Nonlinear Dynamics in the Life and Social Sciences
W. Sulis and I. Trofimova (Eds.)
IOS Press, 2001

Universals and Specifics in Psychology

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1. In search of appropriate measurement: universal headaches

1.1. Baby-psychology tries adult's clothing.

An understanding of the specifics of psychological phenomena, on the one hand, and of the universal aspects between these characteristics and phenomena in other sciences, on the other hand, provide important steps towards the unification of the natural and social sciences. Philosophy and mathematics give both universal and useful concepts to any science and help reduce the range of significant empirical characteristics to a more compact set of parameters and principles. Psychology is no exception, and during its short history, it modestly attempted to adapt the methods of measurement and observation from the natural sciences.

Immediately after its birth as an official science, psychology (as would any child) started to test tools and elements of the language that «adults» (or more mature sciences, such as math, physics and chemistry) used at that time. The final years of the 19^{th} century and the first half of the twentieth century were very productive for the generation of all kinds of <u>differential equations,</u> and an attractive word «psychophysics» was coined to define a discipline that promised to find a formal presentation for all psychological phenomena. Psychophysics started from the idea of a measurement of a subjective distance between two or more sensations and sought to write down a function that would describe the dynamics of sensation.

Regarding the compactness of description, a short functional expression was meant to replace a long verbal description of the changes in various psychological states and would allow the modelling of the psyche by analogy with the modelling of the dynamics of physical systems. The early application of the differential equations of classical physics, which considers more or less deterministic systems, to psychological systems gave rise to at least one useful discovery: that the states of a psychological system are too fuzzy and cannot be exactly localized using coordinates (parameters, variables).

We can approach a person at the same time of day, with the same instruction, the same motivation and the same family situation; and we can ask this person to assess absolutely neutral things, such as the changes in size of a circle, or a change in colour or the identity of two lines. We shall try to find a point, at least for this subject, where his/her internal presentation of the world detects a difference between two of the simplest stimuli. We shall not be able to do even this simple thing, because there will not be a point-value in this person's assessment. Instead, it will be a range of values, described by an S-like function: for extreme values, when it is obvious, the subject will give us a very certain answer; for intermediate values, the answers will vary, and can be described only with probability function. We thus face **headache N 1** in measurement, which is similar to a situation in quantum mechanics: *a state of a psychological system is not described by a point in a function, but by a range of values.* To deal with the «fuzziness» of measurements, psychologists started to apply probability theory and statistics.

Probability distribution functions are used now mostly in psychophysics, but we can certainly call the psychology of the second half of the twentieth century «statistical». Modern statistics allows one to operate on lower scale levels - nominal and ordinal, and it seemed that they are ideal for the measurement of psychological phenomena. Scientists just needed to choose the right set of parameters and to learn what was connected with what. What was connected with what? Gee, it was a wrong question to ask: everything appeared to be connected with everything. Psychological journals and psychological science itself started to expand exponentially by careful and not very careful studies of «what was connected with what». It appeared that a statistical language was not just insufficiently compact for the description of phenomena, but made matters even much worse and fuzzy in comparison with old-fashioned empirical descriptions.

Problems with statistical methods demonstrated the universal **headache N 2** in measurement: *all of these methods are one-dimensional measurements*, while the measured object can change along with several parameters simultaneously.

New hope appeared with the introduction of factor and cluster analysis: it was still a method of linear functions, but it helped to fight with the excesses in numbers of variables, decreasing the number` of dimensions in which psychological phenomena were described. It divided all possible variables into groups (factors, clusters) of those which are interconnected between each other more than between the others. The number of dimensions could be controlled now. It seemed that mathematical «tricks» helped one to see the invisible global structure of the investigated objects.

Then researchers started to admit that sometimes «bunches» of interconnected variables within each of these factors showed a strange (if not absurd) combination. A researcher was required to use all available creativity to find a name for each of these combinations and to interpret the global picture, resulting in a set of such factors. But this was not the worst problem. Factor analysis demonstrated another **headache, N 3**, which was lying within the traditional methodology of measurement: *factors should be orthogonal and independent, presenting dimensions analogous with Cartesian coordinates*. Independence of the resulting factors was a criterion of their quality and allowed one to use them as a set of scales. If these scales were not orthogonal, the value of one of them would be dependent upon the values of the others - and so could not be a measurement device in the standard presentation. (The main way to control the independence of a variable from all others was the use of a large sample, which can «randomize» extra influences).

On the other hand, this independence was very hard to achieve, because in natural systems, it almost does not exist. Various properties of an observing object and its environment appear to be connected sooner or later. Nothing is wrong with that, except scales should be allowed to interact, and still serve as a measurement device. The situation required invariant solutions, similar to the high energy physics using combined scales (such as time-space, entropy-temperature), but a larger quantity of them.

Development of the analysis of variance seemed to solve this problem. MANOVA and its relatives could give us measurements by several parameters, and show an interaction between them. It certainly avoided the one-dimensionality of many statistical methods but did not escape **headache N 4:** it still *operated with linear functions*, just as the majority of other statistical methods. In natural systems such linearity is a rather exclusive case, holding over a very small range of values. Most natural systems, including psychological systems, taken in a natural environment with natural interactions, demonstrate nonlinear dynamics in their functioning.

The reasons why we keep applying linear methods are: 1) there are some regions of values where dependencies are more or less linear or could be transformed into linear functions; 2) for stochastic behavior of psychological systems with the number of dimensions (parameters) higher than 10, a linear approximation, Fourier analysis or power spectrum calculation gives the same results as do sophisticated nonlinear methods. Approximation, however, does not give the details of the interaction between parameters, and a picture of «how the mind works» remains unclear.

1.2. Nonlinear path: following physics and math

In a case in which the data do not fit a linear function, but could be described with a curvilinear function, scientists apply several methods that help them to identify the function that best describes the curve (fitting data to curve) and by this means to present relations between the variables used. After a function has been found, they test its "goodness-of-fit" to their data using nonlinear estimation techniques. If the curve is monotonous (continuously decreasing or increasing), we can transform variables to, for example, logarithmic functions and then apply the usual linear statistical methods to these new variables.

In this sense such a «nonlinear» method, as, for example, a polynomial regression, is linear in nature: the regression equation, having terms with the power more than 1 could be transformed into linear logarithmic or exponential equations. If we add two solutions of these functions, we receive another solution. Such nice "arithmetic" behaviour is a sign of linearity.

Nonlinearity becomes truly nonlinear when the addition of two solutions of an equation is not a valid solution, that breaks linear arithmetic of interval relations and requires special treatment. Methods of nonlinear dynamics, developed originally in physics and chemistry gradually were coming to the life sciences, that have had the same problems with statistics as psychology has had. The number of publications using some kind of nonlinear methodology increased about three-fold during the last 10 years (Fig.1.) and reached a level of 1,939 publications in the year 2000. In addition to that, publications on chaos theory and its applications to psychology reached 883 in the year 2000.

