
Magritte

A new explainable, computationally efficient, and novelty-detecting neural network

Prof. Dr. George Mengov
Sofia University St. Kliment Ohridski

"I thought the neatest idea in neural networks was Grossberg's Adaptive Resonance Theory (ART) that you learn only if you resonate."

Bart Kosko

In: Anderson, J.A. & Rosenfeld, E. (Editors). (1998) *Talking Nets: An Oral History of Neural Networks.* The MIT Press, Cambridge, MA.

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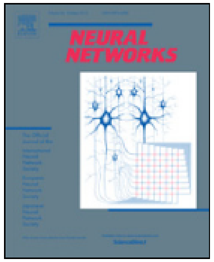

A survey of adaptive resonance theory neural network models for engineering applications

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ABSTRACT

This survey samples from the ever-growing family of adaptive resonance theory (ART) neural network models used to perform the three primary machine learning modalities, namely, unsupervised, supervised and reinforcement learning. It comprises a representative list from classic to contemporary ART models, thereby painting a general picture of the architectures developed by researchers over the past 30 years. The learning dynamics of these ART models are briefly described, and their distinctive characteristics such as code representation, long-term memory, and corresponding geometric interpretation are discussed. Useful engineering properties of ART (speed, configurability, explainability, parallelization and hardware implementation) are examined along with current challenges. Finally, a compilation of online software libraries is provided. It is expected that this overview will be helpful to new and seasoned ART researchers.

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A survey of adaptive resonance theory neural network models for engineering applications

Islam Elnabarawy [a], Donald C. Wunsch II [a]

In Wunsch II (2009) the conjecture is made that the dichotomy of match-based learning (i.e., Hebbian learning and ART) and error-based learning (i.e., using backpropagation (Rumelhart, Hinton, & Williams, 1986; Werbos, 1974, 1990) in feed-forward neural networks (Haykin, 2009) such as deep learning architectures (Goodfellow, Bengio, & Courville, 2016)) is likely a false one. This still lacks a definitive resolution. Some contributions

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to new and seasoned ART researchers.

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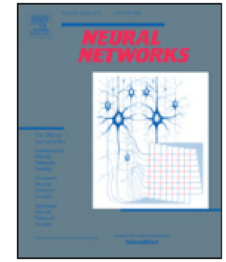

A survey of adaptive resonance theory neural network models for engineering applications

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ever, the problem of building a system that can do both match- and error-based learning like animals appear to be capable of remains a more complex and interesting challenge that holds great promise for much more stable and effective machine learning.

Keywords:
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ART models, thereby painting a general p… over the past 30 years. The learning dynamics of these ART models are briefly described, and their distinctive characteristics such as code representation, long-term memory, and corresponding geometric interpretation are discussed. Useful engineering properties of ART (speed, configurability, explainability, parallelization and hardware implementation) are examined along with current challenges. Finally, a compilation of online software libraries is provided. It is expected that this overview will be helpful to new and seasoned ART researchers.

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ing. The ability to master both types of learning and resolve this conjecture is believed to be a gateway to building machine learning systems that are fast and stable, possessing the ability for life-long learning and being resilient in the face of unpredictable changes in the environment.

Classification
Regression
Reinforcement learning
Survey

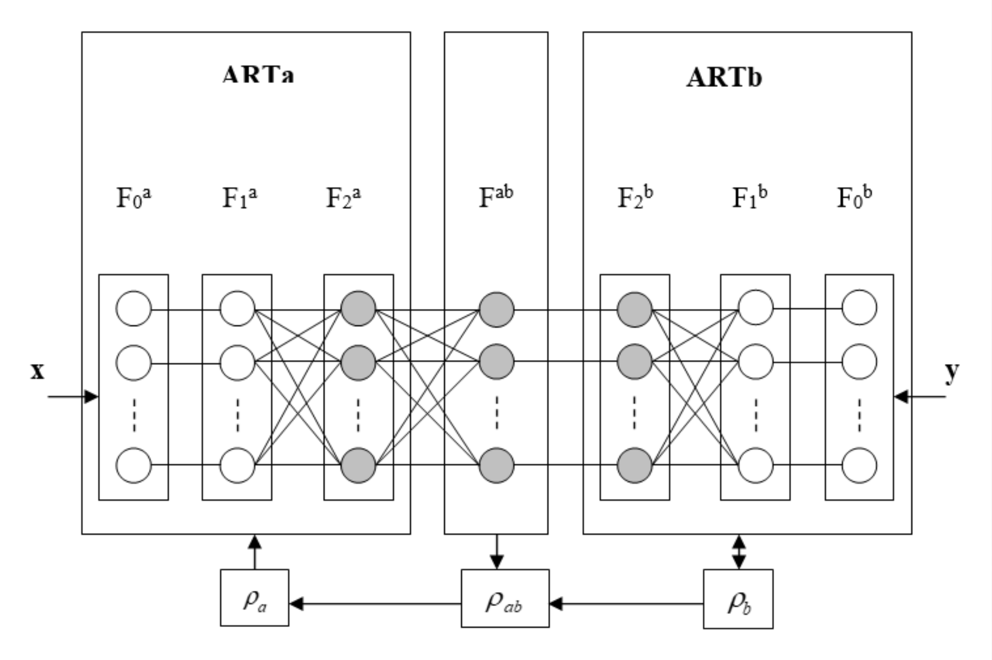
... pretation are discussed. ... parallelization and hardware implementation) are examined along ... compilation of online software libraries is provided. It is expected that this overview will be helpful to new and seasoned ART researchers.

<u>ARTMAP NN</u>

Computes

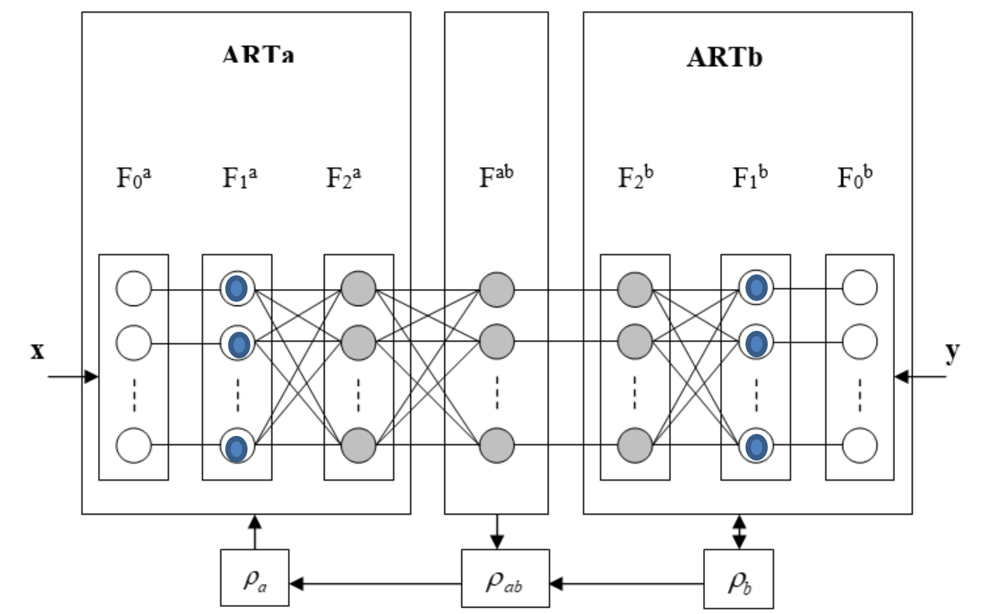
$$y = f(x)$$

Creates input and output clusters

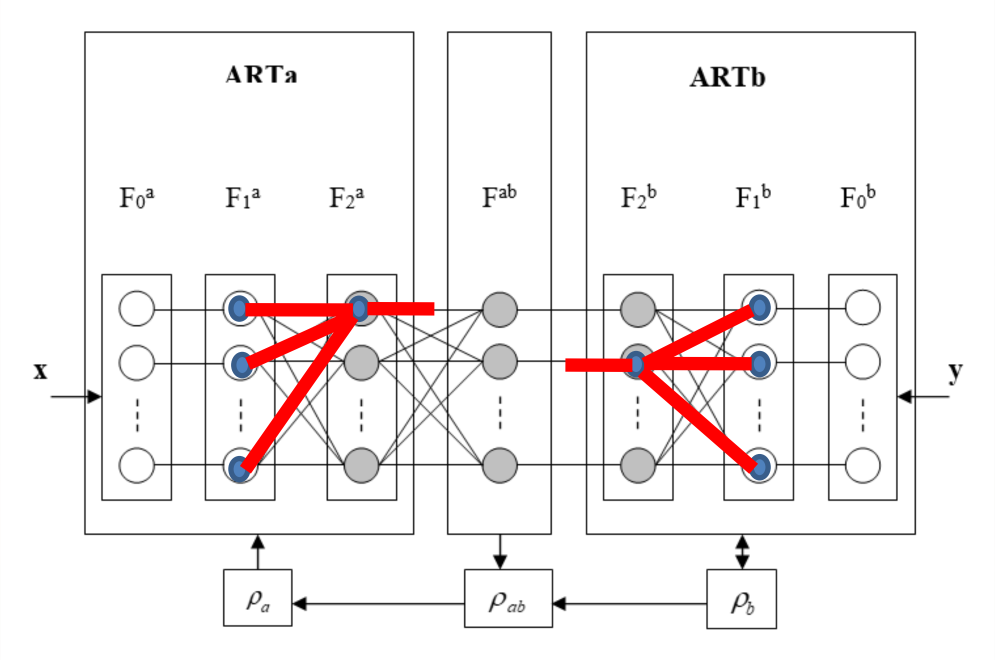


Each ART module performs 'hypothetico-deductive reasoning'.

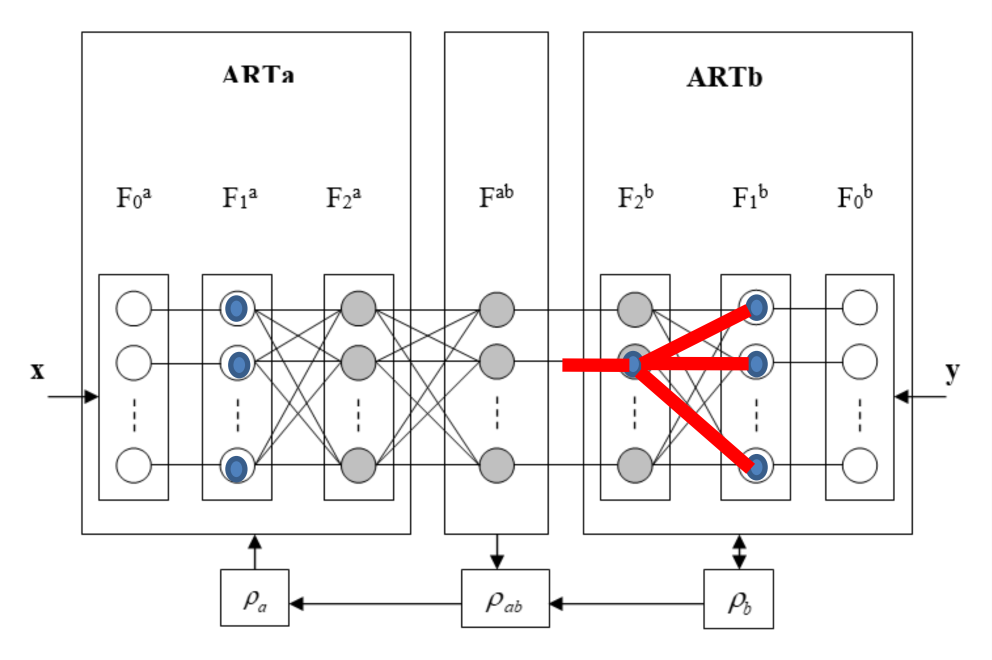
The NN 'knows' if it has seen this **x**, or similar, before. (E.g., "Similarity of 91%").
The same about **y**.



