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The problem of causality, determinism, and mind and brain are discussed, and new solutions are offered. To begin, a pragmatic structuralism is assumed, asserting the functional equivalence of mind and brain activity. A problem-solving model of mind-brain activity is defined, employing the mathematical theory of probablistic automata. With this model it can be determined whether mind-brain activity is deterministic. This is accomplished if an adequate definition of strict causality is developed. Logical models of strict causality which define the causal relation in terms of "material implication" or "strict implication" are rejected. Causal relativity is assumed, and certain system-theoretical assumptions are made with respect to the problem-solving model of mind-brain activity. Thus, strict causal structures are deterministic if the etiologic relation "↛" is representable by a function which is (1) irreflexive, (2) transitive, (3) asymmetric, and (4) temporally ordered. The representing function must be one-one or many-one, and "↛" must be relativated to a model, L, and a domain, D. The results are, the representing functions of the models are not one-one or many-one, and thus mind-brain activity is indeterministic. But to avoid the result that mind-brain systems are chaotic in their behavior, the problem-solving model of mind-brain activity is given a game-theoretical interpretation.

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INTRODUCTION

The problems of causality, determinism, and mind and brain have occupied philosophers from the beginning of philosophical enquiry. This paper examines the activity of mind-brain systems and whether the activities of these systems are ordered by strict causal structures; thus, whether they are deterministic or indeterministic. It is argued that a solution to this problem requires a model of strict causality and a solution to the mind-brain problem which is methodologically practical.

Many so-called solutions have been advanced to the mind-brain problem (*e.g.* the identity of the material with the mental, various mind-brain dualisms, etc.) which are no longer plausible since they are open to a number of serious objections, among them the following:

> The Beethoven symphony to which I am at the moment listening is not in one sense reducible to the mechanics of the score, nor of the recording, receiver, amplifier, and speaker system which is emitting it; nor is it completely described by the contortions set up in my auditory apparatus by the describable wave patterns impinging on my ears. All these and more are components – but something more than this constitutes the symphony. This something more is not mystical. Musicians call it structure (Pribram, 1969).

We must reach a similar conclusion with regard to the mind-brain problem; *i.e.,* neither mental, phenomenal, or psychological descriptions on the one hand, nor material or physical descriptions on the other, are adequate to describe, for example, intelligence, memory, and imagination. Thus, a structural pragmatism is adopted. As Eddington (1959) pointed out, a structural pragmatism is a method which allows us to describe a structure without making a commitment to the material or the mental. Further, structural pragmatism takes the difficult, but practical, approach that what is true about mind-brain activity must be established at each level (brain-activity and mind-activity), and that only then is such a structure valid (Pribram, 1969). Now, the following thesis of *Functional Equivalence* is adopted: The activity of the mind (perception, memory, imagination, language, etc.) is functionally equivalent to the activity of the brain.

To begin, therefore, the structure of mind-brain activity is defined as a problem-solving model. This is accomplished by employing the mathematical theory of finite probablistic automata. Once the structure of mind-brain activity is formally defined, we are able to determine whether the representing functions of the models fulfill certain requirements of strict causality, and thus whether mind-brain systems are indeterministic. But this, in turn, depends on finding a satisfactory definition of strict causality, a task to which we now turn.

THE CONCEPT OF STRICT CAUSALITY

Hume emphasized that the most important features of causality are contiguity, constant conjunction, and succession in time (Dormotor, 1972). Dormotor (1972) pointed out the two most important questions with regard to the problem of causality. *Q1:* In a causal relationship, what are the entities usually referred to as causes and effects? *Q2:* With respect to the causal relation or causal operator which is either attributed to or associated with the causal entities, what kind of relation, operator, or something else is it?

For the purpose of *Q1*, we begin with certain entities called events, the exact nature of which does not matter now, but which will be determined later. Thus, for now what is important is that they belong to a set υ which is non-empty and fixed.