The overview of all publications on chaos and nonlinearity in psychology gives us the following major groups:

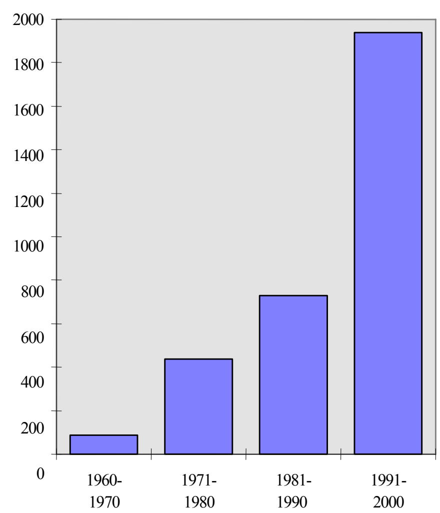
1. Publications which use just metaphorical conceptions of nonlinear dynamics, for example, sensitivity to initial conditions, chaos, phase spaces and attractors related to some psychological dynamics. Such types of analogies are especially popular in clinical, developmental and organizational psychology.
2. Publications that described fitting polynomial curves, for example, nonlinear regression equations (least squares method) [1] or «structural» equations [43], which operate with a set of linear equations as well. The former method allows calculating an interaction between variables and «nonlinear effects», that are basically various types of nonlinear estimation (curve fitting again).

A weakness of these methods is too big a trust in the integrity of the variables. If a psychologist would like to describe an observation formally, the traditional way is to assign numbers to various states of a system (observations), and thus to create a scale for measurements. As soon as we have numbers in our hands, it is very easy to forget the conditionality of these numbers, as well as intervals between them. Relations between the states of a psychological (or any living system) are not so stable as the relations between numbers, so some operations with numbers do not correspond to relations between the corresponding states (mathematicians would say that our labels do not constitute morphisms).

For example, after exposure to some «middle» range of loudness of an auditory signal, we attribute larger intervals to the increase/decrease in loudness with smaller and smaller differences in this signal. We can easily lose 500$ on some risky activity and be OK with this loss if it was expected, yet could get depressed spending an extra few cents per litre at a gas station as we were not ready for that. Mathematically well behaved traditional scaling does not show equality in its intervals in human responses. When you are rushing somewhere, you feel like your body is moving too slow because for you the time flies too fast. When you are sitting in a boring social meeting, the time moves too slow, and you count how many useful things you could be doing during the time of this meeting. It leads to the **headache N 5:** *mathematically equal and fixed intervals on the scales*, that measure various sensations, attitudes or success rates in learning, *are not equal and are not stable in subjective reports*. That is why in many cases of measurement in psychology only nominal scales (of the form «subject is upset or not») or ordinal scales (for example, when the subject can indicate what makes him upset more, or less) work, without achieving an interval and ratio level of scaling.

More unpleasant is **headache N 6**: *dependent variables have regions in which they do and do not have a dependency upon other variables, areas where they do not have any value or have more than one stable value* in response to an independent variable. We have complications because we attempt to measure a changing world, in which nothing is truly stable, and any structures which we attempt to measure or to utilize for measurement can change, disappear, or merge with other structures. Worse, these structures often require different levels of description. Also, the search for a direct causality (what variable has an impact on what), popular in structural equation methods, usually does not give us much information, because such a causality does not exist in natural systems. If two processes or characteristics are connected, they influence each other via mutual feedback and in this sense have cooperative, synergetic relations.

Fig. 1. Number of publications in psychology using nonlinear methods



3. Publications dealing with the structural stability of parameters in multi-dimensional cases: applications of catastrophe theory, nonlinear estimation for existing dimensionality, including polynomial and nonlinear regression calculations for catastrophe models and dimensions. Technically these publications are of the "curve-fitting" approach too, only in a multi-dimensional space. They present nonlinear relations between more than two parameters and the existence of several possible states of dependent variables in response to certain states of the independent variables. Catastrophe theory (based on Poincare's topological theory of particularities) numerically expressed such an effect as a hysteresis, inertia in switching from one set of values (responses of the dependent variables) to another. Hysteresis was found in perception, attention, motivation, social interaction, etc. and appears to be a popular dynamical pattern in psychological systems. Mathematicians (for example, [41], [48], [56]) were the first to show some examples of this effect in psychology, which finally convinced psychologists to look for bifurcation

structure between parameters. Guastello has an expanded overview of this topic as well as an introduction for psychologists to the main concepts of nonlinear phenomena [18].

4. Publications in time series analysis, dealing with the global dynamics of a system, such as periodic orbits or chaotic shifts from one to another set of states:
   - ♦ reconstruction of phase space and attractors, as certain stable "orbits" of sequential states of a system, related to certain values of an independent variable. This is popular in neuropsychology, examining the processes of cortical activation in brain activity (for example, [39]; [60].
   - ♦ finding unstable periodic orbits that are a sign of chaos (for example, [11], [44]);
   - ♦ polynomial models for the logistic map's bifurcation structures (for example, [18]);
   - ♦ calculation of Lyapunov's exponent that allows one to measure how much spreading occurs in a system's dynamics (expansion rate) and the degree of its dependence on initial conditions (for example, [12], [35];
   - ♦ a measure of topological entropy, introduced in ergodic theory a century ago: breaking the phase space of a system into blocks and checking for their relations to each other [19];
   - ♦ analysis of exceptional events;
   - ♦ complexity measures, such as entropy rates or algorithmic complexity: what is the least number of algorithms (states, programs, rules, etc.) or the amount of information necessary to produce the same data that we received in the experiment [29], [34].

Are these methods of nonlinear dynamics sufficient to study psychological phenomena? Basically no, though possible sometimes but only during very short (in comparison with the lifetime of the system under study) periods of measurement. Dynamical systems methods were borrowed from physics, which operates with a concept of a state space, representing all possible states of the system. Physicists usually know in advance, where and what a system can be, so they can just map the orbits and rules of transitions of the system from state to state. Each state is described by a certain value in chosen parameters and potentially exists in calculating matrices. Researchers face the problems mentioned above with a large number of dimensions needed for the description of their system, and this is certainly true for biological or social systems. The worst problem, however, is not even this: the worst problem with the application of a traditional nonlinear dynamical systems approach to the life and social sciences is that natural systems DO NOT HAVE A STABLE STATE SPACE. That is **the biggest headache, N 7** in measurement: they develop, and they develop irreversibly, they lose some states, gain other states and never come back to the previous arrangement.

5. Publications dealing with simulations of nonlinear behaviour in psychological systems. The rest of this article will discuss its success and failure, but there are three interesting facts related to modelling in psychology:

1) the popularity of this topic among the other publications on nonlinear dynamics in psychology (Fig.2);
2) a poor presentation of models other than neural networks and AI types of models in psychology, and
3) although originally based on the visible architecture of a brain, this modelling now exists separate from the psychological sciences, and one finds more similarities and applications to engineering devices than to the study of psychological phenomena.

It seems that modelling in psychology appeared to be the most popular tool, associated with psychology, but existing models are not sufficient enough to do this.