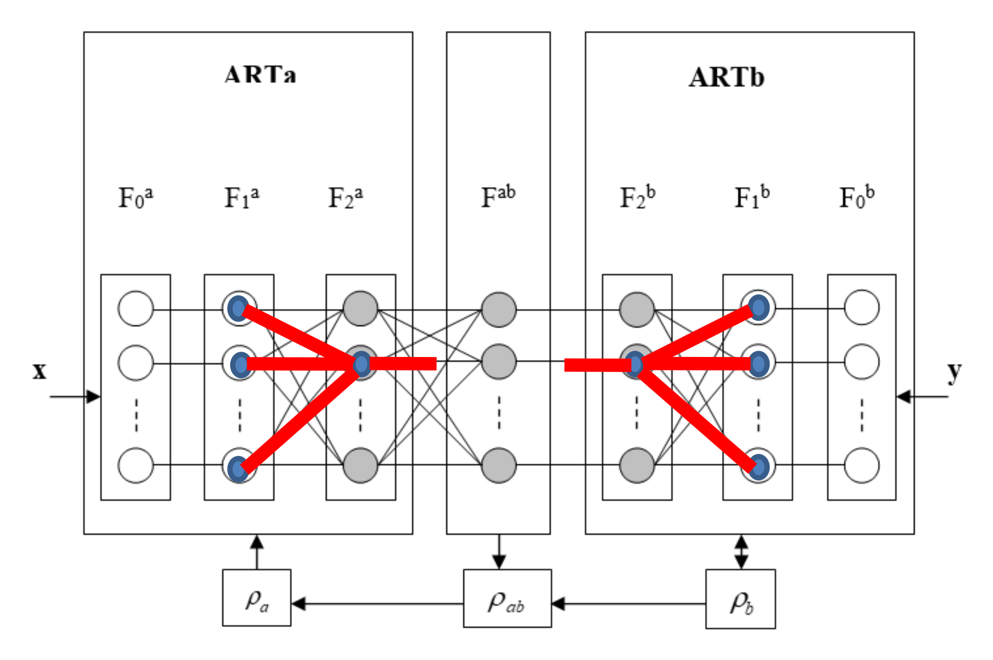
Hypotheses are made about the I/O mapping



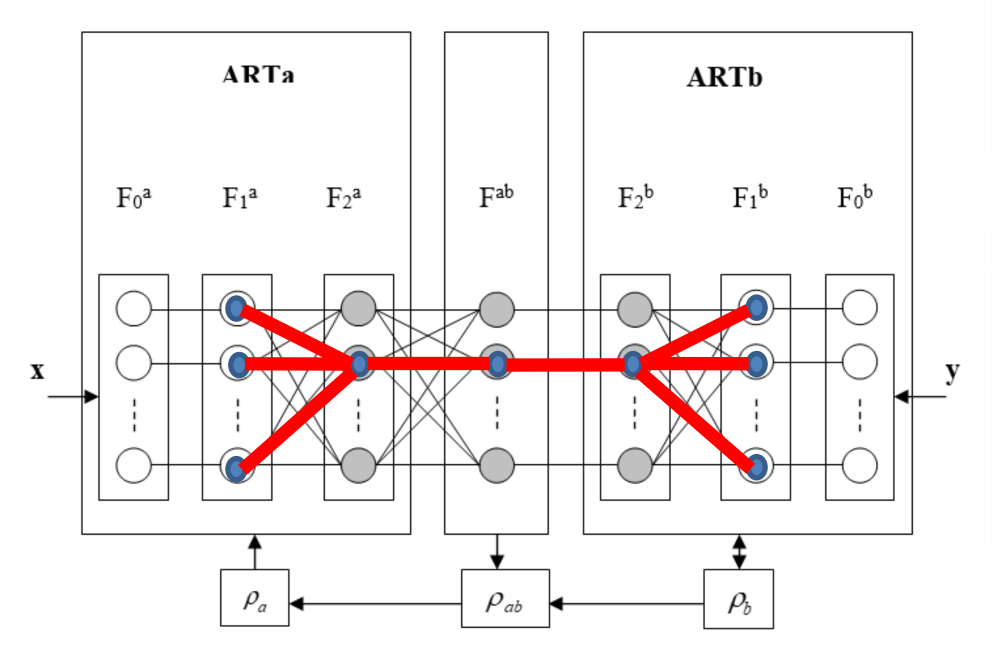
When a hypothesis is turned down…



… a new one is made.

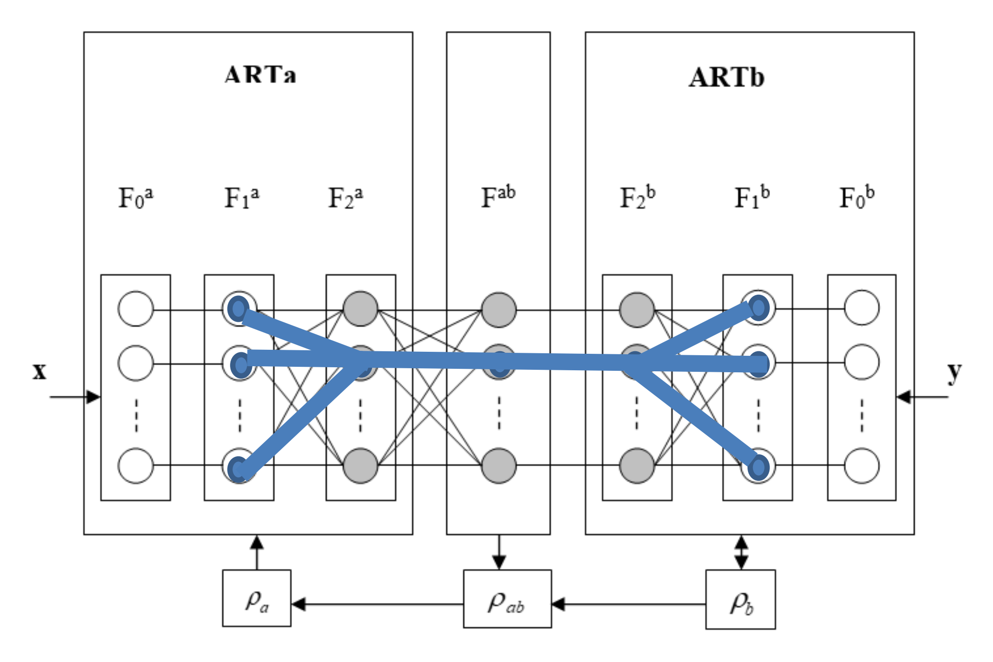


Eventually, a correct matching is identified.



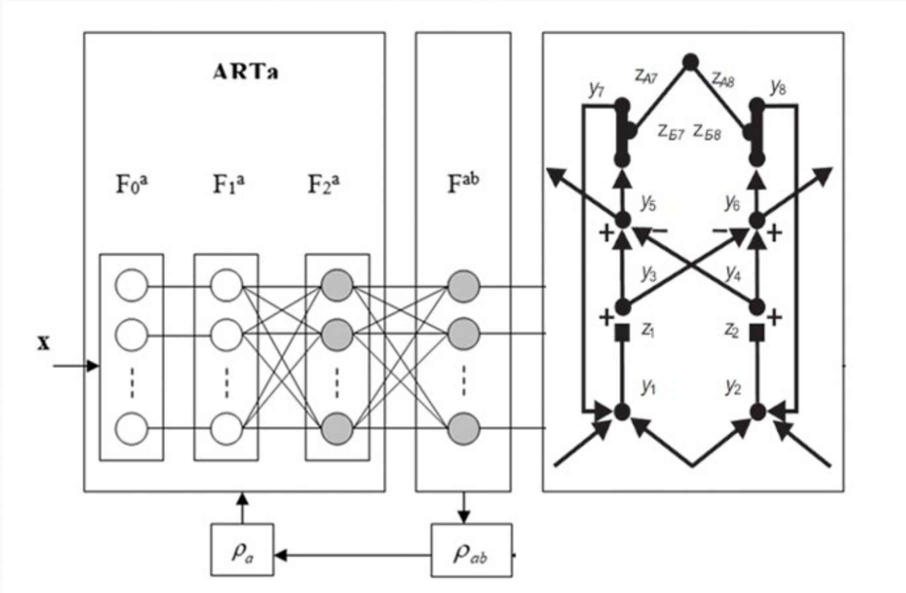
And learning takes place.

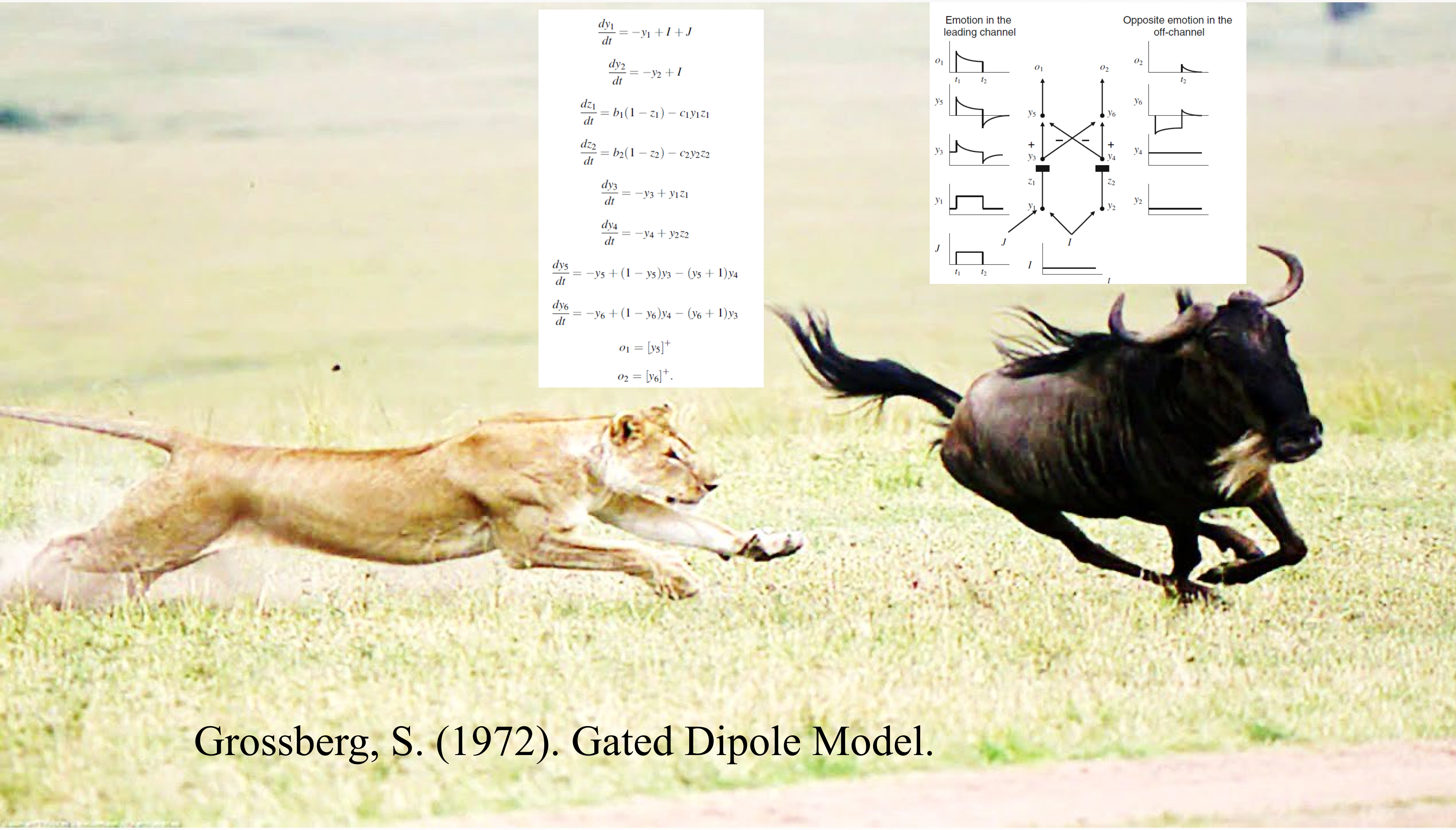
(The relevant connections among neurons are changed.)



