, is a statement for which X is able to realize the condition he has to realize before he can give this statement the status "scientifically founded" (the condition about proof of derivability). As a consequence, all probability models in the potential explanatory knowledge of X are models for which he is able to realise the conditions (a proof of derivability for each statement) which allow him to call it "scientifically founded". This brings us to the second lemma:

(L_2) If the primary scientific knowledge of person X grows, the number of scientifically founded probability models which X can construct grows too.

The expression “number of scientifically founded probability models which X can construct” is an abbreviation of “number of probability models for which X is able to realize the conditions that allow him to assign the status ‘scientifically founded’”.

3.4 My first lemma links SE-explaining to growth of a person’s primary scientific knowledge. The second relates growth of primary scientific knowledge to increase of capacity to construct scientifically founded probability models. My last lemma links this increase to assigning more rational belief values in decision contexts:

(L_3) An increase of the number of scientifically founded probability models a person can construct sometimes has the effect that this person assigns more rational belief values to the k_i’s.

I will first present two examples (Game I and Game II) and then develop an argument in support of this lemma. The examples have two functions: they are the starting-point of my argument, and I will use them to clarify the meaning of the expression “more rational belief values”. In the introduction I defined that a set of belief values is more rational than another (in some situation S) if and only if in this situation the first set leads to a more rational choice, i.e. a choice that results in more really obtained utility. I will use the examples to clarify this definition.

Game I has the following set-up. An urn contains 35 green cubes, 5 green balls, 15 yellow cubes and 45 yellow balls. The candidate, who is blindfolded, only knows that the urn contains 40 green objects and 60 yellow ones, and that the objects are either balls or cubes. On the left of the urn is a green box, on the right is a yellow one. The games master takes an object out of the urn, and the candidate decides in which box this object is laid. If the games master puts a green object in the green box or a yellow one in the yellow box, the candidate receives 10$. For an object that is posed in the wrong box, the candidate receives nothing (but looses nothing either).

What does the decision process in game I look like if the candidate follows procedure (SK)? He has to choose between two actions:

a_1: Instruct the games master to put the object in the green box.
a_2: Instruct the games master to put the object in the yellow box.

The first move of the candidate will consist in constructing a model of the decision context (step 1 of (SK)). The simplest model that takes all relevant causal relations into account consists of four consequences and two states:

c_1: a green object in the green box
c_2: a yellow object in the green box
c_3: a green object in the yellow box
c_4: a yellow object in the yellow box

k_1: the object the games master has chosen is green
k_2: the object the games master has chosen is yellow

Having constructed this model, the candidate starts calculating the expected utilities of the two actions (step 2 of (SK)). Because of the set-up of the game it is rational to assign the following belief values:

$b(c_j \mid a_1\&k_1)$ is 1 if $j=1$ and 0 otherwise
$b(c_j \mid a_1\&k_2)$ is 1 if $j=2$ and 0 otherwise
$b(c_j \mid a_2\&k_1)$ is 1 if $j=3$ and 0 otherwise
$b(c_j \mid a_2\&k_2)$ is 1 if $j=4$ and 0 otherwise

As a consequence, the formulas for calculating the expected utility of the actions can be reduced to:

$$EU(a_1) = [b(k_1 x 1 x d(a_1\&k_1\&c_1)] + [b(k_2) x 1 x d(a_1\&k_2\&c_2)]$$
$$EU(a_2) = [b(k_1 x 1 x d(a_2\&k_1\&c_3)] + [b(k_2) x 1 x d(a_2\&k_2\&c_4)]$$

In view of the money that can be won, $d(a_1\&k_1\&c_1) = d(a_2\&k_2\&c_4) = 10$ and $d(a_1\&k_2\&c_2) = d(a_2\&k_1\&c_3) = 0$ are rational desirabilities. So the formulas can be reduced to:

$$EU(a_1) = [b(k_1) x 1 x 10] + [b(k_2) x 1 x 0]$$
$$EU(a_2) = [b(k_1) x 1 x 0] + [b(k_2) x 1 x 10].$$

To complete step 2 of procedure (SK) the candidate has to assign a belief value to k_1 and k_2. This can be done in many different ways. I will discuss only one procedure, which I call the *method of true probability models* (TPM-method).