1.3. Adult clothes are too small for the baby-psychology, or why modelling is popular

Why is it so complicated to describe the psychology of one person, using standard natural-sciences tools? One can say: «too many parameters». Suppose that we have a nice computer that allows us to control all factors and corresponding parameters, describing the linear, nonlinear and structural relationships in psychological phenomena. If we do not use our natural senses and if we are not told in advance what we are observing, we shall not be able to put all this parametrical information together. We need to know some patterns, knowledge and language in advance to be able to recognize the results of the measurement.

Pushing a key on a piano produces a certain frequency of the sound wave, which we could certainly measure with traditional scales. We could receive several such measures, including the sequence and duration of each note and formally present the melody, without hearing it. Will this complete our perception of music, or will we even recognize it? No, because music «works» on another, associative level of presentation, it operates in a certain psychological context and resonates with certain psychological patterns. Without this associative processing, our measurements don't provide music; we only register a set of sound waves. In the same way, situational context becomes a part of psychological regulation and experience in many other cases of measurements, when socio-cultural factors work as order parameters for physical behaviour, and, vice versa, physical capacities determine semantic perception [50-51, 53]. This multi-level integration is rather a law than exclusion in psychological processes.

In this sense, curve-fitting approaches, including catastrophe theory, are not sufficient. The internal integrity of living systems and their vital dependency on the environment make these approaches inefficient in the life and social sciences. It would be the same thing if we presented a 3-dimensional picture of a room in one-dimensional form, making a careful description of each point of the room. We can't "unfold" somehow our dynamical, multi-dimensional, multi-frame natural and social world, using some set of one-dimensional metrics and control it, by analogy with the mechanics of artificial devices.

Simulation is becoming popular in psychology because it provides a more compact and holistic presentation of psychological phenomena. Simulations allow the visualization of dynamical patterns and dynamical relations that are not obvious in the variables' unfolding. This makes simulation a powerful tool to measure qualitative effects if the model is based on the principles of organization of the natural system, and the qualitative effects of the model confirm a match with the behaviour of the real system.

Simulation can be an effective tool of measurement because it is a partial solution to the «observer problem». This problem arises every time we choose variables and scales of measurement, i.e. languages of description, rejecting other possible forms of description. In order to get a more valid description of an object, our measurement tools have to basically «run after» the objects and events that are happening with it. Simulation helps to restore the dynamics of an object and its environment if it uses correct principles. In this sense the ideal measurement tool is an "insider"-observer, or an object itself, measuring its own dynamics and still interacting with the world in its usual manner. It sounds, of course, too extreme, but it seems that nature invented such a

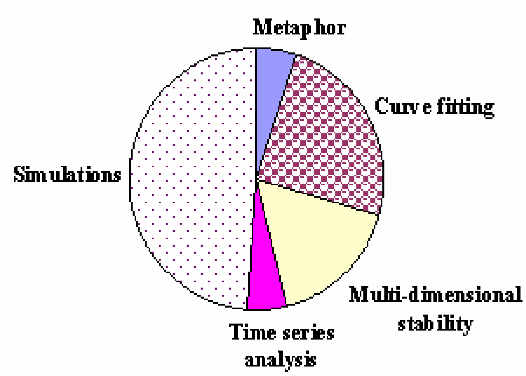


Fig 2. Type of publications on nonlinear dynamics in psychology

measurement device. Let's talk about it later, and now let's look at the models of cognitive sciences.

Mathematicians, physicists and computer scientists, enjoying popular literature about a nervous system with simple and understandable pictures decided to help psychology with formalisms. Neurophysiologists, being sure that they are doing psychology, accepted formalisms from natural scientists with pleasure, as it is too difficult to develop it without a mathematical background. As a result, we receive a Cognitive Science, which is rather a science of «how to apply programming to the neurophysiology» (i.e. a branch of computer sciences), than cognitive psychology. The majority of simulations were done with neural networks and knowledge-based, or artificial intelligence (AI) systems to simulate learning, recognition, assessment or decision-making processes (about a thousand of them, but I would recommend [3] for a review).

2. Cognitive science's version: mechanics of neuronal structures

The most basic principle of pre-psychological models «about» psychology is a population of many agents, having more or less simple rules of activity at each step of simulation (for example, neural networks, cellular automata, models of population dynamics, such as prey-predator, game theory models). While the rules for each of the agents are simple, more complex behaviour appears on the macro-level of the entire population. Multi-agent simulations first started in the work of Ulam, a colleague of Van Neumann, on cellular automata having a finite number of possible states and a table of rules for transitions between them, which depend on the states of neighbours [57]. This approach received much attention after John Conway created the cellular automaton "Life" [15], which was capable of producing propagating patterns, exhibited sensitivity to initial conditions and even phenomena of replication [9].

It appeared that while each agent of the population should have simple rules and simple behaviour, it is not so easy to choose what rules are better for the simulation of complex population dynamics. Cellular automata did capture the importance of local interactions, but globally these models have too rigid connections between elements to be able to demonstrate the dynamics of living systems.

Craig Reynolds used a more flexible population. He simulated the behavioural phenotype of flock movement, based on three main rules for each member of a flock: maintain a minimum distance from any object, maintain a speed similar to the neighbours, and maintain the direction to the centre of the flock. An artificial flock with such rules was able to pass obstacles, kept itself together and demonstrated very dynamical behaviour [38].

The most popular till recent time multi-agents simulations were neural networks (NN) which simulated exchange in a population of interconnected agents, receiving signals from each other, by analogy with neurons in our brain. A big advantage of NN was its parallel processing, which happened to be an obligatory property of living systems. A weakness of NN was a direct reproduction of the visible morphology of the nervous system, but an ignorance of the basic principles of its operation. Agents in NN are inter-connected and work as transmitters of a signal: they accept an input, send output, and inhibit each other using the same input-output arrangements.

First, a *neuron's activity is not one-directional input-output process*, by analogy with radio-devices, even when it comes to transmission of a signal from one cell to another. Any transmission is a mutual play for "sending" and "receiving" parties, and the transmission happens only if there is a mutual agreement between these neurons "to play in transmission", i.e. if the receiving party is chemically ready to release neurotransmitter from the vesicles, or if G-proteins cascades have enough resources to perform it. In many cases, there is no such agreement. Neurons often fire for nothing, as the other party does not want to open up its gates to receive it. An input becomes an input only when the neuron-receiver wants to receive it and is ready for it (otherwise neurotransmitters will not be released from vesicles to open the postsynaptic membrane).

It is often overlooked that the presence of this complicated chemical mechanism of transmission of a signal indicates that the role of neuronal activity is not to "transmit signals": after all, for that nature would use the same electrical conduit in synapses that it uses for the conduction of an impulse along a nerve. It would be much cleaner and faster, instead of complex G-protein-couple receptor mechanisms that can delay the transmission up to 3 days. The role of neuronal activity likely relates to synchronization of several levels of organization in the regulation of psychophysiological processes (including tuning the goal and cognition to the needs of the body), and also to the situational context. We believe that that "mutual agreement" mechanism that we see in synapses is universal in interactions within various biological and social systems. If we want to model these systems, therefore, any connection between two parties in our models should have some compatibility operators and algorithms.