- The ARTMAP NN has huge advantages and one handicap –
- It could not perform error-based y-value learning
- But only class-membership learning

A new NN is proposed…





$$\frac{dy_1}{dt} = -y_1 + I + J$$

$$\frac{dy_2}{dt} = -y_2 + I$$

$$\frac{dz_1}{dt} = b_1(1 - z_1) - c_1 y_1 z_1$$

$$\frac{dz_2}{dt} = b_2(1 - z_2) - c_2 y_2 z_2$$

$$\frac{dy_3}{dt} = -y_3 + y_1 z_1$$

$$\frac{dy_4}{dt} = -y_4 + y_2 z_2$$

$$\frac{dy_5}{dt} = -y_5 + (1 - y_5)y_3 - (y_5 + 1)y_4$$

$$\frac{dy_6}{dt} = -y_6 + (1 - y_6)y_4 - (y_6 + 1)y_3$$

$$o_1 = [y_5]^+$$

$$o_2 = [y_6]^+.$$

Grossberg, S. (1972). Gated Dipole Model.

$$\frac{dy_1}{dt} = -y_1 + I + J$$

$$\frac{dy_2}{dt} = -y_2 + I$$

$$\frac{dz_1}{dt} = b_1(1 - z_1) - c_1 y_1 z_1$$

$$\frac{dz_2}{dt} = b_2(1 - z_2) - c_2 y_2 z_2$$

$$\frac{dy_3}{dt} = -y_3 + y_1 z_1$$

$$\frac{dy_4}{dt} = -y_4 + y_2 z_2$$

$$\frac{dy_5}{dt} = -y_5 + (1 - y_5)y_3 - (y_5 + 1)y_4$$

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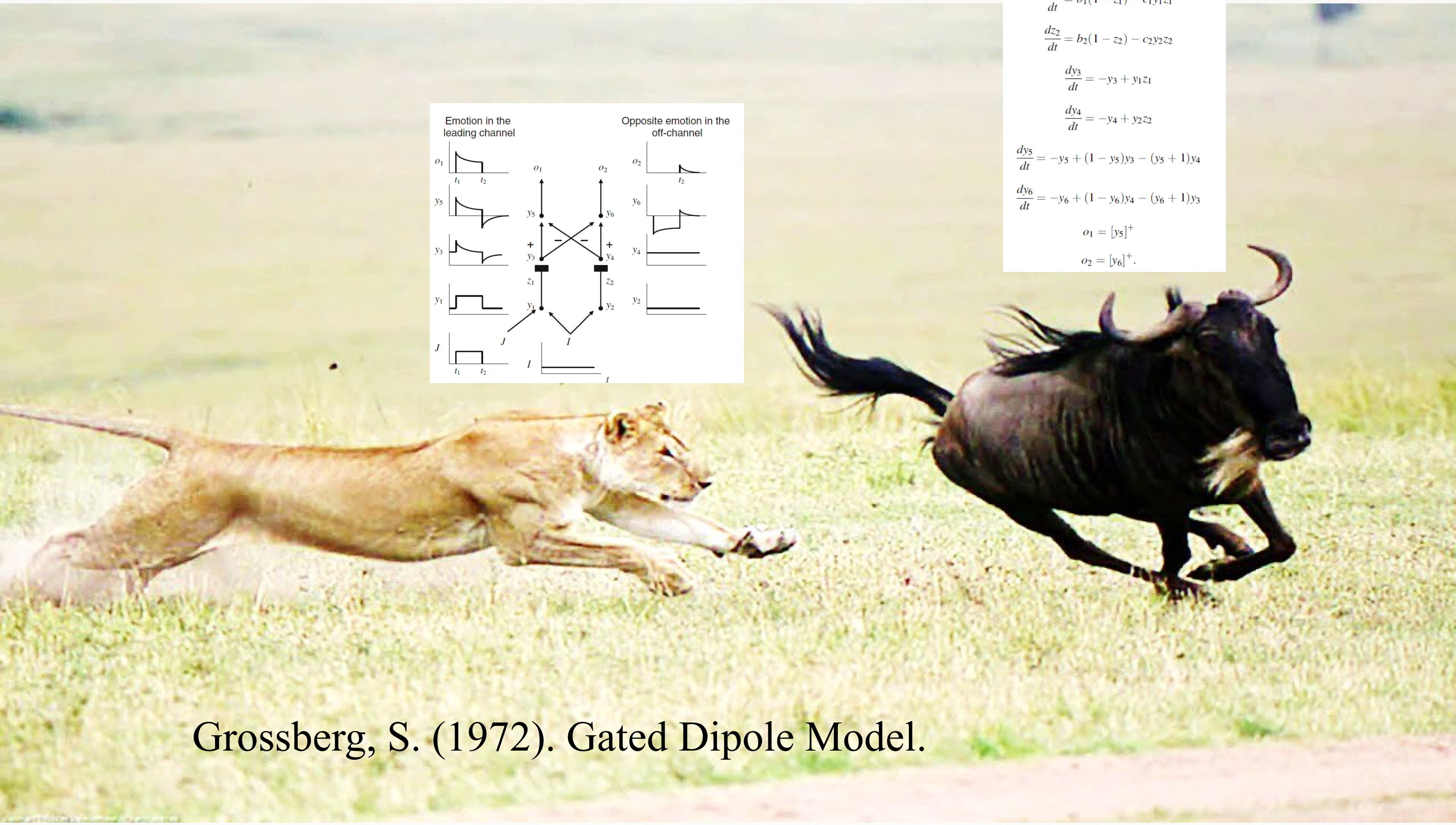
$$o_1 = [y_5]^+$$

$$o_2 = [y_6]^+.$$



Grossberg, S. (1972). Gated Dipole Model.


Covid 19
International
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The Gated Dipole neural circuit model

Explains the rapid generation of positive and negative emotions in response to surrounding opportunities and threats.

GD Useful Properties

1. Needs very few data in a non-stationary world.
2. Explains the mechanism of reaction to external shocks.

Some Literature

Grossberg, S. (1972). A neural theory of punishment and avoidance, II: Quantitative theory. *Mathematical Biosciences*, 15, 253-285.

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Fast computation of a gated dipole field

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Abstract

We address the need to develop efficient algorithms for numerical simulation of models, based in part or entirely on adaptive resonance theory. We introduce modifications that speed up the computation of the gated dipole field (GDF) in the Exact ART neural network. The speed increase of our solution amounts to at least an order of magnitude for fields with more than 100 gated dipoles. We adopt a 'divide and rule' approach towards the original GDF differential equations by grouping them into three categories, and modify each category in a separate way. We decouple the slow-dynamics part — the neurotransmitters from the rest of system, solve their equations analytically, and adapt the solution to the remaining fast-dynamics processes. Part of the node activations are integrated by an unsophisticated numerical procedure switched on and off according to rules. The remaining activations are calculated at equilibrium. We implement this logic in a Generalized Net (GN) — a tool for parallel processes simulation which enables a fresh look at developing efficient models. Our software implementation of generalized nets appears to add little computational overhead.

Keywords: Gated dipole field; Adaptive resonance theory; Generalized net

1. Introduction

The continuous-time behaviour of neural circuits is often described with systems of ordinary differential equations, usually integrated numerically as their complexity rules out analytical solutions. Today's software packages that do this are of high quality but require substantial computational resources. Naturally, a demand develops for algorithmic modifications aimed at efficiency.

One example for a set of computationally intensive tasks are the models based on adaptive resonance theory (Grossberg (1976); for an overview on ART see for example Carpenter and Grossberg (2002)). Their implementations have addressed the need for computational economy in a number of ways. One has been to retain differential equations for only the adaptive weights and use equilibrium solutions for all activations as in ART 2 (Carpenter & Grossberg, 1987). ART 2-A (Carpenter, Grossberg, & Rosen, 1991) has excluded the differential equations altogether. In some recent examples (Grossberg & Raizada, 2000; Grossberg & Seitz, 2003; Grossberg & Williamson, 2001) the fastest cell reactions have been computed at steady state, other activity equations have been solved with the Runge–Kutta–Fehlberg 4–5 method, and adaptive weights have been solved at a reduced time scale with Euler's method. However, computational complexity still remains an issue that limits simulations to relatively small neural networks. In the case of a complex model with even moderate dimensionality one may have a situation where "each simulation… takes from a day to a month to run on a 1.4 GHz Athlon processor" (Grossberg & Seitz, 2003).

Some ART implementations solve numerically all differential equations but this approach has worked for relatively small-scale tasks as in Exact ART (Raijmakers & Molenaar, 1994; Raijmakers, van der Maas, & Molenaar, 1996; Raijmakers & Molenaar, 1997). These authors have developed a realistic continuous-time model and have used a software package for stiff problems. Naturally, their implementation requires a lot of computing resources. Raijmakers and Molenaar did not consider it as a problem because their objective had not been

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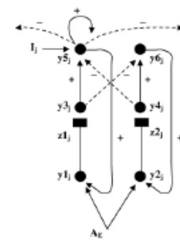

Fig. 1. The Raijmakers & Molenaar model of the gated dipole field.

(1997) to facilitate the understanding of our paper. The model is shown in Fig. 1.

Note that this GDF configuration differs from what Grossberg (1980) proposed — here the transmitter change is also function of activity y5 rather than y1 only, due to the feedback y5 → y1 (Fig. 1). Raijmakers and Molenaar (1994) needed this to implement GDF function No 3 from above. Other gated dipole arrays that fulfill the same three functions, for example (Leven & Levine, 1996), may also benefit from this change (Fig. 1) and hence from all the modifications proposed in this paper.

2.2. *Modifications*

Our approach sought to achieve computational efficiency due to joint action of three modifications to Eqs. (1)–(8), discussed in the following sections. We implemented the GDF in a generalized net operating in a fixed discrete-time scale. Its time step coincided with that of the numerical integration procedure. In our further discussion we rely on the fact that the computation process is stepwise.

2.2.1. *Neurotransmitters computed with an analytical formula*

We solved the neurotransmitter Eqs. (7) and (8) analytically and adapted the boundary value solution to account for a continuously changing input. When an arousal burst causes GDF reset, all dipoles compete for a short period. One dipole wins and its $y5_J$ stays active long enough to update its connected memory weights. During that period $z1_J$ is consumed, while all other transmitters $z1_j$, $j \neq J$, refill towards equilibrium. Thus, for some time the GDF operates in a regime when its slowest process is continuously changing while its fast node activations stay constant. The signals affecting the release and replenishment of **z1** are constant.

Consider the interaction in the jth pathway $y1_j \to z1_j$ (j may also be J). The input into $z1_j$ depends on node $y1_j$ (Fig. 1) and is $S1_j = \delta[y1_j - \Gamma]^+$ as per Eq. (7). With this substitution Eq. (7) becomes

$$\frac{1}{\varepsilon}\frac{\mathrm{d}z1_j}{\mathrm{d}t} = \beta(\gamma - z1_j) - S1_j z1_j. \tag{9}$$

Let $S1_j$ change at moment t_0 and stay constant for long enough. Term $S1_j^{\mathrm{old}}$ denotes the input value at time step $t_0 - 1$ and $S1_j^{\mathrm{new}}$ at t_0. While in general $S1_j$ may change abruptly, $z1_j$ cannot, and therefore

$$z1_j(t_0 - 1) \approx z1_j(t_0). \tag{10}$$

For $S1_j = \mathrm{const.}$ Eq. (9) has this solution:

$$z1_j(t) = \frac{\beta\gamma}{\beta + S1_j^{\mathrm{old}}}\exp\left(-(t - t_0)(S1_j^{\mathrm{new}} + \beta)\varepsilon\right) + \frac{\beta\gamma}{\beta + S1_j^{\mathrm{new}}}\left[1 - \exp\left(-(t - t_0)(S1_j^{\mathrm{new}} + \beta)\varepsilon\right)\right]. \tag{11}$$

Grossberg (1984) used essentially the same formula to describe transmitter release for a new sustained input. Eq. (11) expresses the gradual shift of $z1_j$ from equilibrium with $S1_j^{\mathrm{old}}$ to equilibrium with $S1_j^{\mathrm{new}}$. If the rate of input change is high the transmitter does not have time to reach its new asymptote $\beta\gamma/(\beta + S1_j^{\mathrm{new}})$, and the formula is inapplicable. However, with a modification, the latter can account for a continuously changing input. Note that Eq. (11) can take $S1_j^{\mathrm{new}}$, corresponding to time step t_0, and cannot take $S1_j^{\mathrm{old}}$ for $t_0 - 1$ as the transmitter could not habituate. We introduce an equivalent hypothetical $\hat{S}1_j^{\mathrm{old}}$ defined as the signal which, had it been maintained for sufficiently long, would have equilibrated the transmitter exactly to its value at $t_0 - 1$. In other words, we consider $z1_j(t_0 - 1)$ being the product of a different history but with the same outcome. In that 'alternative past', a *finished* habituation produced 'mock' equilibrium

$$z1_j(t_0 - 1) = \frac{\beta\gamma}{\beta + \hat{S}1_j^{\mathrm{old}}}.$$

Therefore the needed equivalent value is

$$\hat{S}1_j^{\mathrm{old}} = \frac{\beta\left(\gamma - z1_j(t_0 - 1)\right)}{z1_j(t_0 - 1)}.$$

In summary, at each time moment we calculate the new $z1_j$ in two steps. First, the actual previous $z1_j(t_0 - 1)$ is used to determine an adjusted previous $\hat{S}1_j^{\mathrm{old}}$. Then in the second step the new $z1_j(t_0)$ is computed by Eq. (11) with $\hat{S}1_j^{\mathrm{old}}$ and $S1_j^{\mathrm{new}}$. The same is done with transmitter $z2_j$. This procedure decouples Eqs. (7) and (8) from the rest of the system (Section 2.1). In practice $\hat{S}1_j^{\mathrm{old}}$ can be computed at a slower time step, for example only at moments when the reset signal A_E is activated and then switched off. And even less frequent $\hat{S}1_j^{\mathrm{old}}$calculation can be satisfactory, for example only in the events of winner change.