Let U be the set of objects in the urn, G the set of green objects and Y the set of yellow objects. Then G,Y is a family of predicates which is characteristic of U. Moreover, this family can be used to represent the states k_1 and k_2: if the object of action (the object the games master selects) is called *e*, state k_1 can be written as Ge and state k_2 as Ye. The TPM-method goes as follows:

(TPM) (1) Choose a family $K_1,\ldots,K_m$ which is characteristic of D and by which the states $k_1,\ldots k_m$ can be represented.
(2) Compile a list of all probability models for $K_1,\ldots,K_m$ in D that satisfy the following conditions:
(a) you have empirical evidence which enables you to determine to which cell of the antecedent family the object of action belongs, and
(b) your knowledge of the decision context implies the truth of all probability statements of the model.
(3) Select one of the models on the list obtained in step 2.
(4) Equate $b(k_i)$ to $P(K_i \mid F_a)$

Ad 1: D is the set of potential objects of action (in our example: the set U)
Ad 4: F_a is the cell of the antecedent family to which the object of action belongs; K_i is the element of the consequens family that is used to represent k_i.

The set-up of game I implies that there is only one probability model that satisfies the conditions (2a) and (2b):

(P_1) $P_U(G)=0.4$
$P_U(Y)=0.6$

So if the candidate uses the TPM-method to assign belief values, his final result will be:

$$EU(a_1) = 0.4x10 = 4$$

$EU(a_2) = 0.6x10 = 6$

As the expected utility of a_2 is higher than the expected utility of a_1, the candidate will tell the games master to put the object in the yellow box.

Game II is a variant of game I. There are only two differences. Firstly, the candidate not only knows that the urn contains 40 green objects and 60 yellow ones, but also that there are 50 balls and 50 cubes, that 70% of the cubes are green, and that 90% of the balls are yellow. Secondly, he can buy information about the shape of the object the games master has chosen: if the candidate pays 1$, the games master tells him whether it is a ball or a cube.

Until the moment when the belief values of the states of the world are fixed, the decision process in game II is identical to that in game I; so like in game I, the formulas for calculating the expected utility of the actions can be reduced to:

$$EU(a_1) = [b(k_1)x1x10] + [b(k_2)x1x0]$$
$$EU(a_2) = [b(k_1)x1x0] + [b(k_2)x1x10]$$

However, the conditions of the second step of (TPM) no longer exclude all probability models other than (P_1). If the candidate does not buy information about the shape of the object, the only adequate probability model is (P_1). But if he buys the information, the list which is obtained at the end of step 2 of (TPM) contains a second probability model, viz.

(P_2) $P_U(G \mid C)=0.7$
$P_U(Y \mid C)=0.3$
$P_U(G \mid B)=0.1$
$P_U(Y \mid B)=0.9$

where C is the set of cubes and B the set of balls.

If the candidate uses the TPM-method to determine the belief values of k_1 and k_2, he has to choose between three options:

o_1: Do not buy the information about the shape of the object, and use probability model P_1 to assign the belief values.

o_2: Buy the information about the shape of the object, and use probability model P_1 to assign the belief values.

o_3: Buy the information about the shape of the object, and use probability model P_2 to assign the belief values.

Each option is a combination of two metadecisions. The second metadecision constitutes the third step of (TPM).

If the candidate chooses the first or second option, the belief values are the same as in game I; so he will choose action a_2. If he chooses option 3, he will choose a_1 if the games master tells him that the object of action is a cube, and a_2 if he tells him that it is a ball. For a cube, the expected utilities are:

$$EU(a_1) = [0.7x1x10] + [0.3x1x0] = 7$$
$$EU(a_2) = [0.7x1x0] + [0.3x1x10] = 3$$

For a ball, the expected utilities are:

$$EU(a_1) = [0.1x1x10] + [0.9x1x0] = 1$$
$$EU(a_2) = [0.1x1x0] + [0.9x1x10] = 9$$

As announced at the beginning of this section I will use these examples to clarify my definition of "more rational belief values". Let the net degree of rationality of a decision be its gross degree of rationality minus the cost of the information one has collected in order make the decision; and let the gross degree of rationality of a decision be the average utility one obtains if the same decision is made (in the same context) an infinite number of times. Then we can formulate the definition of "more rational belief values" in a different way: a set of belief values is more rational (in situation S) than another if and only if in this situation the first set leads to a decision with a higher net degree of rationality.

To illustrate this new definition, we consider the three options in game II. If the candidate chooses the first option and then decides to perform action a_2, the gross degree of rationality of this latter decision is 6; as he did not buy any information, the net degree of rationality is equal to the gross degree. If the candidate chooses the second option, the gross degree of rationality is 6, while the net degree is 5 (the price of the information is 1\$). Finally, the gross degree of rationality given the third option is 8 ((0.5x7)+(0.5x9); I assume that in the long run the number of balls the games master selects is equal to the number of cubes he selects), while the net degree is 7.

The second function of the examples is to provide a starting-point for an argument in support of my third lemma. To see what we can learn from them, I start with a very bold generalization:

(L_{3A}) The belief values assigned to states of the world by means of the TPM-method become more rational if the number of true probability models the decision maker knows increases.