Second, in reality, *neurons operate not individually, but in ensembles*, which Hebb called «assembles» [22], Anochin called functional systems [2], and Bernstein - units of action [7]. Every single act, whether it is perception, memorization, lifting a hand or pronouncing a word - every act has a team of neurons, sampled from various areas of the brain (visual, associative, motor, limbic). It means that an exchange of signals and mutual connections is happening between these diverse teams, and not between single neurons.

Another trick of a neuron's cooperation is that these teams or *functional systems change their recruitment* in the repeated performance of the same act: the functional diversity of agents inside a team remains the same, but there is a change in the «faces» of individual neurons. As Bernstein underlined in his neurophysiological studies of motion in the middle of the past century, no action repeats twice; it is always *constructed* anew on the basis of the current team for performance and the current level of control over action.

Fourth, and it is obvious from the previous points, neurons *have morphological and functional diversity*, while NN models have a very low diversity of agents.

The fifth point to mention here is that NN has a strong dependency on the local connectivity of its agents. It is understandable to see the excitement of physicists and mathematicians who look at the photos of real cells and brain structures and see them connected. It is understandable to see their trust in the concept of a «grandmother cell», meaning that we could always find the localization of our memories in concrete cells. In reality, our brain does not operate locally: an adult person has about 10^{10} cells, each having thousands of dendritic connections with other cells and sending axonal branches to thousands more, many of these at considerable distances. The white matter of the brain is solely made up of axons. In addition, neurons can communicate through neurohumoral factors with other neurons and, in fact, with other systems such as the immune and gut systems. It means that the *connectivity of neurons is very conditional*.

These properties of a neuron's activity contradict the connectionism of neural networks, but these properties make the real brain appear to be dramatically more adaptive and effective than models. Recognition of these facts led to the addition of complex features to neural networks during the past 20 years, such as: multi-layer structures (that made a model have a dynamics, similar to functional systems), various learning rules, nonlinear latent variables [14], coupled map lattices applied to the oscillation dynamics in artificial cells [DeMaris], backward propagation of error, cascade correlation for the approximation of nonlinear functions connecting inputs to outputs [49] (which compensate a lack of mutual agreement principle), time-delay arrangement [58], «associative reward penalty» algorithm for estimation performance gradient without back-propagating error information [6], Markovian signal movements between neurons, Poisson external signal arrivals in recurrent random neural network model [16].

Bernard Widrow and Rodney Winter suggested a large set of adaptive tools: linear combiner, with adaptive filters and adaptive threshold elements, adaptive signal modelling on the basis of statistical prediction, noise cancelling and nonlinear separability [59]. Gail Carpenter and Stephen Grossberg suggested formal analogues of ion exchange and even more adaptive «code reset property», responding to changing input patterns and optimizing nonlinear feedback interactions [10]. Walter Freeman and William Sulis provide a detailed criticism of NN models in this volume, and we will make just one more comment.

All these mathematical "extras" in models attempt to deal with the fact that it is not the morphology of the brain that makes our behaviour and cognition so effective and adaptive. Creatures having just one cell and not connected with anybody can demonstrate quite complex behaviour: hunting, avoidance, searching, aggression... It appears that there are some principles of dealing with dynamics and the diversity of the world that are more important than the morphology of the system. Morphology is a part of the operation of these principles and just one of many possible organizations. A mechanical presentation of a system («what part goes where») was popular at the beginning of human science and remains in the most «ancient» sciences - physics, math, chemistry. This mechanical, structures-oriented approach appeared on the other level of modelling in psychology as well.

3. AI version: knowledge-based systems

Modelling psychological phenomena promised all sorts of technological, economic, political, even strategic advantages, so while one group of specialists tried to understand these phenomena through simulating brain structures, another group went from the other end, simulating the very surface level of human psychology: decision making and problem-solving process. The basic elements of knowledge-operating systems were a block of memory with structured and labelled knowledge, classifications of labels, learning rules, such as rules of labelling or rules of their change and rules of decision making. These systems usually should be very logically organized to be able to operate. The major trick, of course, is to find an optimal structure and classification of knowledge, which will not be in contradiction with the structure of incoming information.

Among various systems of artificial intelligence (AI), machine learning and knowledge-based systems of the twentieth century, the biggest appreciation was given to the "Problem Solver", constructed by Samuel and Holland [42]. This model had a learning program, by analogy with natural selection and feedback, that could accumulate experience and find optimal solutions. It looked really intelligent and found numerous applications in engineering, medicine, geography, navigation, law practice, etc.

These models are superior in those cases where it is necessary to store and process a large amount of knowledge, which a human mind can not operate with during the short period of time. What these models could not do is to change and to choose the shape of the knowledge to be stored or used, to create a solution which is not in a list to choose from, to create an interpretation which is not in a knowledge base. These models operate only with units and algorithms that were put into it. In this sense, these models, in comparison with a human's productivity, were as productive and as flexible as large cars attached to a train, which are restrained to go only along certain railways, and only under the close supervision of humans. A huge amount of knowledge and its continuous accumulation though the learning algorithms did not make these models smarter than a calculator.

Sometimes it is useful to look at the subject that you model. Let's compare models with the real cognitive system.

4. Meanwhile, we have a misbehaving subject

4.1. Sensors

The subject of studies in psychology meanwhile didn't want to behave to facilitate our measurement. It showed properties that not only psychologists but also older scientists could not measure.

For example, every AI system begins from the input device, which is supposed to be as sensitive as possible to the incoming information.

The sensation is the only way for us to learn something from the world at the beginning of our life, and all consequent abstract knowledge that we produce is based on our previous sensory experience. Look at the range of human sensation (Table 1): as you see, it is very narrow – the majority of existing waves are not registered. Basically, we do not see the world, we are blind, deaf and cannot sense a large variation in temperature or mechanical impact.

Table 1. The range of human sensation

Physical processes	Wavelength	Frequency of oscillations, sec	Organ of perception	Sense
Mechanical waves	-	up to 1500	skin	touch
Sound waves	12-13	20 - 20000	internal ear	hearing
Electrical waves	0.004 - 0.1	$8*10^{14}$	skin	warm
Light waves	0.004 -0.008	$4*10^{14}$ - $8*10^{14}$	retina of eye	light, color

4.2. Acceptors of input

Perception, a process that "interprets" sensation for us, is supposed to give us an object-related knowledge of reality. It is a mistake, however, to consider perception as the "input" of an information process. We have illusions and wrong attitudes in every kind of perception. Remember that the moon on the horizon is larger than when it is up in the sky? Remember how many times you perceived the same object differently your knowledge about it has changed? If you are prepared to receive troubles or good news - remember, how difficult it is to perceive reality if it does not match expectations? Any undergraduate psychology student can give you a number of examples of perceptual illusions, but it is much harder to find out where we do not have them.