2.2.2. *Fast node activations*

We simplify Eqs. (3), (4) and (6) by setting the derivatives to zero. The error thus introduced vanishes very quickly and has no effect on the circuit performance. It is seen from Fig. 1 that nodes $y3_j$ and $y4_j$ receive signals from nodes $y1_j$ and $y2_j$ conveyed by transmitters $z1_j$ and $z2_j$ respectively. Grossberg and Gutowski (1987) and Grossberg and Schmajuk (1987)

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Neural networks letter

Emotional balances in experimental consumer choices

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ABSTRACT

This paper presents an experiment, which builds a bridge over the gap between neuroscience and the analysis of economic behaviour. We apply the mathematical theory of Pavlovian conditioning, known as Recurrent Associative Gated Dipole (READ), to analyse consumer choices in a computer-based experiment. Supplier reputations, consumer satisfaction, and customer reactions are operationally defined and, together with prices, related to READ's neural dynamics. We recorded our participants' decisions with their timing, and then mapped those decisions on a sequence of events generated by the READ model. To achieve this, all constants in the differential equations were determined using simulated annealing with data from 129 people. READ predicted correctly 96% of all consumer choices in a calibration sample ($n = 1290$), and 87% in a test sample ($n = 903$), thus outperforming logit models. The rank correlations between self-assessed and dipole-generated consumer satisfactions were 89% in the calibration sample and 78% in the test sample, surpassing by a wide margin the best linear regression model.

1. Introduction

John Watson, founder of behaviourism, is quoted to have said in 1922, "The consumer is to the manufacturer, the department stores and the advertising agencies, what the green frog is to the physiologist" (DiClemente & Hantula, 2003). Many decades later, we cannot but agree with this provocative insight, although we know a lot more about consumer behaviour, its conditioning, and economic psychology in general. Today fMRI methods help us discover how brain systems interact when we think about economic decisions (see for example Camerer, Loewenstein, and Prelec (2005)). Yet, these studies still try to locate regions in the cortex involved in forming emotions, judgments, and decision making (cf. Winkielman, Knutson, Paulus, and Trujillo (2007)). It might be advantageous to complement such an observational approach, or even step aside from it for a while, by using more extensively the available theoretical models.

In this paper, we present experimental evidence that the mathematical theory of Pavlovian conditioning, known as Recurrent Associative Gated Dipole (READ) (Grossberg & Schmajuk, 1987) is able to capture essential features of consumer behaviour. A computer based experiment showed how a supplier of a fictitious service provoked satisfaction and disappointment, and gradually built its own reputation in the minds of participants as consumers. Accommodated by READ, these factors turned out to be strong predictors of customers' decisions to retain or abandon their current supplier. Our work borrows ideas from affective balance theory (Grossberg & Gutowski, 1987) and the Leven and Levine (1996) neural model of a consumer.

2. Experiment

This experiment investigates the links between (1) monetary outcome and momentary affect, (2) previous emotional experience and supplier reputation, and (3) provoked emotions and consumer decisions to retain or abandon the current supplier. It was conducted in May 2007 and involved 129 students of economics from Sofia University. Its content bears 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 with other markets in other countries would have been just as useful.

In each of 17 rounds the participant sees on a computer screen an advertised price (P_a) offered by the current supplier, which serves as orientation about what final price (P_f) might be expected (Fig. 1). No payments with real money are made. Prices P_a were adjusted to fluctuate slightly around an average monthly bill obtained in a survey among another 40 students. Thus, P_a varied within 40 ± 5 Bulgarian leva, and 1 lev is 0.5 euros.

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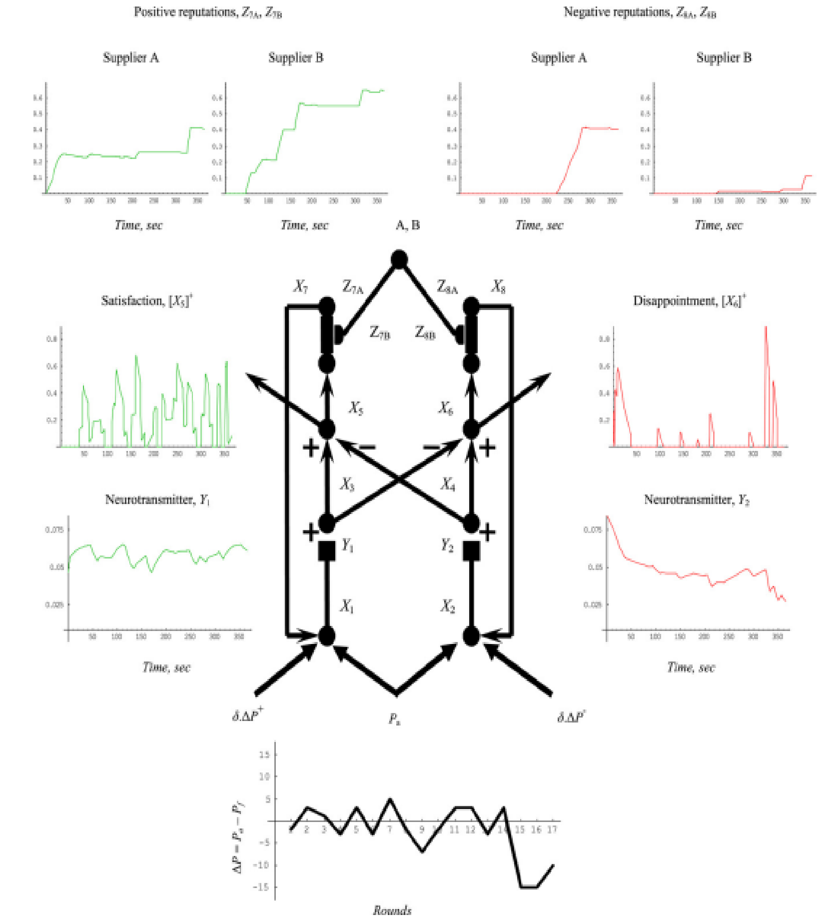

Fig. 3. Relating a participant's data to the READ model. Market is 'Saturated'. All plots show variables computed with that person's best set of constants obtained with simulated annealing. Note the Y_2 neurotransmitter release and increased disappointment in the last rounds due to larger unfavourable price differences ΔP. In addition, because the participant switched from Supplier A to B at the end of the first round, A's positive reputation did not change much for a while, while B's increased over the next couple of rounds.

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Person-by-person prediction of intuitive economic choice

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ABSTRACT

Decision making is an interdisciplinary field, which is explored with methods spanning from economic experiments to brain scanning. Its dominant paradigms such as utility theory, prospect theory, and the modern dual-process theories all resort to formal algebraic models or non-mathematical postulates, and remain purely phenomenological. An approach introduced by Grossberg deployed differential equations describing neural networks and bridged the gap between decision science and the psychology of cognitive–emotional interactions. However, the limits within which neural models can explain data from real people's actions are virtually untested and remain unknown. Here we show that a model built around a recurrent gated dipole can successfully forecast individual economic choices in a complex laboratory experiment. Unlike classical statistical and econometric techniques or machine learning algorithms, our method calibrates the equations for each individual separately, and carries out prediction person-by-person. It predicted very well the behaviour of 15%–20% of the participants in the experiment – half of them extremely well – and was overall useful for two thirds of all 211 subjects. The model succeeded with people who were guided by gut feelings and failed with those who had sophisticated strategies. One hypothesis is that this neural network is the biological substrate of the cognitive system for primitive-intuitive thinking, and so we believe that we have a model of how people choose economic options by a simple form of intuition. We anticipate our study to be useful for further studies of human intuitive thinking as well as for analyses of economic systems populated by heterogeneous agents.

1. Introduction

General Charles de Gaulle of France once remarked that it was difficult to govern a nation that had 246 different kinds of cheese. Besides the obvious message about developed countries being sophisticated, these words hint that economic choice is not only important but also somewhat frustrating. Economists have studied its more traditional aspects extensively and have come to the understanding that the axioms used in economic and political theory need revision (Sen, 1997). To better explain and predict, they ought to account for the subtle rationality of seemingly irrational decisions as in Amartya Sen's famous example of somebody taking a fruit from a basket with two fruits, but refusing to do so when only one is left. Behavioural economics has addressed the general issue by relaxing its axioms as well as by equipping them with more empirical knowledge about the human being's cognitive characteristics.

In the meantime, psychology has gone a long way in understanding human decision processes. Kahneman and Tversky's research programme enriched economic analysis with findings about the heuristic and emotional aspects of decision making (Kahneman, 2003, 2011; Tversky & Kahneman, 1971, 1981). In our time, it has been established that a decision is reached in the complex interaction of two cognitive systems. Different theories have labelled them in different ways, but in general it is believed that there is one system for "intuitive", "experiential", or "impulsive" reasoning, also called "System I", and another for "logical", "rational", or "reflective" reasoning, also called "System II" (Epstein, 1994, 2003; Kahneman & Frederick, 2002; Schneider & Shiffrin, 1977; Stanovich & West, 2000; Strack & Deutsch, 2004). Recent reviews on the subject can be found in (Alós-Ferrer & Strack, 2014; Brocas & Carrillo, 2014; Dayan, 2009), while some of the recent modelling advances constitute (Andersen, Harrison, Lau, & Rutström, 2014; Fudenberg & Levine, 2006; Fudenberg, Levine, & Maniadis, 2014; Mukherjee, 2010). In this view, the intuitive system is automatic, effortless, emotion-driven, governed by habit, but difficult to change, while the logical system is effortful, controlled and slow, but flexible and able to adopt complex decision rules. Easy tasks are dealt with

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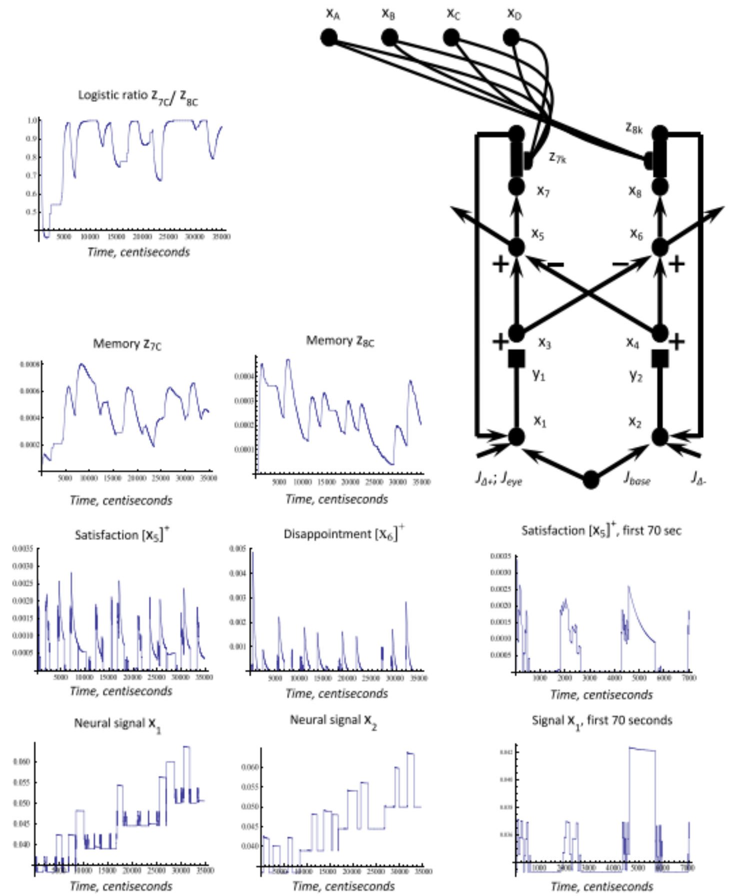

Fig. 3. Dynamics of the neural circuit. ***Bottom left and middle plots***: Signals x_1 and x_2 are the responses to the incoming stream of offers, deliveries, and to the participant's eyeballing before choosing. In the example, the person kept choosing Supplier C in the first three rounds and received extra omnium bonum in the third, which is reflected in the two "first 70 seconds" plots (***third column, below the neural circuit***). There, x_1 produced "ripples" at the onset of each round and then jumped around the 4500th centisecond (45th s) due to the surplus delivered. Around the 2000th centisecond, the corresponding $[x_5]^+$ signal shows that eyeballing four positive options can cause satisfaction, almost as intense as that of the actual lavish treatment. ***Upper-left plots***: The memory for positive emotions z_{7C} initially rose negligibly due to eyeballing, and then increased around the 50th second after the generous delivery in the third round. In contrast, the memory for negative emotion z_{8C} rose steeply in the first round and remained high in the next due to disappointingly unfulfilled promises. The supplier's dynamic reputation was defined by the logistic ratio z_{7C}/z_{8C} reflecting the two memories' joint action.

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Virtual social networking increases the individual's economic predictability

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ABSTRACT

Forecasting economic choice is hard because today we still do not know enough about human motivation. A fundamental problem is the lack of knowledge about how the neural networks in the brain give rise to thinking and decision making. One way to address the issue has been to develop simplified economic experiments, in which participants need skills of little complexity and their minds employ cognitive mechanisms, already well understood by mathematical psychology and neuroscience. Here we take a neural model for rudimentary emotion generation and memorizing and use it as a guiding theory to understand decision making in an experimental oligopoly market. For the first time in that line of research, participants are put in a lab virtual social network serving to exchange opinions about deals with companies. On average, choices become significantly more predictable when people participate in the network, in contrast to working alone with expert information. Calibrating the model for each person, we find that some people are predicted with startling precision.