For the purposes of *Q2* (Dormotor, 1972), the most natural steps to be taken are the following: (a) The causal relation is a binary relation, $\nrightarrow$ defined on υ. (b) The causal operator φ is a mapping $\upsilon \rightarrow \upsilon$ with certain properties. (c) T is a fixed set of time instances structured by a before-after time ordering relation $\langle$, or if equality of time instances is included, then $\leqslant$ is substituted for $\langle$. (d) For an event $A \epsilon \upsilon$, then A is a mapping from the time-set into the event-set $A: T \rightarrow \upsilon$. (e) Step (d) does not make it clear whether an event does or does not occur, since it is merely a description. Thus, the predicate *occurrence* is introduced denoted by $\Vdash$; *e.g.*, A occurs at time t is denoted by $\Vdash_t A$. (f) The desirable properties of $\nrightarrow$ and φ, and the semantics controlling the correctness of these properties are the following:

(1) $-A \nrightarrow A$ (irreflexivity);
(2) $A \nrightarrow B \rightarrow -(B \nrightarrow A)$ (asymmetry);
(3) $A \nrightarrow B \;\&\; B \nrightarrow C \rightarrow A \nrightarrow C$ (transitivity); and
(4) $As \nrightarrow Bt \rightarrow s \langle t$ (time order).

Logical Models of Strict Causality

In this section some examples of logical models of causality are examined. In answer to *Q1*, the logical view holds (Dormotor, 1972) that the set υ is a collection of well-formed formulas of a specific language. The answer to *Q2*, however, has been more difficult.

Burks (1951) proposed the following definition of the causal relation: $A \nrightarrow B =_{df} \Box (A \rightarrow B)$ where $\Box$, is an "empirical" or "physical" necessity operator, and where $A, B \epsilon \upsilon$. But as Dormotor (1972) showed, tautologies (*e.g.* $A \rightarrow A$) lead to undesirable causal statements. And, formulas such as $A \nrightarrow (A \nrightarrow B)$ if $A \nrightarrow B$, are true but have no empirical significance.

Czervinski (1960) attempted a perhaps more-realistic approach in defining the causal relation as: $A \nrightarrow B =_{df} (x), s(\Vdash sAx \rightarrow (\exists y), t(s \langle t) \;\&\; \Vdash tBy)$. This says that an event, A, causes an other event, B, precisely when for an arbitrary object, x, if the associated A occurs at time s, then there will exist a later time, t, and perhaps another object, y, such that the associated B will also occur. But simple counter examples (Dormotor, 1972) arise, *e.g.*, if $\Vdash tBy$ means that a person, y, will die at time t, then $A \nrightarrow B$ is true when the time of death of y is substituted.

Other logical models of causality have also been defined, but as Dormotor (1972) showed, these models also lead to similar undesirable consequences.

System-Theoretical Definition of Strict Causality

The problems that arise with the logical models of strict causality primarily result from defining causal structures as a universal relation, defined in terms of "strict implication" or "material implication." Causal relativity is, therefore, assumed. To accomplish this, a model is defined for the system to be examined making the following assumptions (system-theoretical): (a) A linguistic representational system (set-theoretic model) is an isomorphic or homomorphic system, mapping empirical structures (STR^e) into set-theoretical structures (STR^t): $STR^e \rightarrow STR^t$, context or model L; and the axiomatization expresses the invariant (causal) interdependencies. (b) Any representational linguistic system, which is a model of a theory has a domain of empirical reference, D. (c) Context- or theory-dependency and reference to a certain domain constitutes the context or theory-relativity of all invariant relations. (d) Structures consist of systems (S^e, R^e), where $S^e = S^e_1, S^e_2, \ldots, S^e_n$ and $R^e = R^e_1, R^e_2, \ldots, R^e_m$. (e) For the purpose of *Q1*, any change in a system is defined by a system event A, b, . . . , Z, occurring at a certain timepoint. (f) The relations in any system are characterized by system events and relations obtained (or functions) can be either one-one or many-one functions (*e.g.*, $y = F(x)$), or one-many or many-many statistical functions (relations, *e.g.*, $E(y/x = \alpha + Bx + \epsilon$. (g) Among the static or dynamic empirical structures are invariantly re-occurring empirical structures or systems events, if they belong to hierarchically independent systems, *i.e.* etiological systems (Leinfellner, unpublished manuscript, Invariance and causality) (Invariance Thesis).