Perception does not give us «objective reality», it cheats us, trying to give us want we what, and not what it really is. People used to think that perception simply "copies" the world to our cognitive system, and thinking or imagination does the majority of creative work. It is paradoxical, but perception is the most creative of all cognitive processes (imagination is a product of perception). This fact first was pointed out by Leibnitz and then by Wundt, who used a special word for this active perception - apperception. Psychophysiologist P.Anohin called perception «afferent synthesis», based on motivation, memory and sensation, and later Neisser [31], Norman [33], Kahneman [23], Bruner [8], Stevens [45] proved that it is «creative synthesis» rather than the simple acceptance of information.

Every time that we perceive something, our perception generates several hypotheses, images, interpretations and one of them finally wins. This afferent synthesis is based on the number of motivations, number of memories and number of incoming stimuli for the construction and interpretation of an image. It operates with much more information than only memory, or only motivation do, so does much more creative work than any other psychological process. Context and experiential dependency (check the Fig.3), as well as grouping (gestalt) effects in perception provide additional complexity.

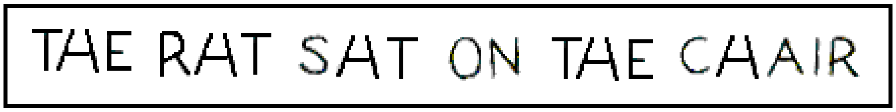


Fig.3. A Context Effect

In this example, the same pattern is recognized as an A or an H depending on its context.

4.3. Processing of information

OK, we can’t sense much, we perceive only heavens know what - maybe thinking is the key of our human potential, which gives us The Truth about reality? Some models in artificial intelligence indicate that a lot of people believe in it. An illusion, which is popular in the modelling of knowledge-based and other AI systems is that human thinking is effective because it uses reasoning and logic. It is true that sometimes people play with logical reasoning, but it is not a universal trait of human thinking. Cross-cultural studies show that the use of formal logic tends to be a uniquely western phenomenon that is highly related to the degree of formal education. Further, even in western culture, conclusions tend to be based more on empirical and experiential facts, illogical inferences, or communal knowledge. Daniel Kahneman and Amos Tversky [24] have identified a small number of heuristics that are the foundation for systematic thinking and guide the decision-making process but often mislead us into the wrong conclusion.

For example, most people evaluate the sequence TTTHHHTTT of outcomes from a coin toss as much too regular to be a random event, because we judge the likelihood of an event based on the prototypes and gestalts. Unfortunately, the probabilities and statistical outcomes are based on large sample sizes, while we are making judgments here that involve small sample sizes. Statistically, the indicated sequence has the same probability as say, THHTHTTHT. The same type of mistake in judgment lives in the majority of our social stereotypes.

The other heuristic is to make a decision on the basis of how easily examples come to mind. People judge frequency by assessing whether relevant examples can be easily retrieved from memory or whether this memory retrieval requires great effort. Because availability is generally correlated with the true, objective frequency of an event, the use of this heuristic usually leads to valid conclusions. However, since recent items are more available in our perception, we feel that they are more likely to occur than their real probabilities, and we overrate the highly familiar to us events regarding their likelihood, in comparison to less familiar events.

In addition to that our prior beliefs, background context of choice, the way in which the problem is worded (framed), and the degree of risk has a major impact on our decision making. The majority of adults do not use abstract reasoning very often, to the big disappointment of Piaget’s school. The reasoning usually goes not before a decision, but after, as in real life, we do not have time to «think things through» in every single case of decision making. We tend to «keep in mind» possible solutions for a problem, then choose whatever seems «not bad» and then, when we have time, to run our reasoning as rationalization, adjustment, evaluation of our solutions and other knowledge. This type of reasoning is rather «free fall», associating many fields of knowledge and producing some post hoc conclusions for future cases («I will never do it again», or «It was a nice move»), but when the time comes, we often tend to repeat our strategies, no matter whether they were successful or not, forgetting about our reasoning. In comparison with «super-intellectual» AI models, «a human is not a rational individual», as Hume noted at the 18^{th} century, or, by Baron, human decision making is "systematically irrational" [5].

4.4. Storage of information

The memory stores some statistics about events and give us a probabilistic picture of what an object is, and what to expect, so maybe knowledge about the probability of events and properties of objects gives us the power of the human mind? Computer metaphor, which was popular in cognitive psychology two decades ago calls memory «storage», by analogy with a computer disk: we can write something on it, and then retrieve it when we need it.

Expert systems and other knowledge-based systems (KBS) copied a principle of labelling during memorization: as soon as we label something in storage, it is easy to find later, using the labels. Usually, a KBS has a classificator of labels and improves it during the «learning» of the KBS. The first problem with labelling is that there is *multi-modality* of a stored unit, thanks to the holographic nature of memory. We are better able to use cues in recalling something if we act out the sentences, or imagine the words when we first hear them. When we memorize something, it always involves various aspects of an image: visual, sound or other properties, situational context, motivation and experiential dependency, as well as the relation to social values, language and technology. In this sense, the number of necessary labels exceeds the number of objects to remember and will explode any potential classificator. What saves our memory from the explosion is forgetting and recording.

KBS can «forget» too, with three possible causes of forgetting: encoding failure (so it never gets stored), storage failure (gone from storage) and retrieval failure (loss of labels). Forgetting in AI systems can be regulated, while we forget whether we intend it or not, and that makes KBS much more durable than human memory. Just a little problem left - the choice of what and how to forget in KBS. It appears that our forgetting is a game between at least three algorithms: the decay of knowledge with the passage of time, repression and interference with other items of memory, previously existent or acquired later. All three of them together or each of them separately can cause forgetting of every single item that we learn, and finally, we forget these items, if we are not reminded about it.

The other factor that helps to mess up our memory is a dynamics of labels, *re-coding,* re-grouping of elements of storage into the other code. When we learn something new, we re-label our previous knowledge. It is not obvious, however, that **even without incoming information memory storage tends to constantly re-organize itself**. It would be perfect if our memory would actually remember an event or an object exactly, so during re-organization it would not mix the labels. Unfortunately, our memory is not careful with the integrity of the units that it stores. Elizabeth Loftus, who did a series of experiments on false memories, showed a film to subjects, in which a *green* car drives past an accident scene. Subjects were asked a series of questions including "Did the *blue* car that drove past the accident have a ski rack on the roof?" Subjects then are asked to pick the colour of several items (including the car) out of a colour wheel, and they tended to pick a bluish-green colour [28]. In the study of Lampinen & Faries [26] subjects listened to a story about a guy named Jack who performs several activities, and then they were asked to indicate what kinds of actions were in the story. About 20% of the «recognized» actions were false statements, which might have taken place but were not in the story.

Our memory is an extremely lousy copier, remembering things that never happened and forgetting even basic facts that happened. Then the mistakes in our memory only multiply during the constant reconstruction of our knowledge and its re-labelling. Even during the recall, we don't mechanically «read information» from the "storage" - we reconstruct this information, sometimes adding non-existent details that we assume, in the most convenient form for us, on the basis of our current mood, motivation, competence, social situation, time of day and place, where recall happens. Cognitive psychologists like the sense of this phrase of Mark Twain: *«When I was younger I could remember anything, whether it happened or not»*. In fact, even a little portion of knowledge, whatever remains in our memory after forgetting, is not «objective knowledge», it is composed of fragmented tales about the reality that we constructed for our convenience to deal with this reality.