1. Introduction

Trying to predict people's actions is hard because not enough is known about the decision making mechanisms of the mind. Cognitive psychology has reached a consensus that the brain does not compute value or utility but conducts ad hoc and direct comparisons between the available options in the specific situation, circumstances, framing, and context (Rieskamp et al., 2006; Vlaev et al., 2011). Any choice forecasting effort, therefore, should humbly accept the prospect to accomplish very little. One approach could be statistical – gather data and use it to anticipate human behavior in the long run. In our time, machine learning with big data has done exactly that, with respectable success. Its main problem though, is that its key component – the artificial neural network – is a black box, not capable of discovering cognitive mechanisms and causal relationships. This lack of strictly scientific knowledge makes the method less effective with unknown data and new situations, posing an upper bound to its achievements.

One alternative is the bottom-up approach developed by mathematical neuroscience. It studies how neural circuits in the brain give rise to cognitive phenomena like emotion, memory, learning, etc. This endeavor has already identified the neural substrate of a variety of complex psychological processes. As the field matured, some researchers made pioneering attempts – initially at the conceptual level only – to envision what neurobiological structures in the human brain could be at work in some economic, consumer, and utility-based choices in general (Leven & Levine, 1996; Levine, 2006; Levine, 2012; Grossberg, 2018).

A parallel line of research conducted experiments with monkeys to identify brain areas and single neurons, believed to encode the usefulness of goods (Padoa-Schioppa & Assad, 2006; Padoa-Schioppa & Assad, 2008; Grabenhorst et al., 2012). These efforts, alongside the entire field of neuroeconomics, have successfully related economic concepts with brain regions in which they are processed. Yet never a serious attempt was made at forecasting economic decisions, obviously due to the huge theoretical gap between neural circuits and actual behavior (Carandini, 2012; Kriegeskorte & Douglas, 2018; Marr, 1982; Palmieri et al., 2017; Turner et al., 2017). Several ways to connect neural with behavioral data have been developed (Zhang et al., 2017; Forstmann et al., 2016; Hein et al., 2016; Schulte-Mecklenbeck et al., 2017; Wang, 2008; Klein et al., 2017; Meder et al., 2017) but no method for their integration has prevailed.

Finally, another forecast-aiming approach sought to bridge the neuron–behavior gap by designing lab economic experiments needing only that kind of cognitive processes, for which neurobiological theory is already available. One such study put participants in the role of consumers, choosing to retain or abandon a service provider resembling a mobile-phone operator (Mengov et al., 2008; Mengov & Nikolova, 2008). The authors applied an established neuroscience model of opposite emotions (Grossberg & Schmajuk, 1987; Grossberg &

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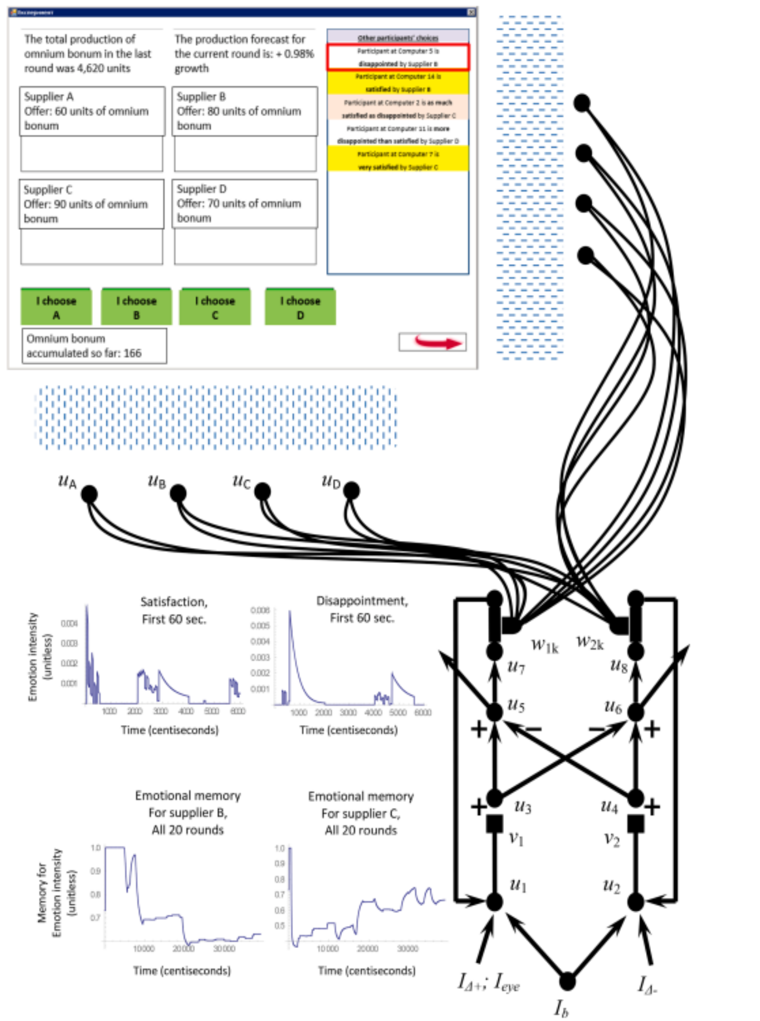
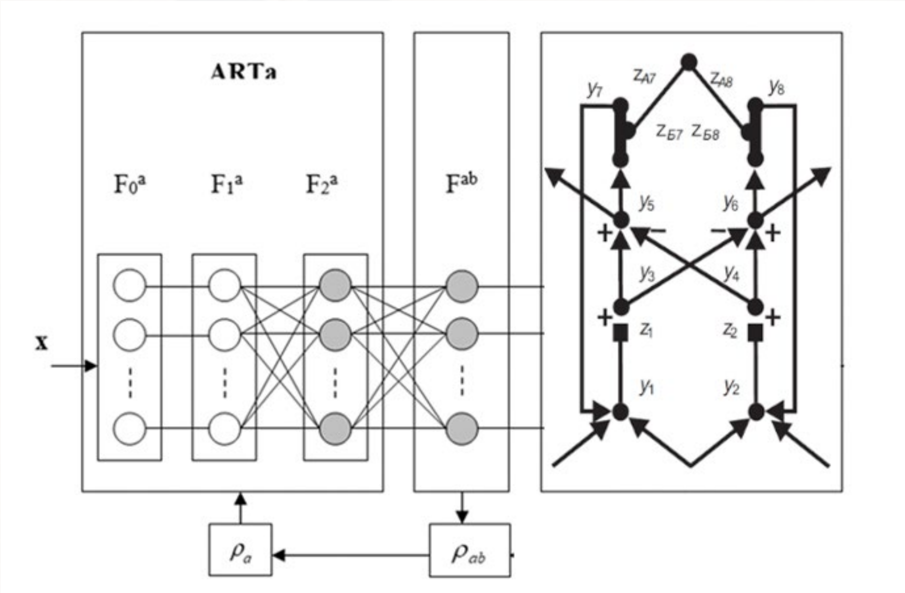


(caption on next page)

The new neural network should be tested with

1. Interesting problems and
2. Difficult data

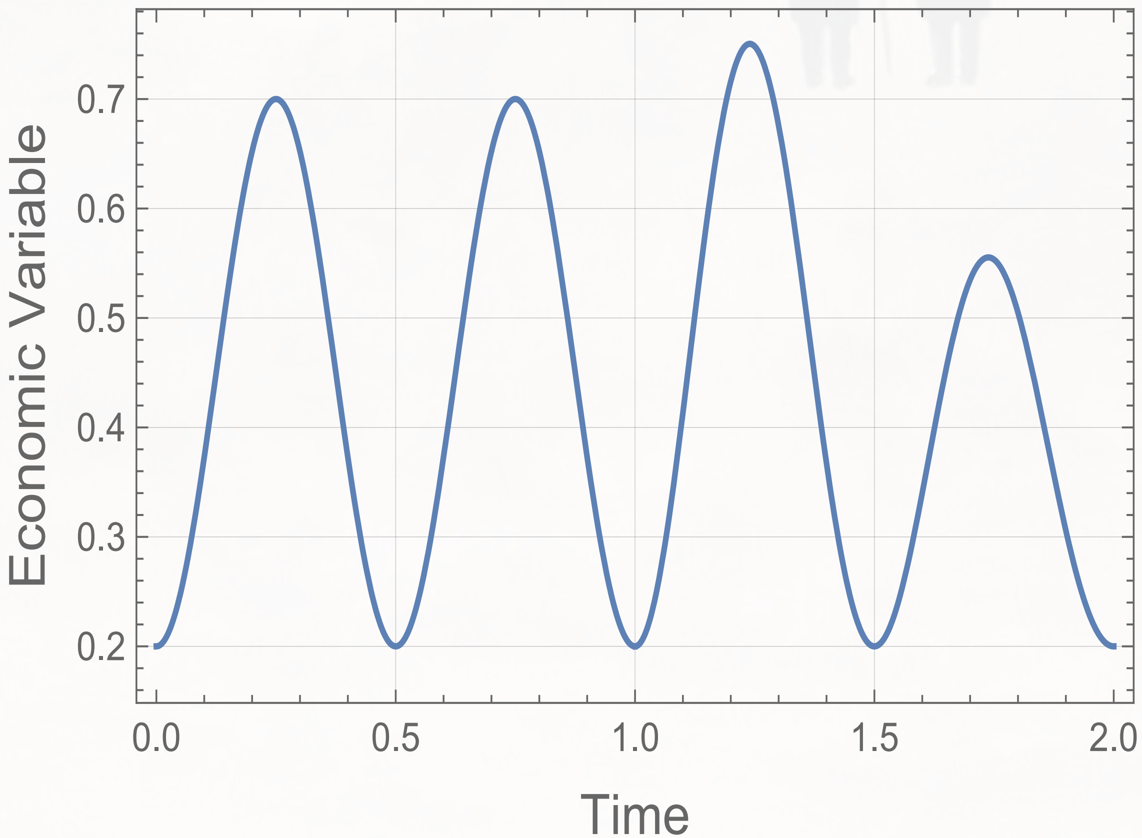


Problem 1: The Lucas Critique

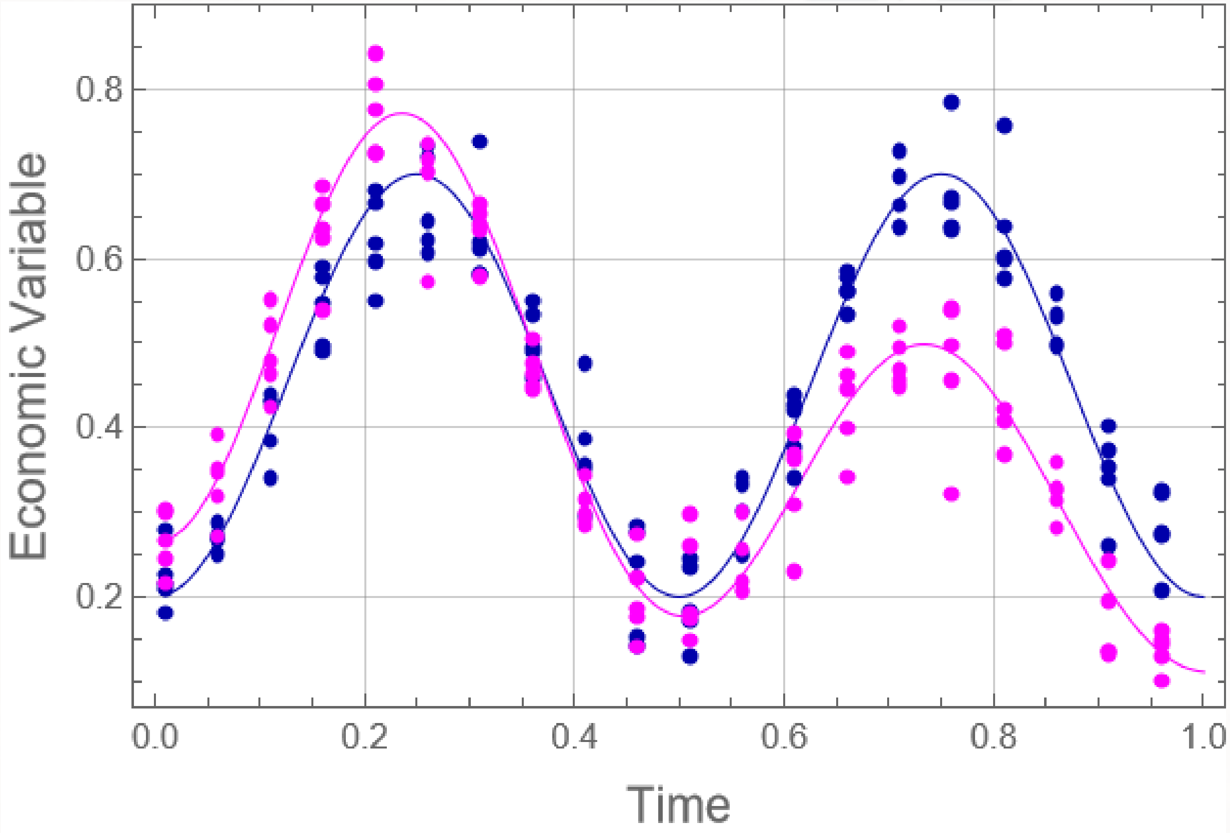
In the economy, if you have a forecasting model, and it is working, it is no longer working.