It is clear that strict-causally invariant structures are deterministic in the strict sense (Leinfellner, unpublished) if the etiologic relation "↛" is representable by a function which is (1) irreflexive, (2) transitive, (3) asymmetric, (4) temporally ordered, and if (5) the representing function is one-one or many-one, and (6) "↛" is relativated to L (a model) and D (an empirical domain).

MIND-BRAIN SYSTEMS AND CAUSAL STRUCTURES

The mathematical theory of finite-probablistic-automata (FPA) is employed to define models of mind-brain activity. These models fulfill the system-theoretical assumptions made in the previous section. Nevertheless, objections may be raised to application of models from the field of artificial intelligence to that of natural intelligence. For example, Dreyfus (1972) set out the following objections: (a) such models do not account for phenomenal evidence, (b) they do not reflect the way people perform, and (c) they are *ad hoc*, lacking generality. But with respect to (a), phenomenal evidence is accounted for by assuming a pragmatic structuralism. Secondly, with respect to (b), as Pylyshyn (1974) points out, "There is no simple and obvious relation between level of performance and fidelity of simulation." Finally, with respect to (c), this is a relative matter. In this paper the attempt is made to define the most general processes in mind-brain organization, and although the models to be defined are not completely satisfactory, this by no means invalidates the approach.

Now it is hypothesized that the most important characteristic of mind-brain activity is its problem-solving ability. Problem-solving is defined (Leinfellner, unpublished manuscript, Invariance and causality) as the termination of a conflict. A conflict consists of open alternatives $A_1, A_2, \ldots, A_n$. Alternatives are events, situations, opinions, hypotheses, and ideologies. The termination of a conflict is accomplished by selecting one, or more than one, or a mixture of the alternatives, $A_1, A_2, \ldots, A_n$. The solution is obtained by application of criteria (*e.g.*, evaluations, values, estimations, etc.) either one criterion (one-dimensional criterion) or multi-dimensional criteria. This ability to solve problems has been shown to be characteristic of brain activity (Pribram, 1971; Schank, 1979), and is called intelligence.

Further, it is hypothesized that fundamental to the problem-solving ability of mind-brain systems is representation, *i.e.*, the representation of one process by another process. This fits well with recent research in brain physiology (*e.g.*, Pribram, 1971) where convincing evidence is found that the process of representation is fundamental to brain organization. Moreover, this fits well with the view that language is crucial to problem-solving, and that language itself is a representational system. In order, therefore, to define a problem-solving model of mind-brain activity, a computational method is defined for representation of one process by another.

The physiological function of the neuron is specified as the empirical domain of the problem-solving model to be defined. Thus to begin, a model of the physiological function of the neuron is defined, based on established hypotheses: *i.e.* (7) The primary function of the neuron is spike-generation; and (8) There is a random or unpredictable element acting in the spike-generation process. Moore, Perkel, and Segundo (1966) showed that (7) and (8) are well-established. They presented numerous studies showing that spike-generation occurs when the membrane potential exceeds a threshold. Further, Moore *et al.* (1966) found with regard to (8) that the random element acting in spike-generation was the result of internal and/or extrinsic processes of the neuron. In support of (a), there are well-known and empirically established "noisy" processes of cellular function. For example, Fatt and Katz (1952) provided a theoretical justification of the fluctuations in membrane potential attributable to thermal agitation, and the probablistic character of neuronal excitability was shown by numerous studies (Moore *et al.*, 1966). Deterministic expressions of the intrinsic spike-generation process, with the random aspect introduced by the random character of the input arriving at the neuron characterize (b). Models of this have been investigated recently by Harvey (1978).

