Neurobiology and Decision Making: An Intriguing Rendezvous?

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Key Words: *Decision making; neurobiological modeling.*

Abstract. *We focus on aspects of the neurobiological approach to modeling human decision making. We outline three differential equations, which comprise the heart of the method and give an example how they have been used in a neural network, modeling emotional reactions and reflex conditioning. An economic – psychological experiment serves as an example how the approach can perform and what it can contribute to our understanding of decision making processes. We conclude with a discussion about the interesting implications arising from the new approach.*

Introduction

Traditionally, studies in decision making have been associated mainly with Expected Utility Theory, with a more recent shift of attention to Behavioral Economics. In this paper we popularize a less known approach, the *neurobiological modeling* of the decision maker. It has little in common with the former two as it rests on an entirely different set of concepts and first principles. Three separate sciences – biophysics, neurophysiology, and psychology contribute to this interdisciplinary method of studying human decision making. Initially the area was not connected to decision studies, as its original goal was to devise postulates to guide research of the human brain. The latter would, at least in terms of structure and functions, eventually be described in a way similar to the technical specification of an electronic computer. In the middle of the 20th century that prospect looked enticing as the difficulties before it were little known. It turned out that the brain was unimaginably more complex than expected, and the early attempts at axiomatizing its operation (McCulloch & Pitts, 1943, 1947) could not deliver success (Lettvin, Maturana, McCulloch, & Pitts, 1959). These authors drew the scientific community's attention to the need for a radically new type of models for understanding neurobiology. Thus, the area of neural networks was born as a set of tools to model complex interconnected parts of brain tissue. Later this research gained huge momentum due to Stephen Grossberg – a psychologist with doctorate in mathematics. Like McCulloch and Pitts, Grossberg initially studied simple neural interactions involving just a few neurons. Having clarified operating mechanisms in the small scale, he described them mathematically and continued with ever more complex interactions. Grossberg's scientific achievement is that he travelled the entire way from a single synapse interaction through short-term and long-term memory mechanisms, image recognition, emotion generation, conditioning, to end up with complex cognitive-emotional interactions. Because the brain operates in continuous time, he chose to model these psychological mechanisms with differential equations. In recent times his ideas were successfully implemented to understand aspects of human thinking in decision making, and economic choices in particular.

In this paper we briefly review the tenets of the neurobiological approach and provide an example of a neural network capable of explaining „macro" behaviour. This is the Recurrent Associative Gated Dipole (READ), which models reflex conditioning with opposite emotions of the type fear – relief, hunger – satiation, which in humans can also be as sophisticated as consumer satisfaction and disappointment. Then we sketch how that approach and the particular neural network have been used in an economic – psychological experiment. We conclude with a discussion about some interesting implications arising from the new approach.

Tenets of the Neurobiological Method

The neurobiological approach is based on three elements: neural activity, neurotransmitters, and local memory, each described with a differential equation. First among them is the classical Hodgkin-Huxley membrane equation of a single neuron's activity. We cite it in a form typically used in gated dipoles (Grossberg, 1972)

$$(1)\ \frac{dx_i}{dt} = -A_1 x_i + (A_2 - x_i) J_i^+ - (x_i + A_3) J_i^- .$$

Here x_i is the bioelectric activity of the i-th neuron ($i = 1,\ldots,M$), that is, the signal it sends to other neurons; J_i^+ and J_i^- are sums of excitatory and inhibitory signals that other neurons send to the i-th; A_1, A_2, A_3 are real positive constants ($A_2 >> x_i$). All neuron equations in this paper are special cases of Eq. (1). Henceforth we use as synonyms the notions 'neuron activity', 'activation', 'neural signal', and denote them all by *x* with a subscript. In addition, all equations here are in dimensionless form, which is done for simplicity and helps avoid unresolved biophysical issues.

A neuron sends signal by emitting neurotansmitters – mediating molecules causing biochemical change in the receiving neuron. The next equation describes neurotransmitter depletion and regeneration in the sending neuron. Here, y_i is quantity of mediator, and B and C are constants

$$(2)\ \frac{dy_i}{dt} = B(1-y_i) - C.x_i y_i\ .$$

Finally, some signals get remembered, i.e., get coded in a memory element z_{ij}, whose biophysical substrate is the synapse between two communicating neurons, say, i and j. By z_{ij} we denote a dimensionless variable $z_{ij} \in [0,1]$ with initial value zero (meaning no learning has happened). A signal x_k, sent to neuron i by neuron k, is remembered only after a lasting biochemical change in a connection z_{ij} between i and j has occurred:

$$(3)\quad \frac{dz_{ij}}{dt} = x_i(-D_1 z_{ij} + D_2 x_k)\ .$$

Constants B, C, D_1, D_2 in Eqs. (2) – (3) are real positive. Grossberg has implemented variations of these three equations to build his gated dipole neural networks, capable of accounting for emotions and reflex conditioning.