4.5. Language

We often ascribe the power of the human mind to cultural factors, saying that language as a communicative tool helps distribute information throughout the population, and it creates distributed processing. It is not obvious, however, that we do not use the same language when we think we do. The same words mean different things for each of us. During my 14 years of psycho-semantic studies of meaning area and structure of consciousness, I have never met two identical semantic spaces. Maybe I was unlucky?

The meaning of each word is based not on the definition from a dictionary, but on our personal history of our first introduction to this word, to the real situations and context in which we used it, our personal relations with other people who were around at this time. The perception of even neutral and abstract words appear to be connected with our temperament, age and gender [50], [51], [53]. It seems that the meaning area of each of us is as unique as fingerprints.

In this case, we should have problems with labelling objects and the exchange of information if we use an analogy with knowledge-based systems. It would be the same situation if one part of knowledge is written in English and another part in Japanese. Our system should have in this case a dictionary of each language being used, meaning that in the human case we should have as many languages as people exist.

Thus, what exactly is the power of the human mind, if our sensation is basically blind, perception is illusory and does not perceive reality, our thinking is systematically irrational, our communication attributes different meanings to the same words, and memory does not remember the majority of what is happening around us, or «makes up» questionable knowledge?

5. Nature's version, or universally forgotten properties

How did we manage to survive, being so (I did not say stupid) imperfect in our observation, and even managed to discover the physical laws of the micro and macro world? In spite of the popularity of the principle of distributed processing, there is an underestimation of its role in human cognition. The size of the distributed processor is not 10^{10} cells in one human brain; it is much larger. It is this number, multiplied by the number of people; but not 6 billion, larger - the number of peoples who live now and who have lived before. Our processor takes knowledge, accumulated by previous generations and uses languages - verbal, mathematical, pictorial, musical, symbolic, which serve as the keys to open the treasures of knowledge for us. Not a single individual, but a large number of them constantly generate and develop these languages, maintaining, losing, reconstructing and improving this knowledge in various cultural shapes.

Distributed processing, however, would not be so powerful without important principles of living systems, which are universally forgotten in the models of cognitive science, but namely, they make living systems so «smart». Let us list them in order of increasing importance, beginning from the easiest one:

◊ sociability limits on stochasticity of connections between elements;

◊ extra-productivity of cognition and developing state space;
◊ holographic processing;
◊ the diversity of elements, which is a basis of their functional differentiation;
◊ joint (team) activity of agents with establishing cooperation, based on the compatibility of their intentions.

5.1. Stochasticity and sociability

The main weakness of AI and machine learning models were that once they had learned something, they did not make mistakes, or they made mistakes different from those of a human. Real cognition is much more effective than AI models because it can afford to be fuzzy, to go outside of the limits of necessary activity, and it knows how far it can do it. We can afford to be imprecise in our recall or even lose memory, because future events will remind us of necessary details, and if not - there will be another attempt, maybe by somebody else. Our memory is fragile and «too creative» because in a complex and changeable environment, we should be able to constantly «renovate» our knowledge, to be adaptive and flexible.

Stochasticity can be considered as a consequence of a high diversity of connections and states. Stochastic activity is a reflection of the degrees of freedom of the system under study, and the degrees of freedom serve as a sign of the adaptivity of a system. It seems that stochastic events are universally important in life and social systems as well as in physical systems.

Recent AI and collective intelligence models use quasi-independent, stochastic agents, interacting locally among each other and with an active environment according to simple rules. Examples from living systems, such as ants, wasps, and bird communities demonstrate that such a design makes a system very adaptive and intelligent even in the absence of hierarchical organization. The phenomena of collective intelligence were carefully studied by William Sulis [46]. Application of stochasticity to cellular automata, such as cocktail party automata demonstrated that these automata are capable of identifying incoming patterns via synchronization of stochastic behaviour. William Sulis, who discovered this effect on various types of stochastic models named it Transient induced global response stabilization (TIGORS) [47].

There is however a factor which creates some structure in the stochastic interactions between agents: even when elements are allowed to potentially contact any point of any other element in the world, in each given moment of time they can contact only a limited portion of it. This factor we call «sociability», and it indicates a limit on how many contacts per given time step agents are allowed to hold, use or establish. In our EVS Compatibility (spin glass) model the structure of connections between elements is very dynamic and stochastic, constantly changing with fluctuations in local energy, but on the macro-level a second order phase transition is observed as a function of sociability.

We found that the sociability of the elements is a critical parameter governing the transition in cluster size behaviour, a transition from the existence of many small clusters in the population to the emergence of a system that unifies the majority of elements into one big cluster. We received the empirical formula for the critical point for this transition which was given as $\boldsymbol{S_c = P^{0.6}}$, where $\boldsymbol{P}$ is the population size, and $\boldsymbol{S_c}$ is the critical value of sociability, above which a population of diverse and stochastically interacting agents start to unify into a system. [54]. The ratio between the size of the population and the sociability could be a factor producing psychological phenomena related to the grouping of elements: the size of our short memory, the number of objects in our attention and perception, the number of people in spontaneously emerging groups, as well as factors facilitating totalitarian or individualistic tendencies in society.

It is important to know however that even if we know how many contacts a population overall will use to be unified into the system, stochasticity, or extra freedom for interactions is still more important for a system's emergence than sociability. If we put limits on stochasticity, a system might not emerge at all. In our other EVS models, we gave to our stochastically interacting population a number of possible connections sufficient to organize a system, but a system did not emerge. Only when this overall amount of connections was unlimited did we receive an emergence of big clusters that unified the population [55].

5.2. Extra-productivity, or many of everything

Natural cognitive systems generate many products of activity, which they choose from and use, in conjunction with their goal, state and other contextual issues. The effectiveness of our cognition is based on this principle, which we can call «many of everything»: during sensation we have many modalities for the presentation of a stimulus, during perception we generate many hypotheses about what we perceive. They compete and operate in our cognition much longer than we use to think; during thinking, we simultaneously play with many images, interpretations and solutions, during memorization or recall we use, again simultaneously, many labels and codes, often logically incompatible. Internal competition between several modes and products of our cognition can be compared with the same dynamics in physical systems. This competition and synergy between elements of our cognition were described in the synergetic approach by Haken [20], [21].

Another «many» is many attempts and many chances to do the same act: to perceive the same object, to solve the same problem, to recall the same fact, to express the same feeling, to understand the same word. Here is a nice place to recall Bernstein's studies on action construction again: we do not exactly repeat an action when we repeat it [7]. Every act is constructed anew, on the basis of the situation and available capacities. Even though Bernstein did his work on physical actions, this conception is true in cognition as well. Modern studies of Walter Freeman demonstrate that the images of memory are not "stored and retrieved" as in computer systems, but are freshly created with each presentation. The construction of each pattern is guided by a chaotic attractor, which was formed during learning. Perceptions are triggered by stimuli, but they are shaped by connectivity patterns that were laid down during the past learning, and by neural messages from the limbic system that modulate the attractor landscapes of the sensory cortices [13].