(A paraphrase of a statement by Robert Lucas)

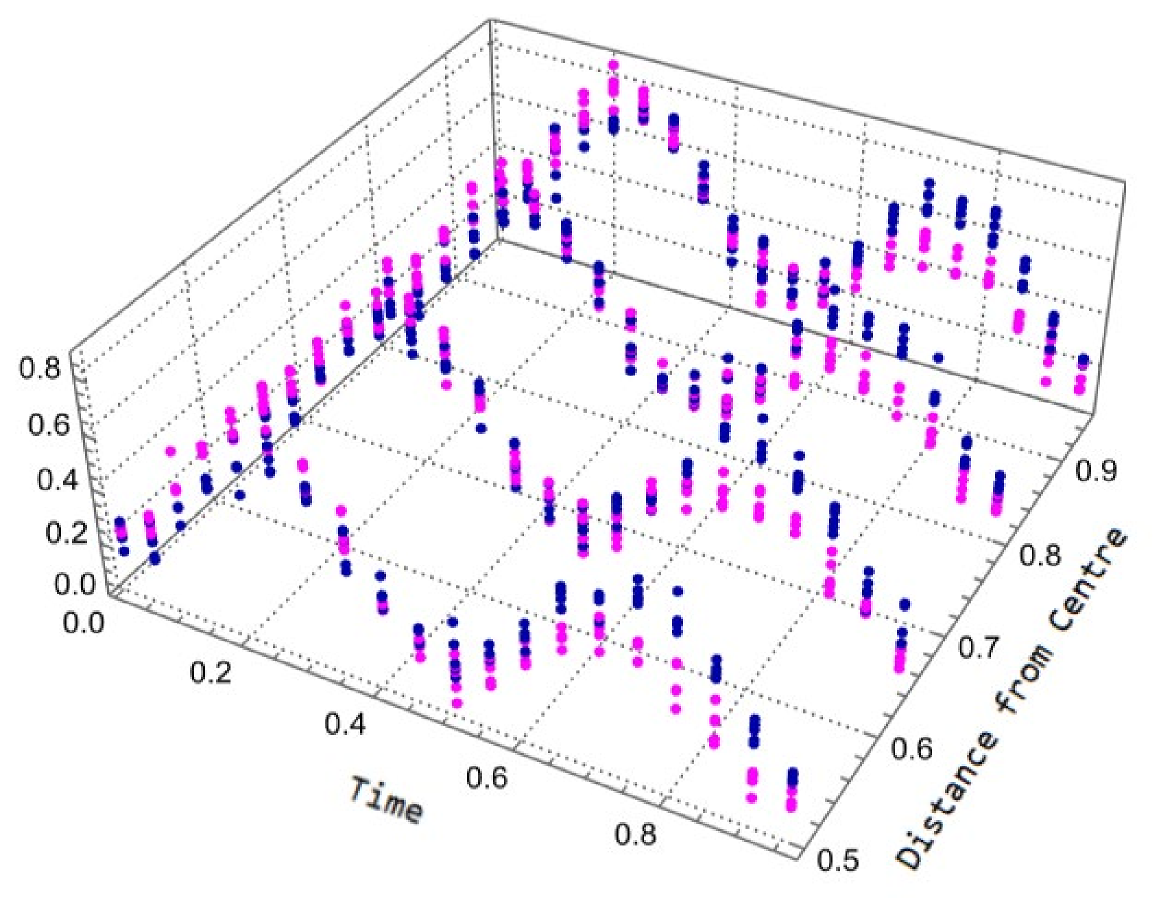
An abstract economic process – after two regular cycles the agents rush and overshoot in cycle 3, leading to a slump in cycle 4.



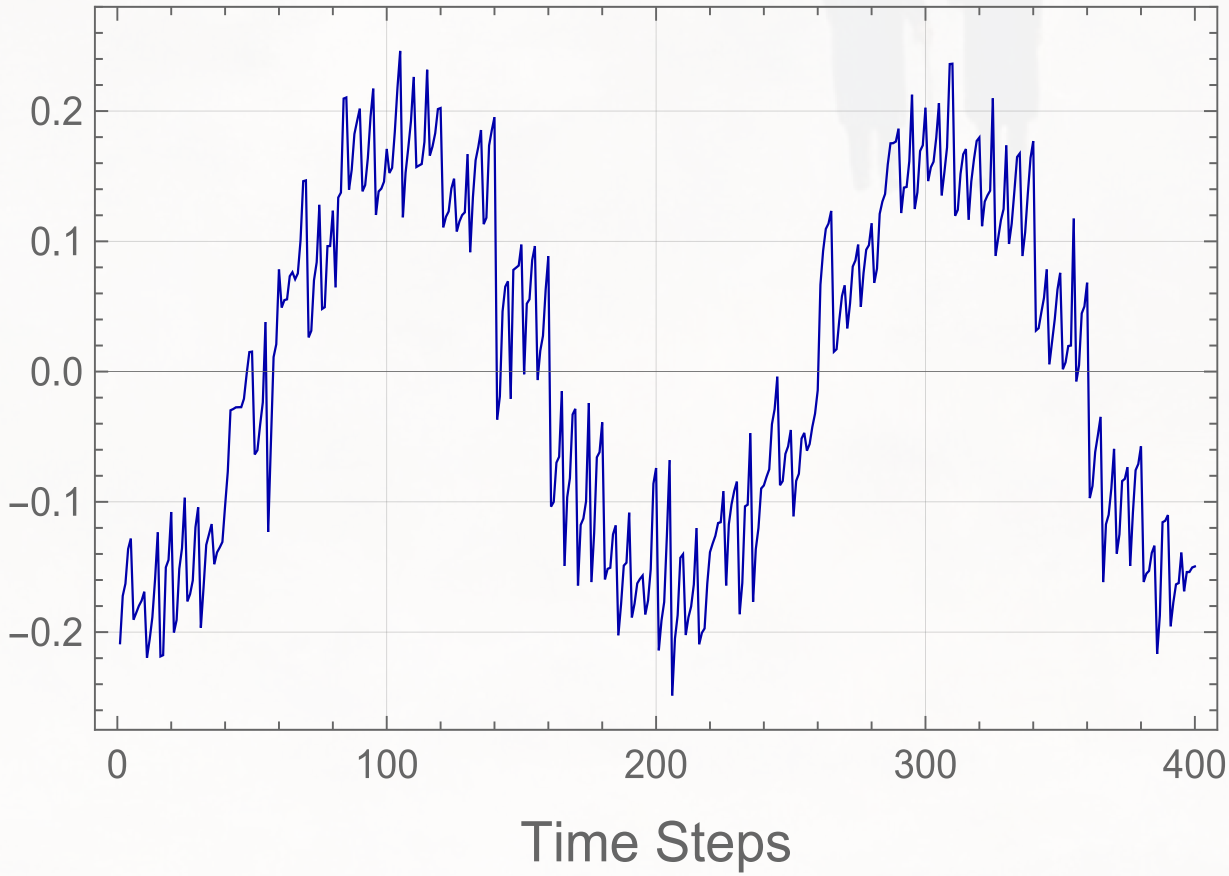
The economic variable (prices, traded volumes, interest rates, etc) has five values at each transaction moment. Blue colour indicates the first two regular cycles, magenta the last two imbalanced cycles.



There are four market locations of different size



Data, actually submitted to the neural network, are ordered in time and from largest to smallest market (only the two regular cycles are shown)



The NN's internal memory

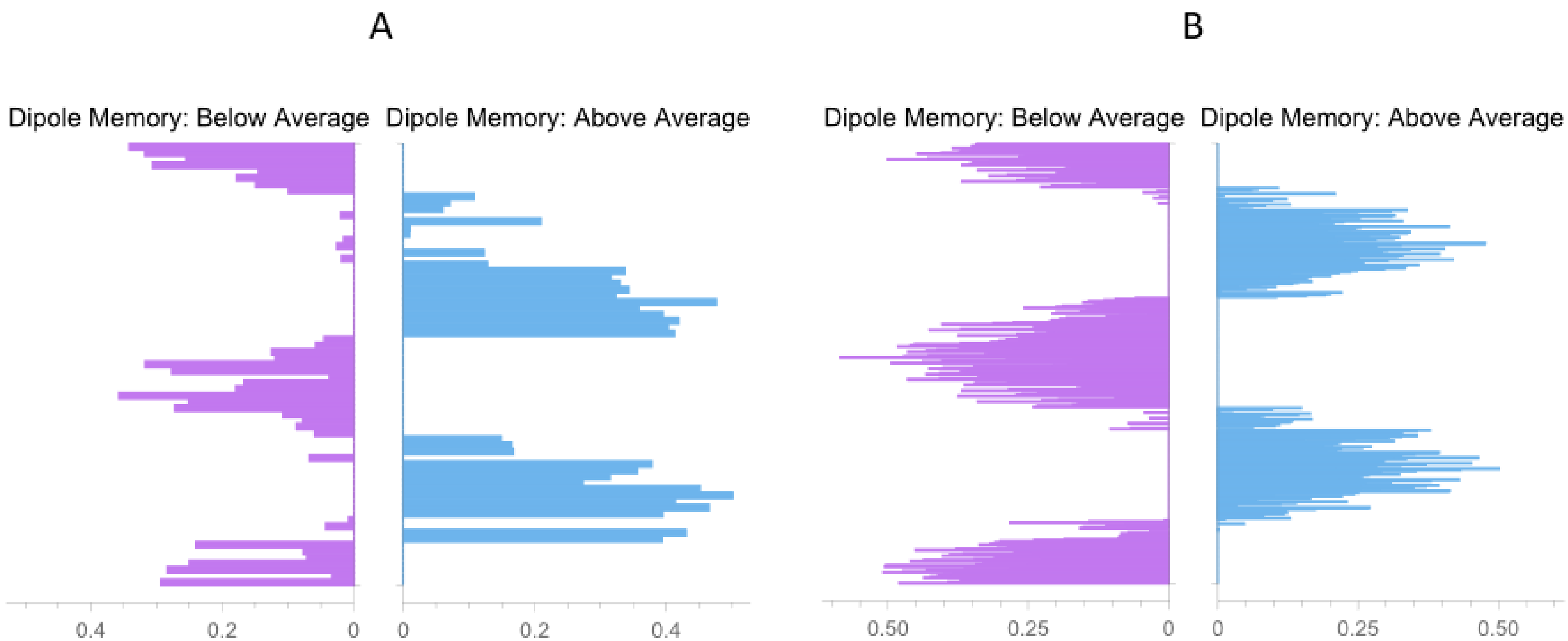


Figure 3. Dipole memory after one epoch of WTA training. **A.** 71 categories, $\rho = 0.75$ and $r = 0.5$. **B.** 400 categories, $\rho = 1.0$ and/or $r = 0.005$.