Furthermore, there is a theoretical justification for (8); that is, by drawing a distinction between two types of probability, *i.e.*, reducible probabilities (*e.g.*, a fair coin has the probability of 0.5 of coming up heads, but each individual event of tossing a coin is either "yes" or "no" with regard to its coming up heads) and irreducible probabilities which are not reducible in a "yes" or "no" manner (Leinfellner, unpublished manuscript, Invariance and causality). Arbib (1972) came to a similar conclusion:

> The most widely received interpretation of quantum mechanics takes this one step further by claiming that there are certain probabilities that are not resolvable even by making arbitrarily fine measurements and that, in some sense, the action of the universe is inherently stochastic. . . .
>
> Many psychologists have studied learning tasks under the heading "stochastic learning theory" in a way which suggests the brain has two states—"task learned" and "task unlearned"—with nothing but random transitions to tie behavior together. Of course, the actual learning process in the real brain proceeds by numerous subtle changes—it is only the output which forces a binary value, masking the neural continuum. This is like the above situation in quantum mechanics, where the state of a system is now described by a function which contains information about the probability distribution of results of measurement. . . . In coming to describe the activity of the brain, we will have to evolve state-descriptions as alien to present-day psychological jargon as the

> quantum state is to the classical position and velocity description of Newtonian physics. Of course, Newtonian mechanics is perfectly adequate for a wide range of phenomena, and so may be much of conventional psychology, but as our powers of observation become more sophisticated, so must the inadequacies of the classical approach become more apparent.

In short, we assume that based both on empirical and theoretical grounds, there is a random or unpredictable element (*i.e.*, an irreducible probability) acting in the spike-generation process of neurons which a model of the physiological function of the neuron, to be adequate, must incorporate.

We are now able to define a model of neuron activity. This model incorporates the features of the McCullock-Pitts model (*in* Arbib, 1964), with the addition of a random element acting in the spike-generation process. The model employed here is taken from Arbib (1964), generalized to an FPA using the method of Suppes (1969), and incorporates a threshold (Lewis and Coates, 1967).

Definition 1: The model of neuron activity is a structure $N = \langle I, O, S; p, d \rangle$, if and only if,

(i) I is a finite set such that

(a) for each i_j in I, i_j there is a set of m inputs $x_1, x_2, \ldots, x_n$

(b) for each x_i in i_j there is an associated weight w_i, *i.e.*, for inputs $x_1, x_2, \ldots, x_m$ there are weights $w_1, w_2, \ldots, w_m$;

(ii) O is a finite set (the set of outputs);

(iii) S is a finite set (the set of internal states);

(iv) p is a function on the Cartesian product S X I such that for each s_i in S, and i_j in I, P_{si} is a probability density over S, *i.e.*.

(a) for each s_j in S, $P_{si}(s_j) \geqslant 0$

(b) $\Sigma\ s_j \epsilon S,\ p_{si}(s_j) = 1$;

(v) d is a function of the Cartesian product S X I such that for each s_i in S and i_j in I, d_{si} is a probability density over O, but if there is a threshold θ, there are two possibilities, *i.e.*,

(a) if $\sum_{j=1}^{n} w_j x_j \geqslant \theta$, then

(1) for each o_j in O, $d_{si}(o_j) \geqslant 0$

(2) $\Sigma o_j \epsilon O,\ d_{si}(o_j) = 1$, or

(b) if $\sum_{j=1}^{n} w_j x_j < \theta$, then

(1) for each o_j in O, $d_{si}(o_j) = 0$

(2) $\Sigma o_j \epsilon O,\ d_{si}(o_j) = 0$.

Further, N works on a discrete time scale, so that if at time t it is in state s_j and receives a set of input i_j (*i.e.*, $x_1, x_2, \ldots, x_n$ with associated weights $w_1, w_2, \ldots, w_m$), then at time t + 1 the probability that it has changed to state $p(s_j, i_j)$ is $P_{si}(s_j)$ and the probability that it emits output $d(s_j, i_j)$ is $d_{si}(o_j)$.

Mind-brain activity, however, is also characterized by, *e.g.*, memory, imagination, and language. Pribram (1971) showed that fundamental to these mind-brain processes, from a brain physiological point of view, is the process of representation. Thus, if a network of formally defined neurons (FPAN) is a representation network, it can be defined as an FPA. That is, let the FPAN net M have m FPANs, n input lines, and r output lines. The input of the net is known when it is known which of the input lines are on and which are off. The state of the net is known at a time, t, if it is known which of the FPANs are firing and which are not firing at time t. Thus Q denotes the set of states, $\triangle$ denotes the set of inputs, and Ω denotes the set of outputs of the net M. The firing of an FPAN of M at time t + 1 is probablisticaly determined by the firing pattern of the FPAN's inputs at time t, and thus is a probablistic result of the state and input of the whole net M at time t. Therefore, a representing network of FPANs is generalized to a representation automaton (FPAR). The model is taken from Knouth (1968) (who considered the problem of how the equivalence between algorithms may be established), and generalized to an FPA by the method of Suppes (1969).