An additional «many» appears because of the death of agents. Limitation of life's duration by genes appeared only recently in evolution. Trees, for example, can live almost forever if environmental factors wouldn't damage them. It's only in animals the mechanism of programmed death emerged. Animals are forced to die but also are being produced in more variety and capacities than plants. As soon as genes and culture emerged in evolution to hold useful information through generations, nature became free to try even «more of everything»: more variety of perceptions and hypotheses, more experiences and memories, more motivations, more dimensions for holographic pictures, updating products of its natural measurement. If the agents of a distributed processor were to remain the same, the structure of knowledge would be more stable, but that is not what nature wants. Nature does not want a stable structure of knowledge about a quickly changing world. It wants a quickly changing structure of knowledge about a changing world. Life expectancy is designed now to let agents spend some time on the processing of some part of the available information, making their comments, producing other agents and transferring some knowledge to them. Then special proteins in our body say: "that's it, thank you, darling, it's time to retire", and speed up the ageing process.

All of these «many-s» create a huge and changing state space for our cognitive system.

5.3. Developing state space

Our cognition is more successful than AI models, because it is not so ordered as these models, and the development of each individual constantly changes the space of possible solutions. AI is more successful than humans only where this space in limited (for example, in playing chess, or the selection of the best trajectory among many), and it takes advantage of immediate access to its knowledge, while humans do not have this access.

How old are you? The answer is different every half year, it never returns to previous points, and can't be predicted for sure, as we do not know how long we shall live. This simple, but crucial age factor determines our motivation, cognitive and learning abilities, needs in achievements and social interaction. In biology, the same factor determines key physiological processes. This factor is not compatible with the notion of stable state space. Another incompatible factor - contextual and environmental dependency in life and social systems, makes these systems highly adaptive. As the space of all possible contexts and environments (which our systems under study «consume into themselves») is not finite, a potential state space of such systems is endless. In this case, a repeating orbit of a system, travelling through the same set of states differs from the previous orbit. We can count them identical only during a very short period of time. Attractor reconstruction, following this dynamic could «recalculate» the coordinates of the system in the developing state space and would give us a fuzzier, «moving» set of orbits, than in classical physics.

The irreversible development of each individual contributes to the state space of the groups, which are in contact with him, and the development of the groups contributes to a state space of the population. With a growing number of individuals, our distributed processor is getting «smarter» every day; it is getting more experience, more solutions, more ways to label and present knowledge.

5.4. Holographic presentation

Multi-agents, multi-connections, multi-product and multi-attempts give to us what Jack Cohen and Ian Stewart call «extelligence» [45]: the possibility to not store information in one place, «packing» all knowledge about this huge world into our little head but reconstructing this knowledge whenever we need it. Construction of the physical location of objects gives us the phenomena of cognitive maps, construction of social interactions gives us the phenomena of consciousness. We process our internal information outside our body because we use language and knowledge, generated in society and transformed into our individual internal form. The social nature of our cognition, however, is not only an origin of languages and past knowledge. It also appears as a dependency of cognition on personal relations with other people, that has an impact on our solutions, perception and memorization. Each human being is designed to carry out a social life, as he can locate himself only receiving feedback from many others.

We see some object and have an opinion about it. Then we hear somebody else's opinion and compare it with ours. Then we receive an opinion of another person and compare them both. In this sense, we have a spatially distributed system, but also a temporally distributed system and contextually distributed system, based on a variety of situations, motivations, social estimations, individual and social experiences. All of these factors and the diversity of appearance provide a multidimensional space of presentation and processing of knowledge, by analogy with holography.

More precise holographic effects were observed by Karl Pribram in the activity of neurons. He suggested a holographic hypothesis of brain processing thirty years ago [36], which was later transformed into his holonomic brain theory [37] and which described brain function concerning a complex spectral representation. He showed that the processing of all exteroceptive sensations, including those dependent on spatiotemporal configurations (such as the shapes of surfaces and forms) could be understood as amplitude modulations of these oscillations. In the case of surfaces and forms, this aspect is described by spatial frequencies of oscillation, and due to the Fourier transformation, spectra enfold the ordinary conception of both space and time. Optimization in perception is achieved by the ensemble calculation of Fourier coefficients, which becomes palpable as an optical hologram. When coefficients of identical value are connected as in a contour map, the resulting schema is what in the holonomic brain theory is called a «holoscape», a cell ensemble, composed of vertically oriented dendritic spine-produced polarization dipoles embedded in horizontal dendritic polarization fields. The contours forming such a holoscape are embodied in the microprocess of polarizations occurring in dendritic networks, thus constituting a sub- and transneuronal manifold.

5.5. Diversity of agents and functional differentiation

Development of processing agents and a processor produces a large number of cognitive products, which allow a system to oscillate between the use of one or another, and make a system very flexible and adaptive. A variety of these products, produced by a distributed processor would be impossible without a diversity of agents and connections.

A real diversity of units in our distributed processor, be it cells, individuals or cultures cannot be compared with the diversity of agents of popular models, such as perceptrons or other multi-layer systems [40], [30]. Our EVS (Ensembles with Variable Structures) models have so far considered up to 256 types of agents in population, but this is still far from the real diversity [54].

The real diversity of units is connected with the fact that all of these units are alive, i.e. open and dissipative systems, producing and passing a flow of some resource though themselves. These units interact and establish connections not because some kind of God-processor forces them to do it but because they have their individual needs, associated with the exchange of a resource. Particularities in dealing with the resource flow can lead to particularities in interaction with other agents. On a big scale, this shows up as functional differentiation and the diversity of behavioural strategies. This fact we used in our models [52], and we discuss it in the companion article in this volume.

An obvious fact is that no living system is constructed from identical elements, and the diversity of elements within a system follows certain rules. As to the processing of information and the regulation of our behaviour, we should remember that the functional systems that control it are supported by a variety of neurons. Not only sensory and associative neurons participate in our perception, but motor neurons, and neurons from the limbic system as well. The same is true for decision making or memorization: we use all of our body, and not only our heads in cognition. Our studies demonstrate a phenomenon of «projection through capacities»: when a person registers only those aspects of objects or a situation, that he/she can properly react to and deal with according to the capacities inherent in the body and behaviour [51, 53].

Thus we process knowledge by functional groups, presented by both parties - executive and sensory systems. These functional systems are created to achieve some goal, but more precisely - some goal unifies various agents to work synchronically or coordinate activity. It sounds similar to economics and social processes, but it seems to be a general principle for all natural systems. Bernstein and Anochin, during the middle of the twentieth century, showed how on the psychophysiological level a goal of activity determines, what team of cells will proceed it, i.e. determines who will constitute a functional system [2, 7].