Some results

Table 3. Lucas Critique Problem: Distributed Training and Testing

ρ_2	Clusters	Test Data	R_{ExAnte}	R_{ExPost}
Results after Epoch 1 WTA, Epoch 2 WTA, and Epoch 3 Distributed training with Regular Cycles 1&2 data. Testing by 26 simultaneously activated neurons				
0.0	422	Regular Cycles 1&2	0.8767	0.9816
0.5	431	Regular Cycles 1&2	0.8471	0.9850
0.75	493	Regular Cycles 1&2	0.7387	0.9903
Results after Epoch 4 distributed training with Imbalanced Cycles 3&4 data after Epoch 3 (line 1 above, $\rho_2 = 0$). Testing by 26 simultaneously activated neurons				
0.0	422	Imbalanced Cycles 3&4	**0.8645**	0.9751
Results after Epoch 1 WTA and Epoch 2 WTA training with Regular Cycles 1&2 data, followed by Epoch 3 training with Imbalanced Cycles 3&4 data. Testing by 26 neurons				
0.0	422	Imbalanced Cycles 3&4	**0.8879**	0.9794

Some results

Table 3. Lucas Critique Problem: Distributed Training and Testing

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Fig. 4c is the Happy End

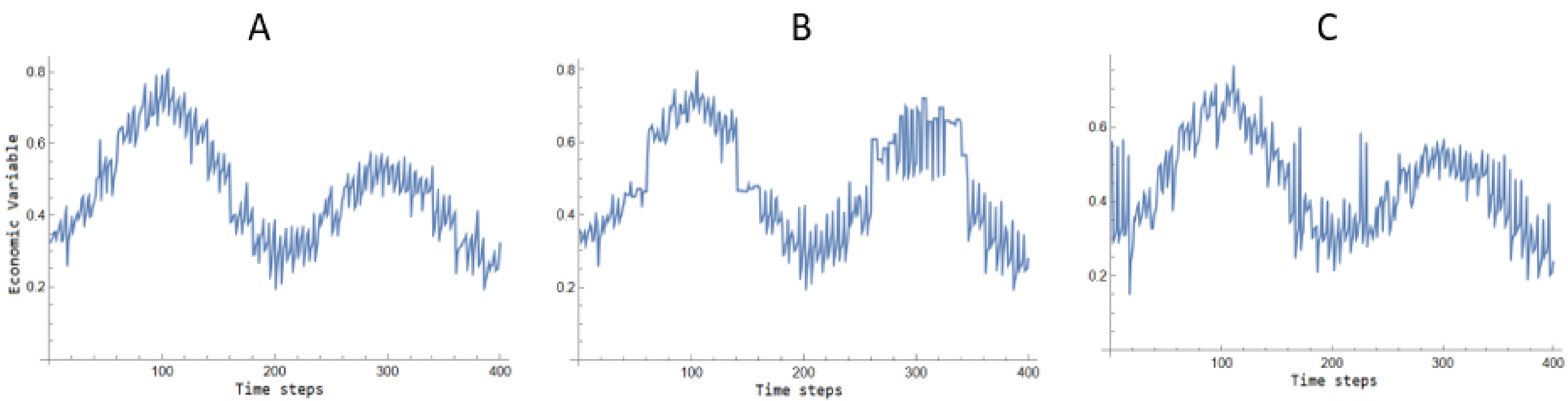


Figure 4. Neural network performance. **A.** Imbalanced cycles 3 & 4 data as submitted. **B.** Forecast ex-ante during WTA learning. **C.** Forecast ex-ante during distributed learning.

Fig. 4c is the Happy End

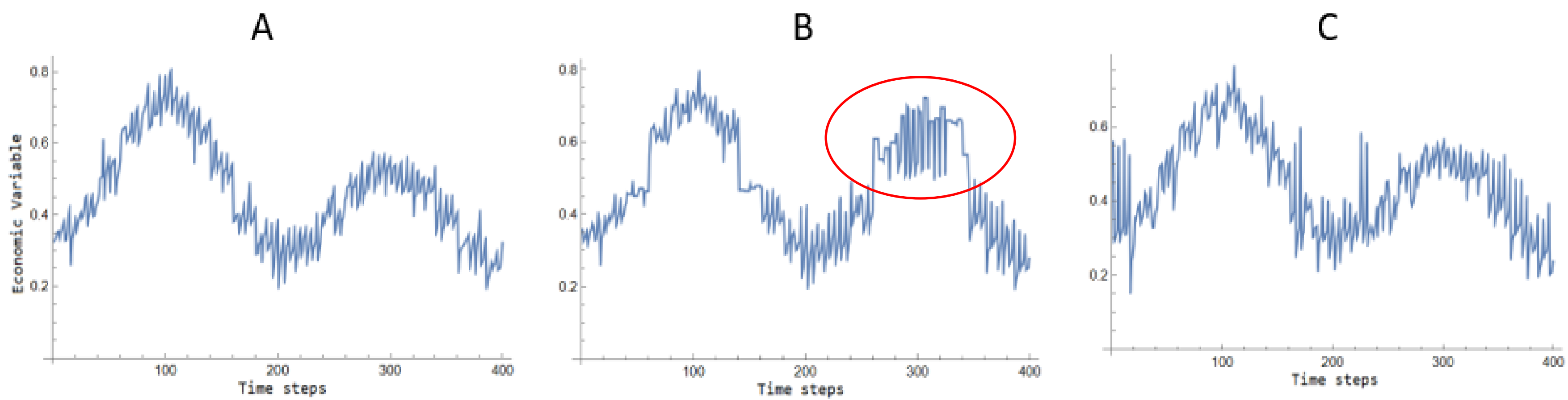


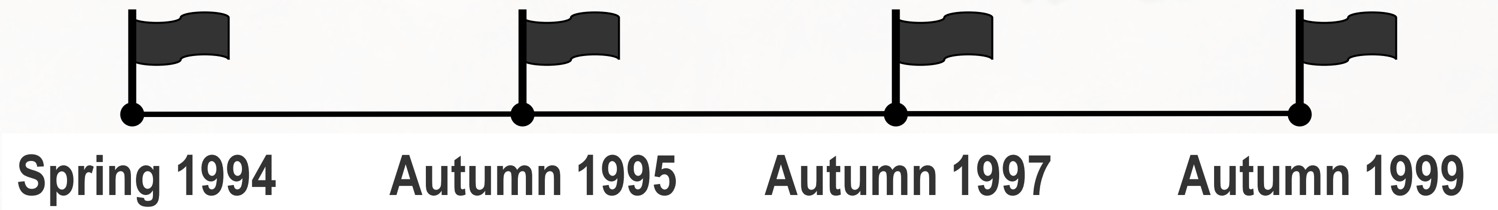
Figure 4. Neural network performance. **A.** Imbalanced cycles 3 & 4 data as submitted. **B.** Forecast ex-ante during WTA learning. **C.** Forecast ex-ante during distributed learning.

- That was a hard problem with synthetic data.

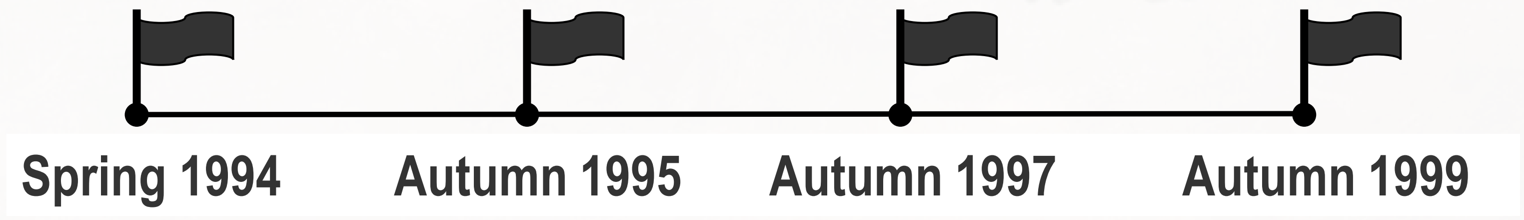
- Now comes a harder problem with real data.

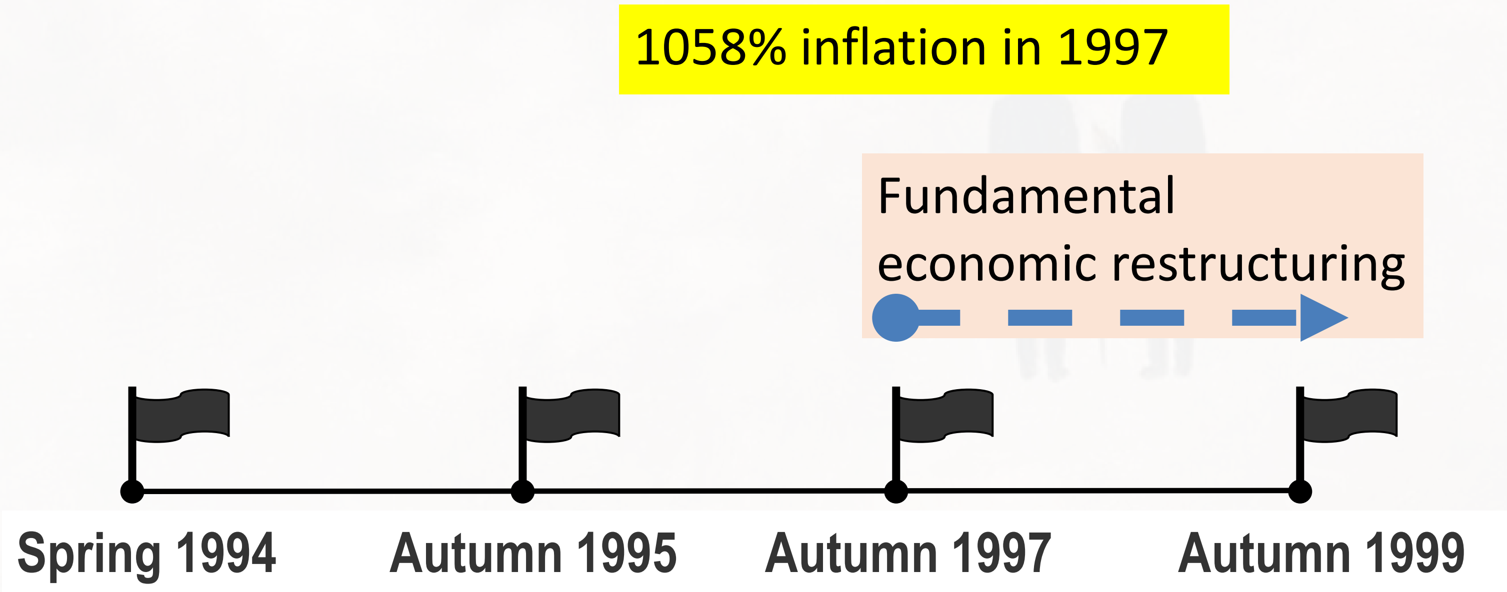
Problem 2: Work Motivation and Professional Life in Bulgaria 1994–1999

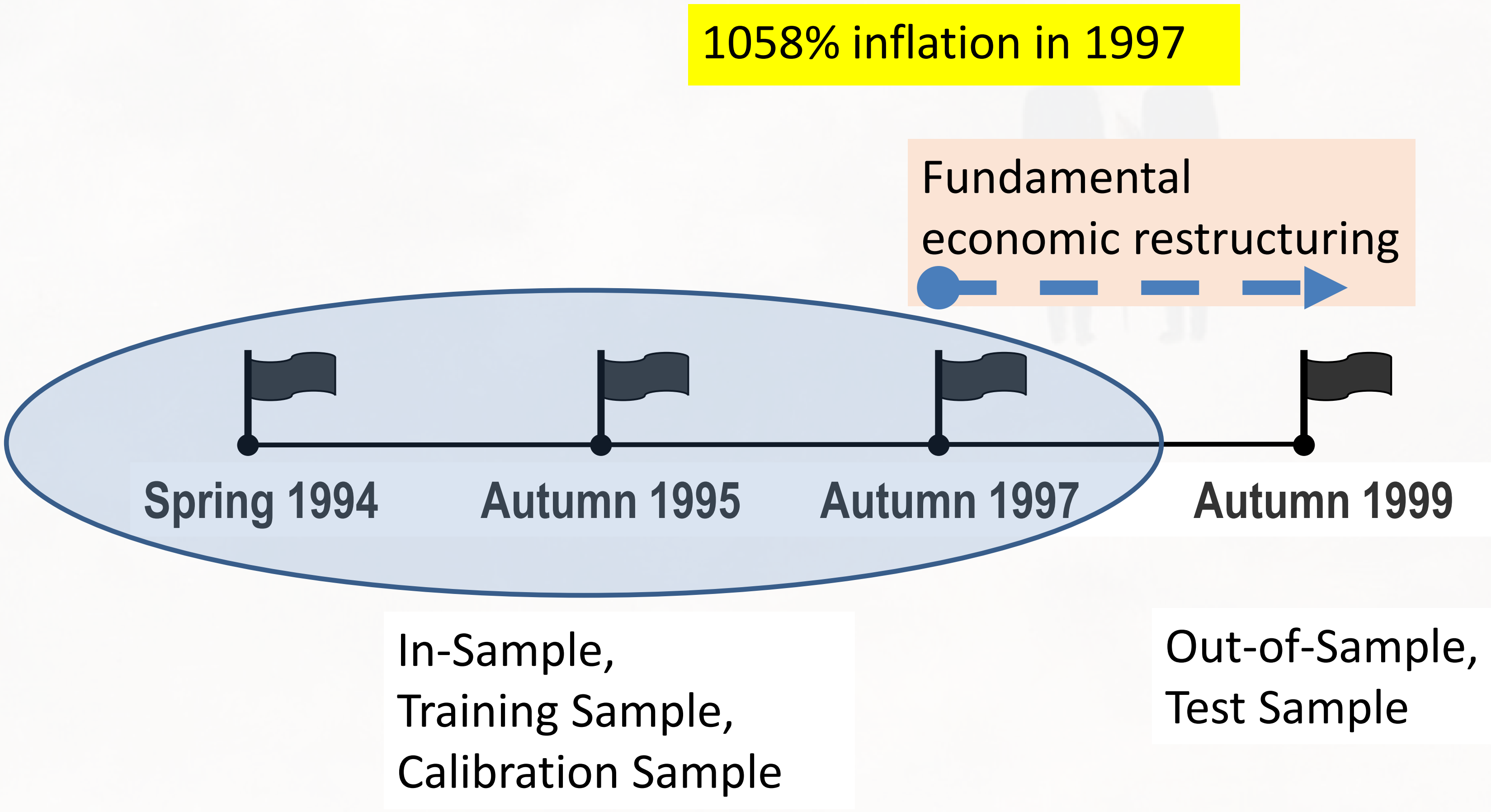
- Comprehensive measurement instrument from work and organizational psychology
- 49 psychological and 4 demographic variables, 450 items
- Representative sample of 1107 people
- Longitudinal, 4 waves


Spring 1994
Autumn 1995
Autumn 1997
Autumn 1999

1058% inflation in 1997




1058% inflation in 1997
Fundamental economic restructuring
Spring 1994
Autumn 1995
Autumn 1997
Autumn 1999



1058% inflation in 1997
Fundamental economic restructuring
Spring 1994
Autumn 1995
Autumn 1997
Autumn 1999
In-Sample, Training Sample, Calibration Sample
Out-of-Sample, Test Sample

To what extent can the new NN predict the elements of work motivation and professional life <u>in 1999</u>, based on all previous waves?