Gated Dipole

The gated dipole was introduced by Grossberg (Grossberg, 1972) to explain complex temporal processes in conditioning and perception. Its main feature is the opponent processing whereby disappearance or unexpected absence of a positive (negative) reinforcer can cause negative (positive) emotion. The gated dipole has been modified to serve different purposes. Applications include, among others, modeling Pavlovian conditioning (Grossberg & Schmajuk, 1987), motor control (Gaudiano & Grossberg, 1991), vision (Öğmen & Gagne, 1990; Öğmen, 1992), decision making (Grossberg & Gutowski, 1987), and consumer decision making in particular (Leven & Levine, 1996; Mengov, Egbert, Pulov, & Georgiev, 2008).

In the experiment described in the next Section we adapted the recurrent associative gated dipole (READ) equations to account for consumer behaviour. In particular, in an economic choice situation, when a customer of a specified service had chosen between one of two suppliers A and B, and had expected to pay the sum P_a leva (price advertised), but at the end of the round, the final price was P_f, then a difference $\Delta P = P_a - P_f$ has occurred. In most cases, a saved amount ΔP^+ would provoke satisfaction; similarly, a surplus charge ΔP^- would be disappointing. However, a discount felt to be too small would also provoke disappointment, and an unexpectedly small surplus charge might cause slight satisfaction. The READ model we discuss here is capable of accounting for exactly those effects. Its adapted equations are:

$$(4)\quad \frac{dx_1}{dt} = -A.x_1 + P_a + \delta.\Delta P^+ + M.x_7$$

$$(4a)\quad \frac{dx_2}{dt} = -A.x_2 + P_a + \delta.\Delta P^- + M.x_8$$

$$(5)\quad \frac{dy_1}{dt} = B_1(1-y_1) - C_1 x_1 y_1$$

$$(5a)\quad \frac{dy_2}{dt} = B_2(1-y_2) - C_2 x_2 y_2$$

$$(6)\quad \frac{dx_3}{dt} = -A.x_3 + D.x_1 y_1$$

$$(6a)\quad \frac{dx_4}{dt} = -A.x_4 + D.x_2 y_2$$

$$(7)\quad \frac{dx_5}{dt} = -A.x_5 + (E - x_5)x_3 - (x_5 + E)x_4$$

$$(7a)\quad \frac{dx_6}{dt} = -A.x_6 + (E - x_6)x_4 - (x_6 + E)x_3$$

$$(8)\quad \frac{dx_7}{dt} = -A.x_7 + G[x_5]^+ + L(S_A.z_{7A} + S_B.z_{7B})$$

$$(8a)\quad \frac{dx_8}{dt} = -A.x_8 + G[x_6]^+ + L(S_A.z_{8A} + S_B.z_{8B})$$

$$(9)\quad \frac{dz_{7A}}{dt} = S_A(-K.z_{7A} + H[x_5]^+)$$

$$(9a)\quad \frac{dz_{7B}}{dt} = S_B(-K.z_{7B} + H[x_5]^+)$$

$$(9b)\quad \frac{dz_{8A}}{dt} = S_A(-K.z_{8A} + H[x_6]^+)$$

(9c) $\frac{dz_{8B}}{dt} = S_B(-K.z_{8B} + H[x_6]^+)$.

(10) $o_1 = [x_5]^+$

(10a) $o_2 = [x_6]^+$.

Here we only briefly discuss these equations and refer to the original works (Grossberg & Schmajuk, 1987; Grossberg & Gutowski, 1987; Mengov, Egbert, Pulov, & Georgiev, 2008) for more detail. It must be stressed, though, that all of them are variants of Eqs. (1) – (3). Variables $x_1,...,x_8$ are neuron activities, and y_1 and y_2 are neurotransmitters. The four $z_{7A},...,z_{8B}$ are memories. Signal S_A in Eqs. (8), (8a), (9), and (9b) is equal to one when supplier A is active, and is zero otherwise. Signal S_B is the opposite. The operator $[.]^+$ denotes rectification $[\xi]^+ = \max\{\xi,0\}$. Variables o_1, o_2 are outputs of the system and comprise a couple of opposing emotions. In our case, those are *customer satisfaction* and *disappointment*, as discussed in the next Section.