This claim is supported by the examples: in game II there are two true probability models, while in game I there is only one. If the candidate makes the right metadecisions (i.e. chooses option 3) the additional probability model will cause the candidate to assign belief values that lead to a decision with a higher net degree of rationality than can be reached in game I: the net degree of rationality if he chooses option 3 is 7, while the net degree of rationality in game I equals 6.

Though (L_{3A}) is supported by the examples, it is easy to find reasons why it is false:

(1) The decision maker may make inappropriate metadecisions (this problem occurs in the examples if the candidate chooses option 1 or 2).

(2) The cost of information acquisition may exceed the increase in gross degree of rationality of the decision (this problem would occur in the examples if the candidate would have to pay more than 3$ for information about the shape of the object).

(3) Sometimes the information we need to apply a probability model can not be obtained (this problem would occur in the examples if we would assume that the candidate can not buy information about the shape of the object).

(4) True probability models can only lead to more rational belief values if they are used in a decision process.

Because (L_{3A}) is false, the starting-point of my argument for the third lemma is a weaker claim:

(L_{3B}) The belief values assigned to states of the world by means of the TPM-method *sometimes* become more rational if the number of true probability models the decision maker knows increases.

Though (L_{3B}) is acceptable, it is not immediately relevant for (L_3): it does not say anything about scientifically founded probability models. To overcome this problem, we have to make an assumption about the efficacy of scientific method. According to the definitions of section 2.2, a person has to give the status "scientifically founded" to a probability statement if and only if he knows a proof that this statement is derivable from his primary scientific knowledge. The primary scientific knowledge of individual X at time t_β consists of all scientific entities that X regards as empirically adequate at t_β. An entity is regarded as *empirically adequate* if and only if it has passed some empirical tests. If we assume that these empirical tests, together with the conditions that govern the statuses "scientifically founded" and "empirically adequate", guarantee that every scientifically probability model is approximately true, then (L_{3B}) entails (L_{3C}):

(L_{3C}) The belief values assigned to states of the world by means of the SFPM-method *sometimes* become more rational if the number of scientifically founded probability models the decision maker has at his disposal increases.

The SFPM-method (the *method of scientifically founded probability models*) is an extension of the TPM-method:

(SFPM)
(1) Choose a family $K_1,\ldots,K_m$ which is characteristic of D and by which the states $k_1,\ldots k_m$ can be represented.
(2) Compile a list of all probability models for $K_1,\ldots,K_m$ in D that satisfy the following conditions:
(a) you have empirical evidence which enables you to determine to which cell of the antecedent family the object of action belongs, and
(b) your knowledge of the decision context implies the truth of all probability statements of the model, or the model consists of scientifically founded probability statements.
(3) Select one of the models on the list obtained in step 2.
(4) Equate $b(k_i)$ to $P(K_i \mid F_a)$

Unless we hold that the SFPM-method is never used to make decisions,

(L_{3C}) entails (L_3).

3.5 If we combine the first and second lemma, we can conclude that SE-explaining sometimes leads to an enlargement of the number of scientifically founded probability models the individual can construct. Combining this conclusion with the third lemma results in the following claim:

(IPF) SE-explaining sometimes changes the epistemic state of X in a way that affects his subsequent decisions: the epistemic state of X sometimes changes in such a way that in subsequent decision processes he assigns more rational belief values to states of the world.

(IPF) states that SE-explaining sometimes has a practical benefit: this activity sometimes improves our subsequent decisions. In the situations we have discussed SE-explaining is not part of a decision process, only the subsequent decisions of the individual are affected. So the potential practical benefit we have discussed constitutes an *indirect* practical function of SE-explaining.

3.6 The indirect practical function of SE-explaining described in 3.2-3.5 resembles the function Wesley Salmon assigns to explanations in his SR-model (W. Salmon 1971, pp. 76-78). On the SR-model, an explanation of the fact that object *a*, which is a member of D, is also a member of G has the following form:

$$P_D(G \mid F_1)=p_1$$
$$P_D(G \mid F_2)=p_2$$
$$|$$
$$P_D(G \mid F_m)=p_m$$
a is a member of $D\&F_k$

The probability statements must satisfy two conditions: (i) $D\&F_1$, $D\&F_2$, ..., $D\&F_m$ is a partition of D which is homogeneous with respect to G, and (ii) $p_i=p_j$ only if $i=j$.

Suppose we explain why *a*, a member of D, has property G. Afterwards we want to assign a belief value to the sentence "*b* has property G". *b* is also a member of D. Then we can use the set of probability statements in the explanation to assign this belief value: we determine to which cell of the partition *b* belongs and then take the frequency number of the corresponding probability statement as belief value. In general, Salmon claims, constructing a SR-explanation is useful because the set of probability statements which an explanation contains constitutes an adequate basis for assigning rational belief values to sentences of the form "*x* has property G" and "*x* does not have property G" (*x* is an element of D for which there is no observational evidence that allows us to decide between G and not-G). Salmon calls the belief values we obtain this way *rational* because they are based on a homogeneous partition of D. In his view, making a rational decision requires rational belief values.