Definition 2: The model of a computational process for systems of FPANs is a structure $R = \langle Q, \triangle, \Omega; f \rangle$, if and only if,

(i) Q is a finite set (the set of internal states);

(ii) $\triangle$ is a finite set (the set of inputs) such that $\triangle \subset Q$;

(iii) Ω is a finite set (the set of outputs) such that $\Omega \subset Q$;

(iv) f is a function on the Cartesian product Q X Q such that for each q_i in Q, f_q is a probability density over Q, *i.e.*,

(a) for each q_j in Q, $f_q(q_j) \geqslant 0$

(b) $\Sigma q_j \epsilon Q$, $f_q(q_j) = 1$ and such that

(c) f leaves Ω set-wise fixed.

Further, R works on a discrete time-scale, so that if at time t it is in state q_j, then at time t + 1 the probability it is in state q_i is f_q such that it leaves Ω set-wise fixed.

Now as Knouth (1968) pointed out, if (i) - (iv) are fulfilled, then process $C_2 = \langle Q_2, \triangle_2, \Omega_2; f_2 \rangle$ represents $C_1 = \langle Q_1, \triangle_1, \Omega_1; f_1 \rangle$ if there are functions (statistical in this case): g from $\triangle_1$ into $\triangle_2$; h from Q_1 into Q_2 taking Ω_2 into Ω_1; and j from Q_2 into L (where L is a language).

Moreover, as pointed out earlier, if we are to have an adequate model of mind-brain activity, it should be a problem-solving model. It was hypothesized that the process of representation is fundamental to problem-solving. The importance of language, memory, imagination, and perception to the problem-solving activity of mind-brain systems is obvious from the above definition of problem-solving. Thus, a model of problem-solving of mind-brain systems should be defined such that representational systems are incorporated (*e.g.*, memory, language, imagination, etc.). This is fulfilled by a system of FPARs generalized to a problem-solving automaton (FPAP). An FPAP is regarded as a "black box" which can accept any of a finite number of internal states and which can emit any of a finite number of outputs. These requirements are expressed mathematically by a model (Arbib, 1964), generalized to an FPA by the method of Suppes (1969).

Definition 3: The model of mind-brain activity is a structure $P = \langle \chi, \Sigma, Z; \varsigma, \omega \rangle$, if and only if,

(i) χ is a finite set (the set of inputs);

(ii) Σ is a finite set (the set of outputs);

(iii) Z is a finite set (the set of internal states);

(iv) ς is a function of the Cartesian product χ X Z such that for each z_i in Z and i_j in χ, ς_{zi} is a probability density over A, *i.e.*,

(a) for each z_j in Z, $\varsigma_{zi}(z_j) \geqslant 0$

(b) $\Sigma z_j \epsilon Z$, $\varsigma_{zi}(z_j) = 1$;

(v) ω is a function on the Cartesian product χ X Z such that for each z_i in Z and i_j in χ, ω_{zi} is a probability density over Σ, *i.e.*,

(a) for each o_j in Σ, $\omega_{zi}(o_j) \geqslant 0$

(b) $\Sigma\ o_j \epsilon \Sigma$, $\omega_{zi}(o_j) = 1$.

Further, P works on a discrete time-scale, so that if at time t it is in state z_j and receives an input i_j, then at time t + 1 the probability that it has changed to state $\varsigma(z_j, i_j)$ is $\varsigma_{zi}(z_j)$ and the probability that it emits output $\omega(z_j, i_j)$ is $\omega_{zi}(o_j)$.