Experiment

We now present in brief our laboratory experiment in consumer decision making. It was computer based and investigated the links between (1) economic expectations, monetary outcomes, and the disappointment or satisfaction they provoke, and (2) the emotional responses and decisions to retain or abandon a supplier of a fictitious service. The experiment was conducted in May 2007 and involved 129 students of economics and business administration from Sofia University. Its content bore resemblance to the Bulgarian market of mobile phone services where two leading providers offered indistinguishable quality and prices at the time of the study. However, similarities to other markets in other countries could be just as relevant.

In the experiment, a participant received a service from one of two suppliers. In each round, the current supplier announced an advertised price P_a, which served as orientation about what actual (final) price P_f could be expected. The latter was announced on the computer screen a few seconds later and was always different from the advertised one. The participant had to assess his or her own disappointment or satisfaction in a psychometric Likert-type scale. Then he/she had to decide if the supplier should be retained for the next round, or should be abandoned in favour of the other supplier. The replacement did not incur any costs. The game was played for 17 rounds. All choices were hypothetical in the sense that no real money was involved.

Our main hypothesis was that in a sequence of such decisions the difference between advertised and actual prices would influence participant emotions substantially. Further, both price difference and emotional condition would be key factors for the choice of the next supplier. It could also be expected that developments in the preceding rounds along with the current one might influence the decisions. To investigate these issues, we designed four experimental treatments. In two of them, the actual prices varied above and below the advertised prices, and in the other two they varied only above or only below the advertised prices. The latter two cases created sequences of events that could lead to 'mini' satisfaction treadmills. For example, having observed only situations with actual price below the advertised price led a participant to expect a 'discount' also in the current round. Provided such a discount was offered but judged too small, it could cause disappointment rather than satisfaction. This might encourage a participant to change the supplier, but also might not. The symmetric situation regarding losses is interesting for the same reason. A person accustomed to being asked to pay more at the end of each round might be pleasantly surprised if in a particular round his or her 'loss' is just negligible. This might cause a mild satisfaction and a wish to continue with the current supplier. In spite of the experimental character of this study, it tapped on the real market experiences of our participants.

Transferring the empirical data from the above experiment into constants of the system of Eqs. (4) – (10a) was a huge task amounting to a complex computational experiment in its own right. We omit its description here and refer the reader to (Mengov et al., 2008) for a technical level discussion. We only note that we solved the system of differential equations about four million times with a Simulated Annealing procedure in which we embedded a Runge-Kutta-Felberg 4-5 algorithm.

Results

Our expectation that the READ neural network would adequately account for consumer behaviour was confirmed. In Table 1 we give a summary of its performance. A detailed discussion of our findings can again be found in (Mengov et al., 2008) as well as in (Egbert & Mengov, 2009).

The model by Eqs. (4) – (10a) was highly successful in predicting our participants behaviour in the experiment. We compared it with the most logical statistical models, i.e., *linear regression* for the satisfaction and disappointment, as shown in Eq. (11), and *logistic regression* for customer choice (Eq. (12)):

(11) $D\hat{S}_i = \beta_0 + \beta_1 \Delta P_i + \beta_2 \Delta P_{i-1} + \beta_3 \Delta P_{i-2} + \beta_4 DS_{i-1} + \beta_5 DS_{i-2}$,

Table 1. READ predicting consumer behaviour in the experiment

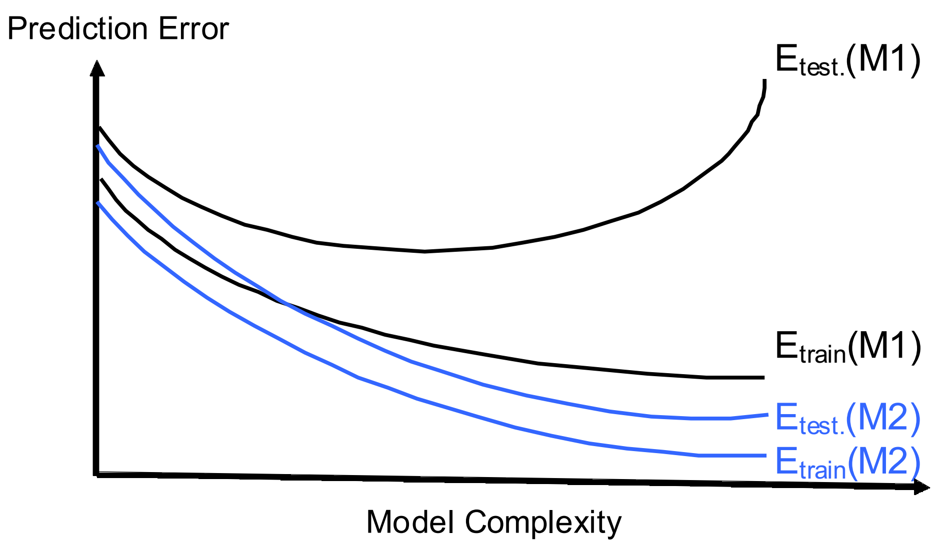
	Prediction of customer satisfaction or disappointment (Spearman rank correlation)	Prediction of retaining or changing a supplier by the READ model (percent of correct choices)
Training sample of the first 10 rounds (n = 1290)	89.30%	95.74%
Test sample of the last 7 rounds (n = 903)	78.46%	86.82%