Existing models can assign to their agents a goal of activity in a certain problem space, but a variety of these goals is not sufficient, and functional groups are not diverse. That does not allow these models to simulate a sense of interaction between agents, semantic information and its processing. Functional systems have an analogy in human society as well, such as a team of workers with various qualification. Such functional systems on the cellular level, individuals as a set of functional systems, and functional groups of individuals in society create a net of subprocessors. It is reasonable to expect stochastic dynamics in this diverse, developing state space and holographical processing of information.

5.6. Cooperation in «playing a product», based on selfish agents

Cognitive scientists from both multi-agents and AI modelling proudly follow a principle «encoding - integration - decoding», related to the process of information in our nervous system. It is necessary to remember, however, that coding activity is not the major goal of living agents, that is why there are so many "mistakes" in animal's cognition in comparison with artificial systems. A dominant principle of natural observers is "to be included" into the relations with various natural phenomena, such as, for example, competition for resources and participation in its exchange.

A stochastic interaction in natural systems is based on a random search for a contact, but not every search results in contact. Stochasticity appears in the living nature of agents and their needs, which orders the degree of their compatibility during contact and determines whether they will «play a function» together, or find another party. If their needs are compatible, they synchronize their activity and produce some action. If their needs are incompatible, as in the majority of cases, they do not establish cooperation, meaning that after checking for a possible connection, they do not continue. On the cellular level, we have a lot of «empty» firing in the community of our brain, on the level of individuals we can meet hundreds of people or their products every day, but we continue interacting only with a small number of them. The majority of our interactive stochastic activity does not bring to us establish contacts.

The ensemble-like activity of neurons, "playing an action" as a team or, in Anokhin's terms, forming a functional system, has an analogy in human cooperation, as well as in the activity of organizations and states. Each "agent" (be it neuron or a social unit) keeps its own interest and goal during such an activity, but as soon as the goals of various agents match, they synchronize their behaviour.

6. Natural measurement device, or specifics of psychology

As was mentioned before, our sensation does not bring us much information about anything around except a very narrow spectrum of waves. During our perceptual processing of this information, language and culture enable us to label specific sensations and to combine them into bigger, semantic blocks. Then we operate by these blocks and invent more and more useful and effective arrangements for our labels. The nature of sensation still remains the same: during our interaction with the world, we get external information in a wave form. No wonder that modern psychophysics actively uses Fourier analysis and any mathematics, dealing with wave equations. During sensation the brain uses its own Fourier and holographic analysis of incoming waves, rejecting those that are not expected. Our perception reconstructs a part of these incoming sensory patterns as attractors, corresponding to a phase space of an object, rejecting the majority of other sensory information and assigning labels to the final products of perception[1]. Such a

[1] Nicolis and Tsuda showed that a very small percentage of “captured” environmental stimuli work as initial conditions for an attractor’s reconstruction and defines solutions of the perceiving dynamics [32]. These solutions make the external world collapse into a set of stable, complementary, and mutually exclusive eigenfunctions or *«categories»*.

reconstruction of an image goes on the basis of previous knowledge about the dynamics of this object and environment, and on the basis of motivation, which orders what part of the object to look at.

In Pribram's holonomic brain theory, both the input and inherent patterns provide initial conditions such that the polarization pattern path of the match between them is probabilistic, with a change in the probability amplitude weighting functions of Gabor coefficients representing synapto-dendritic polarizations.[2]

Our memory does not forget as quickly as we think. It accumulates probability distributions of events or properties, even those that are insignificant and rare. Our intelligence uses these distributions and chooses the most frequent event or properties to approximate and predict the future. Our attention uses these probability distributions from memory and picks up the most rare, extreme events, to control the degrees of freedom of our actions. That is why we say that all cognitive processes - sensation, perception, problem-solving, memory activity - work together, simultaneously, they are not separated devices, as it is in a computer. They are rather different algorithms, methods of processing joint sensory information.

An idea about natural systems as computational systems is becoming popular [27], and we can add to it an idea about natural measurement devices, with an included observer, that nature invented. We live our lives, and at the same time, we serve as insider-observers of our own regulation, with the use of all sorts of language and measures. During only 300-400 years, during just a few generations, our science grew up from a hobby of individuals into a powerful observational system, and we sort of located nature's own measurement and observer's device in our culture. Registering the tempo of development of this observational system, this insider-observer, this natural measurement device is doing very well[3]. It is no wonder that all kinds of engineers and mathematicians tried to model the design of this sophisticated device, but the science, which studies it directly, we call psychology.

Let us understand, however, that it is not the sophisticated mathematics of an individual brain that gives power to human cognition - that is just a subject for neurophysiology. Otherwise, a single person would be able to discover all known laws and invent all existing devices. Cooperation with other members of society and the impact of culture is not just a parallel distributed processing of knowledge. Every element of our joint observational system is a little observer as well, transferring, mapping the world outside into its internal structures, different from such an internal mapping of other elements. Every element creates an internal presentation of the world, developing during one's bodily activity, and «sitting» in this body. This presentation is a form of a constant internal modelling of the world, a disposition to find in the world certain characteristics (that Wundt called «apperception» more than a century ago), and the abilities to check it out and sometimes to use it in the regulation of own activity[4].

Each of us is designed to hold a certain «position of the observer», producing on the macro-level of society a holographic, multi-view presentation of knowledge and processing

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[2] Pribram presented such a dynamics in terms of the amount of uncertainty (amount of structure in the initial conditions) and the amount of residual uncertainty (the result of uncertainty reduction by virtue of the matching procedure), reciprocals of one another and corresponding entropy. These concepts are borrowed from thermodynamics and probability theory, but it only indicates that these are universal principles in the dynamics of natural systems, even such a complex system as cognition.

[3] We can't call this observer consciousness, because 1) it is not about self-observing, it is about observing a world, and 2) consciousness alone could not operate without a body and its activity, without a language which culture gives to an individual and without social relations that «shape» an observer's position. We better call it anticipative reflection, a property that allows to any life or social system estimate, predict and model the world.

[4] The idea about internal presentation of a world is quite old: Augustinus Sanctus (354 - 430) already pointed out this reflection in «scio me scire» (I know that I know), and Descartes' (1596 - 1650) famous phrase «cogito ergo sum» means the same: I can have doubts in anything, but if I think then I exist.

it simultaneously with others in many forms and directions. Holding this certain position means that we are designed not to see the positions of other people, as they see it, we are designed not to be objective. It means that we are designed to make mistakes.

We would not achieve the efficiency of a natural observer without extra-productivity in each stage of processing and holographic principle of processing, without a diversity of elements and their functional differentiation, without a developing state space and the stochasticity of connections between elements, based on an exchange of resource and mutual agreement on establishing cooperation under some sociability limits. Each of these principles could be found in many biological and social sciences, so we should admit their universality in psychology as well. The specifics of psychology are to study how all of them are unified together, producing remarkable effects on our behaviour and cognition. The subject of psychology (from this point of view) can be defined as the study of the social, subjective and neurophysiological mechanisms of operation of that natural measurement device and observer.

Doesn't this monster subject attract you for studying and modeling it?

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