The function of SE-explaining I have described in 3.2-3.5 and the function Salmon attributes to constructing SR-explanations are based on the same intuition: by constructing explanations, it is possible to change our epistemic state in such a way that our subsequent decisions become more rational. The most crucial differences between Salmon's elaboration of this idea and mine are:

(1) Contrary to Salmon, I regard explanations as arguments (my definition of "E_α-scientific argument" may be seen as my explicatum of "epistemic explanation"). I do not have to claim that an explanation contains more than one probability statement because the indirect practical effect of SE-explaining is mediated by an increase of the individual's primary scientific knowledge.

(2) I have taken into account the cost of information; by identifying rational belief values with belief values based on a homogeneous partition, Salmon neglects the fact that using a non-homogeneous partition may be more rational (because much cheaper) than using a homogeneous partition.

4. *The indirect practical function of other types of explaining*

I have established that SE-explaining has an indirect practical function. I think that non-epistemic types of explaining (causal, functional, rational) also have indirect practical functions, and that the nature of these functions can be specified in a way that is similar to the one followed in section 3. I will use causal explaining to clarify my view.

To define SE-explaining, I introduced the concept "E_α-scientific argument", which may be regarded as my explicatum of "epistemic explanation". In the definition of "E_α-scientific argument", the structural conditions of (ARG) are combined with epistemological conditions in which is referred to epistemic statuses. In order to specify the indirect practical function of causal explaining, we have to develop an explicatum of "causal explanation" which has the same characteristics, i.e. an explicatum that combines structural conditions with requirements about epistemic statuses. Let's consider the following proposal:

(CE) A causal explanation is a list of statements about singular causal relations between the members of a set of explanans events and an explanandum event; these statements must have a specific epistemic status indicating that they have been derived from general causal statements (statements about causal capacities) which are backed up by statistical evidence.

On this definition, constructing a causal explanation sometimes requires an enlargement of the number of general causal statements to which the individual can assign the status indicating that the statement is backed up by statistical evidence. Such an enlargement can influence the subsequent decisions of the individual: the outcome of step 1 of (SK) depends on the general causal beliefs of the decision maker.

5. *Concluding Remarks*

The search for explanations has a theoretical direct function (understanding) and several practical direct functions (e.g. diagnosis). These direct functions of explaining were not discussed in this paper. Instead I have shown that SE-explaining has an indirect practical function, and suggested that other types of explaining have similar functions. In this final section I will discuss two questions that are raised by my claim (IPF), viz. (1) does the indirect practical function of SE-explaining make this activity worthwhile irrespective of other potential (practical or theoretical) benefits, and (2) can SE-explaining lead to more rational $b(c_j \mid a\&k_i)$'s?

With respect to the first question two positions can be taken. The first position is that we must not construct and solve SEE-problems unless we want epistemic understanding of an event or this activity has some direct practical use. The second position is that SE-explaining is worthwhile even if there are no direct (theoretical or practical) benefits.

One can defend the first position by means of the following argument. Most SEE-problems can be solved without enlarging the individual's primary scientific knowledge; so the effect described in (L_1) occurs only in a few cases. The same holds for the effect described in (L_3), because the SFPM-method is hardly used and because most of the probability models we acquire by SE-explaining never become relevant for making a decision. As a consequence, situations in which a decision making individual benefits from a probability model he has acquired by means of SE-explaining, are rare. Therefore, the indirect practical function of SE-explaining is not strong enough to justify the efforts we have to make in order to construct and solve a SEE-problem. However, if a person constructs and solves a SEE-problem in order to understand a phenomenon or to make a diagnosis, and this activity improves one of his subsequent decisions, this is a valuable side-effect.

The second position can be defended by inverting the argument for the first position: one claims that only a few SEE-problems can be solved without enlargement of primary scientific knowledge, that the SFPM-method is frequently used, etc.

Can SE-explaining cause an individual to choose more rational values for the $b(c_j \mid a\&k_i)$'s? Yes, but there is an additional restriction. Since a and k_i are always causes of c_j, the quality of the $b(c_j \mid a\&k_i)$'s can only improve if there is an enlargement of primary scientific knowledge which increases the number of *causal* probability models in the individual's potential explanatory knowledge (the distinctive feature of causal probability models is that the properties of the antecedent family are causally relevant for the properties in the consequens family).

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NOTES

1. See E. Weber (1993) for an account of how phenomenological laws can be used to solve SEE-problems.
2. Derivability of probability statements from phenomenological laws is extensively discussed in E. Weber (1993).

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