In parentheses are number of observations

Table 2. Regression models predicting consumer behaviour in the experiment

	Prediction of customer satisfaction or disappointment by linear regression (Spearman rank correlation)	Prediction of retaining or changing a supplier by logistic regression (percent of correct choices)
Training sample of the first 10 rounds (n = 1290)	70.77%	80.31%
Test sample of the last 7 rounds (n = 903)	70.65%	85.49%

In parentheses are number of observations



Prediction errors in both training and test samples diminish due to use of a suitable, though more complex model

(12) $\tilde{CS}_i = [1 + \exp[-(\beta_0 + \beta_1 DS_i)]]^{-1}$.

In these two equations DS_i denotes the psychometrically measured customer disappointment or satisfaction in round i of the experiment, and $\hat{DS}_i$ is its regression estimate. Similarly, $\hat{CS}_i$ is the estimated, or in other words, predicted, choice of the next supplier. Variables of the type ΔP are price differences in the last couple of rounds as discussed in Section Gated Dipole above. All betas are regression coefficients. An alternative model for choice prediction, given by Eq. (13), performed slightly worse than that of Eq. (12). That model was:

(13) $\tilde{CS}_i = [1 + \exp[-(\beta_0 + \beta_1 \Delta P_i + \beta_2 CS_{i-1})]]^{-1}$.

READ outperformed these classical statistical models in predicting both consumer satisfaction and consumer choice, which becomes obvious when *tables 1 and 2* are compared. This situation can be qualitatively illustrated by *figure*, which shows that any class of models (say, M1) can predict better a training sample if it is made more complex by including more parameters. (See $E_{train}(M1)$ in the graph.) This strategy is useful up to a point, but then becomes counterproductive because adding further parameters deteriorates the model's usefulness in predicting unknown data, i.e., test samples. (See $E_{test}(M1)$ in the graph.)

Apart from model complexity, one further factor has a significant role here – this is the scientific insight. A theory-driven model like READ would always have advantage over general-purpose statistical models in the domain of emotional decision making because it had originally been developed to account for exactly that. We illustrate this idea as follows. Denoting with M1 the best possible statistical model, and with M2 the most adequate theoretical model, in our case READ, we can put them together as in *figure*. A deep theory, no matter how complex it might be, would always explain and predict better.

Back to our example, both regression equations – one for satisfaction, and one for supplier choice – contained few (two or three to six) parameters, while READ's constants as per Eqs. (4) – (10a) were 13. In view of what we already discussed, it is not surprising that READ, the more complex model, outperformed statistics both in training and in subsequent testing with unknown data.

Discussion

It is a truism in philosophy of science that a mathematical model can successfully describe and predict a phenomenon only if it captures essential aspects of the nature of that phenomenon. As we have established the value of a neurobiological model, READ, for understanding human behaviour in economic settings, we could ask what new lesson, or what kind of lessons in general that approach could teach us. One line of reasoning could be as follows.

Traditionally, economics has imposed upon the agents a duty to maximize utility in all of their choices and transactions. This scientific view has been maintained since the inception of Utility Theory and has survived even in many of the modern advances of behavioral economics. However, the new neurobiological approach to decision making offers a deeper understanding, unveiling previously unknown mental mechanisms. It can turn out that the latter serve goals very different from utility maximization.

For example, as Grossberg and Gutowski (1987) have argued, neural interactions via neurotransmitters exist for the primary purpose of maintaining emotional balances in the brain, and quickly restoring them when disturbed. Therefore, one conclusion might be that the economic agent would behave optimally only in a kind of „balanced mood", and would be endangered if he/she takes decisions when too angry or too complacent.

It is true, however, that satisfaction, and its main result – the emotional balance, very often come after the maximization of some material or abstract utility. Yet, if the objective of emotional balance engages in a conflict with the more pragmatic aspirations, sooner or later the former would prevail, and our internal *Homo Economicus* would be forced to yield precedence. This is only one example of the unexpected conclusions that we may reach as we develop further the neurobiological modeling of human decision making processes.

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Manuscript received on 19.10.2009

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