We can now easily show that FPAP is an indeterministic system. The representing functions of N = $\langle$I, O, S; p, d$\rangle$ are defined as one-many or many-many statistical functions on both empirical and theoretical grounds. This, of course, violates (5) and thus we conclude that the etiologic relation "$\nrightarrow$" is not a causal structure in the strict sense in such systems. Therefore, FPANs are indeterministic in their function. Further, the representing functions of R = $\langle Q, \triangle, \Omega; f \rangle$ are defined as one-many or many-many statistical functions, since FPANs are indeterministic systems. Thus (5) is violated, and hence FPAR is an indeterministic system. For similar reasons, the representing functions of $P = \langle \chi, \Sigma, Z; \varsigma, \omega \rangle$ are defined as statistical functions, violating (5), and thus FPAP is an indeterministic system.

STABLE PROBLEM-SOLVING SYSTEMS

In the preceding section, FPAPs were found to function indeterministicly. But if FPAPs function indeterministicly, this may result in certain undesirable consequences; *e.g.*, the behavior of such systems may be chaotic. Thus, an interpretation is required which is both empirically grounded and avoids this undesirable consequence.

If the model $P = \langle \chi, \Sigma, Z; \varsigma, \omega \rangle$ is interpreted game-theoretically, it avoids the consequence that mind-brain systems (FPAPs) are chaotic in their behavior. But what are the empirical grounds for this interpretation? One line of evidence comes from social biology. It is now widely known that a majority of genes (*e.g., see* Dawkins, 1976; Lorenz, 1966) are rule or behaviorally oriented; *i.e.*, they predispose individuals to certain strategy mixtures. Another line of evidence comes from behavioral psychology, where it is established that individuals acquire new strategy mixtures with regard to their environment (*e.g., see* Skinner, 1974).

Using the method of Köhler (1974), I shall attempt to show that $P = \langle \chi, \Sigma, Z; \varsigma, \omega \rangle$ can be interpreted as defining a stable system of FPARs. In order to accomplish this, it is shown that certain notions of game-theory correlate with $P = \langle \chi, \Sigma, Z; \varsigma, \omega \rangle$.

We begin with a set of external states G_m^t which are relevant to the behavior of all FPARs in the system FPAP at time t, where m is the number of such states. It is assumed that there is at least a partial memory of relevant past-behavior or output of all FPARs in the system, so that this information is either directly or indirectly obtainable by any FPAR in the system. Now we let I_n be the set of n FPARs and Y_i be the strategy set of the i^{th} FPAR. The strategy set includes all possible outputs that an FPAR might emit given the various external states of the set G_m^t. The strategy set of the individual FPARs is determined either genetically or by interaction (learning) with the external states G_m^t. But it is obvious that the strategy sets of FPARs cannot consist only of *pure* strategies, but must also consist of *mixed* strategies. For example, consider an FPAR which is a perceptual system or a memory system; if the strategy set of such an FPAR consisted only of pure strategies, *e.g.,* a pure strategy instructing such systems to accept or retain all information, then strategies such as these would of course lead to a "break-down" of the system as a whole. Thus, strategy sets of FPARs must contain mixed strategies. The set of probabilities describing the output of FPAR i is called a strategy mixture, designated by r_i^t which is a function of external state G_m at a time t. This can be stated more formally as: r_i^t is the m x n strategy mixtures at time t, *viz.* a probability for each FPAR; and external state k for each strategy $y_i \epsilon Y$ such that:

$$r^t m\,(y_i) \geqslant 0 \text{ and } r^t\,(y_i) = 1.$$

Now the state of the FPAR in which we are interested is the strategy mixture of its output; the input which guides the output is the state $Y_i\ G_m$ at that time. It is assumed that G_m is the same for all FPARs of the system, and thus that all FPARs act on the same information about external states. Thus, since the external state G_m is taken as the input for the system as a whole, it corresponds to χ. The internal state of the whole system is taken as the n-tuple of all n FPAR strategy mixtures at a time, t, *viz.* $\langle r_1^t, r_2^t, \ldots, r_n^t \rangle$. The set of n-tuples, therefore, corresponds to the set Z.

But to interpret the set Σ requires an additional concept of game-theory, *i.e.,* stability of a system (in this case a problem-solving system). This is defined formally as follows: F is the set of stable strategy mixtures and has the following property:

$$r_i^t \epsilon F \leftrightarrow {}_{df} (\exists t')\,(t'')\,(t'' \rangle\, t' \rightarrow p^{t''}(r^t) = 1).$$

With this concept we can say that the set Σ corresponds to the set F of stable strategy mixtures.

We are left with representation functions ς and ω which require interpretation. But to accomplish this, another concept of game-theory must be defined; that is, an important descriptive property of problem-solving systems whose behavior has a certain minimal stability. This stability is such that all FPARs have certain fixed strategy mixtures genetically determined. It is assumed that the individual FPARs, depending on their genetic predispositions, begin their activity predisposed to certain strategy mixtures. These mixtures are then changed to new mixtures according to information received and according to other predispositions. Formally this is stated: p_i^t is the m x n transition probabilities from the Cartesian product G_m^t X r_i^t to r_i^{t+1}.

The individual probability functions p_i^t do not correspond directly to the representation function ς because the latter yields probabilities of the internal states of the FPAP, whereas the former is a probability function only of an individual FPAR's internal state. What is needed is a probability of the n-tuple of strategy mixtures which is the internal state of the system (this is what is needed to interpret ς). Therefore, a new probability function, D_i^t, is introduced, which is determined by the p_i's, and is a function of $\langle r_1^t, r_2^t, \ldots, r_n^t \rangle$. The set of these D_i functions corresponds to the domain of the representation function ς, and thus for every n-tuple of strategy mixtures which holds for the system at a time, t, and for every state, there is a uniquely determined $D_i^t \langle r_1^{t+1}, r_2^{t+1}, \ldots, r_n^{t+1} \rangle$.

Only ω is left to be interpreted, so we specify a function H_i^t which is determined by the individual FPAR probability functions p_i, and is a function of $\langle r_1^t, r_2^t, \ldots, r_n^t \rangle$. This H_i^t function is the same as D_i^t function except that the H_i^t is restricted by property, *viz.* $r_i^t \,\epsilon\, \mathbf{F} \leftrightarrow {}_{df} (\exists t')\,(t'')\,(t'' \rangle\, t' \rightarrow p^{t''}(\mathbf{r}_i^t) = 1)$. Thus, H_i functions correspond ω.

CONCLUSIONS

My conclusions are first that mind-brain activity defined as a finite probablistic automaton and given a game-theoretical interpretation is a new solution to the mind-brain problem. This model is general enough to incorporate the concepts of *feedback* and *feedforward* (Pribram, 1971; Arbib, 1964). With these concepts of feedback and feedforward, it can be shown that mind-brain systems can evaluate, and with the addition of a memory system, mind-brain systems can evaluate with respect to time (Schank, 1979). Moreover, it can also be shown that statistical decision-making can be defined in this model of mind-brain activity, but that this does not exclude the inclusion of deterministic decision-making or logics since such logical systems are special cases of individual decision-making.

Secondly, logical models of strict causal structures are inadequate. Strict causal structures obtain in a system, only if "$\nleftrightarrow$" is relativated to a model L where an empirical domain is specified and where the functions of L fulfill certain requirements (system-theoretical assumptions). In the three models defined the representation functions violated (5), and thus it followed that the etiologic relation "$\nrightarrow$" defined for mind-brain systems is not causal in the strict sense, but is a causal structure, nonetheless, because it fulfills Hume's concept of causality formally stated by Dormotor (1972) and defined by Suppes (1970), *viz.*, $As \nleftrightarrow Bt =_{df} s \rangle t \;\&\; P(Bt/As) \rangle P(Bt)$. That says that an event A at a time s causes an event at a time t is equal by definition to s is before t and the probability of Bt given As is greater than the probability Bt alone. But Suppes (1970) proved using the standard probability theory and the above definition, that (3) is violated.

Finally, determinism was defined in terms of strict causality, but the representing functions defined in our model of the problem-solving activity of mind-brain systems violate (5); therefore, mind-brain activity functions indeterministicly. This is, of course, relevant to the free-will and determinism issue. Nevertheless, although indeterminism is essential to free actions and choices, it is not sufficient, since there may be coercion from outside the system.

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