I/O data plots

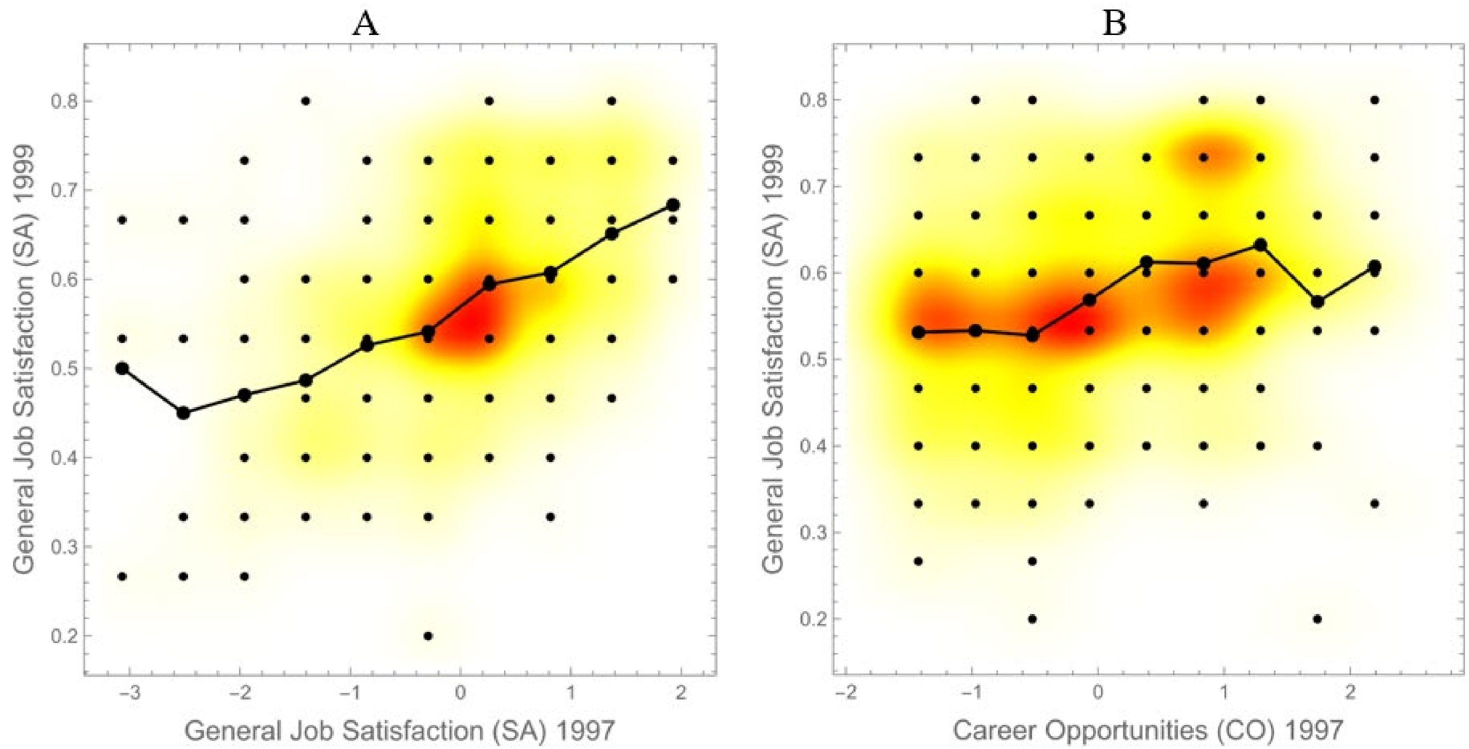


Figure 5. Data for General Job Satisfaction (SA). Small dots are empirical observations. Bigger dots are column averages. Joining lines highlight tendencies. Red and yellow colours indicate data concentration, i.e., areas with more people behind a single small dot. Two out of five predictors for SA are shown.

- Data are noisy
- Dependencies are almost linear

- Any forecasting method cannot be much better than linear regression

An example: What predicts **General Job Satisfaction**

Linear regression analysis identified five predictors:

- Socioeconomic wellbeing
- Previous General Job Satisfaction
- Opportunity for Personal Growth
- Task Identity
- Career Opportunities

Examples: A few people

Figure 6. Examples of input data for General Job Satisfaction (SA) forecasting. (Panel data, input variables are from moment t, output SA is from $t + 1$). **A.** A person who assessed their job satisfaction, personal growth, and career opportunities way above average despite a low socio-economic wellbeing. **B.** A person feeling somewhat dissatisfied with their job although all other

Table 4. Forecasting General Job Satisfaction (SA)

Description	Test with training sample #2, SA 1995/97 (n = 583)			Test sample SA 1997/99 (n = 384)		
	Pearson Linear	Spearman Rank	Kendall Rank	Pearson Linear	Spearman Rank	Kendall Rank
Benchmark: Linear regression Panel data 1994/95 and 1995/97 5 independent variables	0.5583	0.5513	0.4145	*0.4820*	*0.4832*	*0.3610*
1 WTA epoch, fast commit, $\rho = 1$, Data 1994/95 (n = 877) Formed categories: 877	0.5406	0.5503	0.4121	0.4941	0.4861	0.3613
Ep 1: WTA, data 1994/95 (n = 877) Ep 2: WTA, data 1995/97 (n = 583) Fast commit, $\rho = 1$. Formed 1460 categories	0.9585	0.9548	0.9377	0.4958	0.4882	0.3632
Ep 1: WTA, data 1994/95, $\rho = 1$ Ep 2: WTA, data 1995/97, $\rho = 0.9$ Fast commit, moderate recode (0.3), Formed 1183 categories	0.8745	0.8768	0.7816	0.4960	0.4889	0.3636
Ep 1: WTA, data 1994/95, $\rho = 1$ Ep 2: WTA, data 1995/97, $\rho = 0.7$ Fast commit, moderate recode (0.3), Formed 909 categories	0.6630	0.6685	0.5318	0.4991	0.4875	0.3627
Ep 1: WTA, data 1994/95, $\rho = 1$ Ep 2: WTA, data 1995/97, $\rho = 1$ Ep 3: DISTR (100 neurons), $\rho_2 = 0$, Data 1995/97. Formed 1460 categories	0.8296	0.8844	0.7529	0.5007	0.4930	0.3659
Ep 1: WTA, data 1994/95, $\rho = 1$ Ep 2: DISTR (100 neurons), $\rho_2 = 0.1$, Data 1995/97, fast commit, slow recode (0.077). Formed 885 categories	0.5428	0.5566	0.4202	**0.5036**	**0.4930**	**0.3668**

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Further results: the same NN produces different forecasts

Table 5. Distributed forecasts for General Job Satisfaction (SA), best model with 100 active neurons in Epoch 2 distributed training

Number of simultaneously active neurons during testing	Test with training sample #2, SA 1995/97 (n = 583)				Test sample SA 1997/99 (n = 384)		
	Pearson Linear	Spearman Rank	Kendall Rank		Pearson Linear	Spearman Rank	Kendall Rank
1	0.3514	0.4437	0.3302		0.2604	0.3426	0.2491
5	0.4234	0.4809	0.3546		0.3528	0.4271	0.3156
50	0.5317	0.5444	0.4083		0.4941	0.4839	0.3588
100	**0.5428**	**0.5566**	**0.4202**		**0.5036**	**0.4930**	**0.3668**
150	0.5364	0.5527	0.4153		0.4982	0.4838	0.3638
200	0.5297	0.5441	0.4075		0.5017	0.4922	0.3665
500	0.5114	0.5154	0.3816		0.4866	0.4797	0.3548

Forecasting: The best result

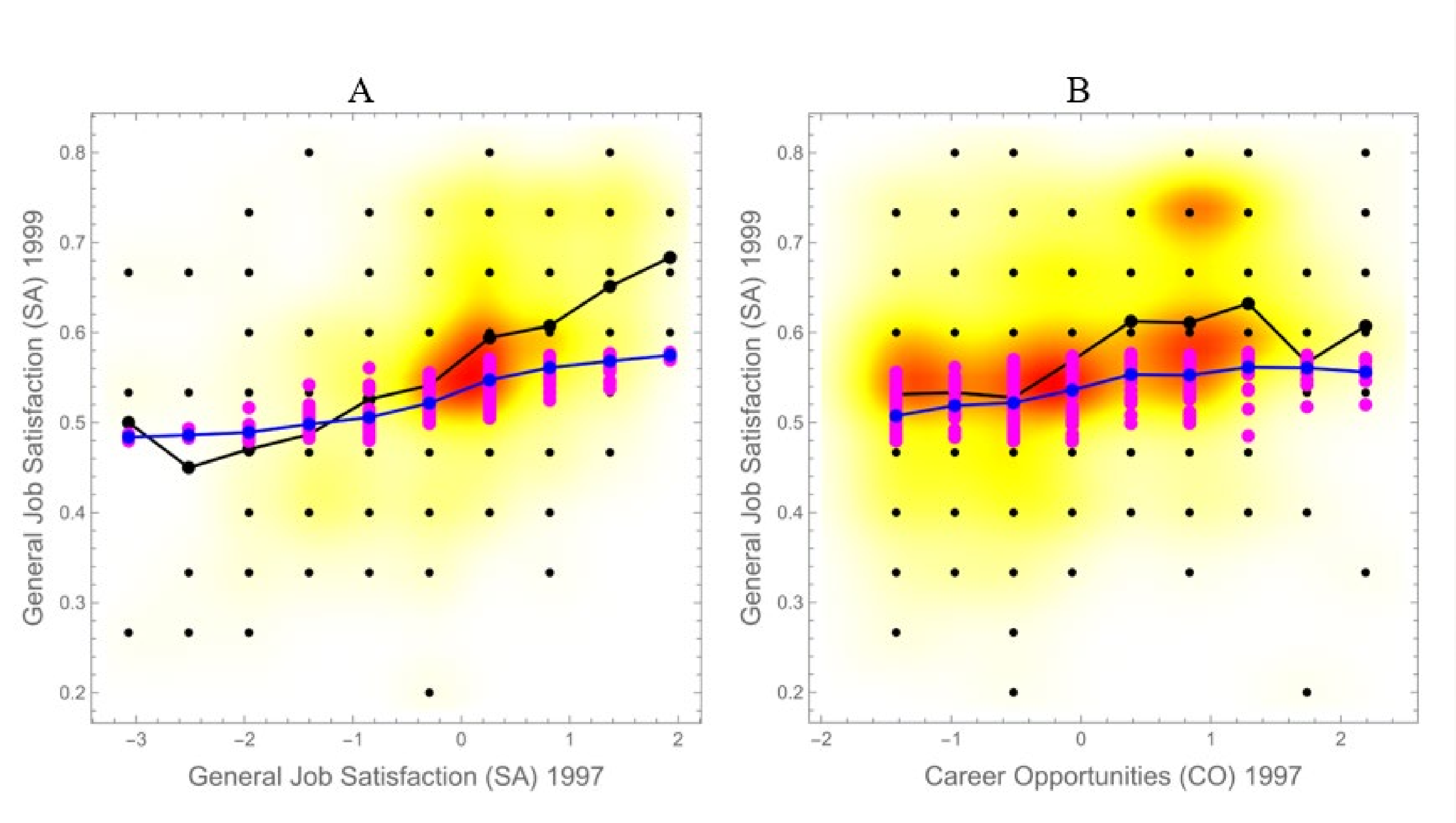
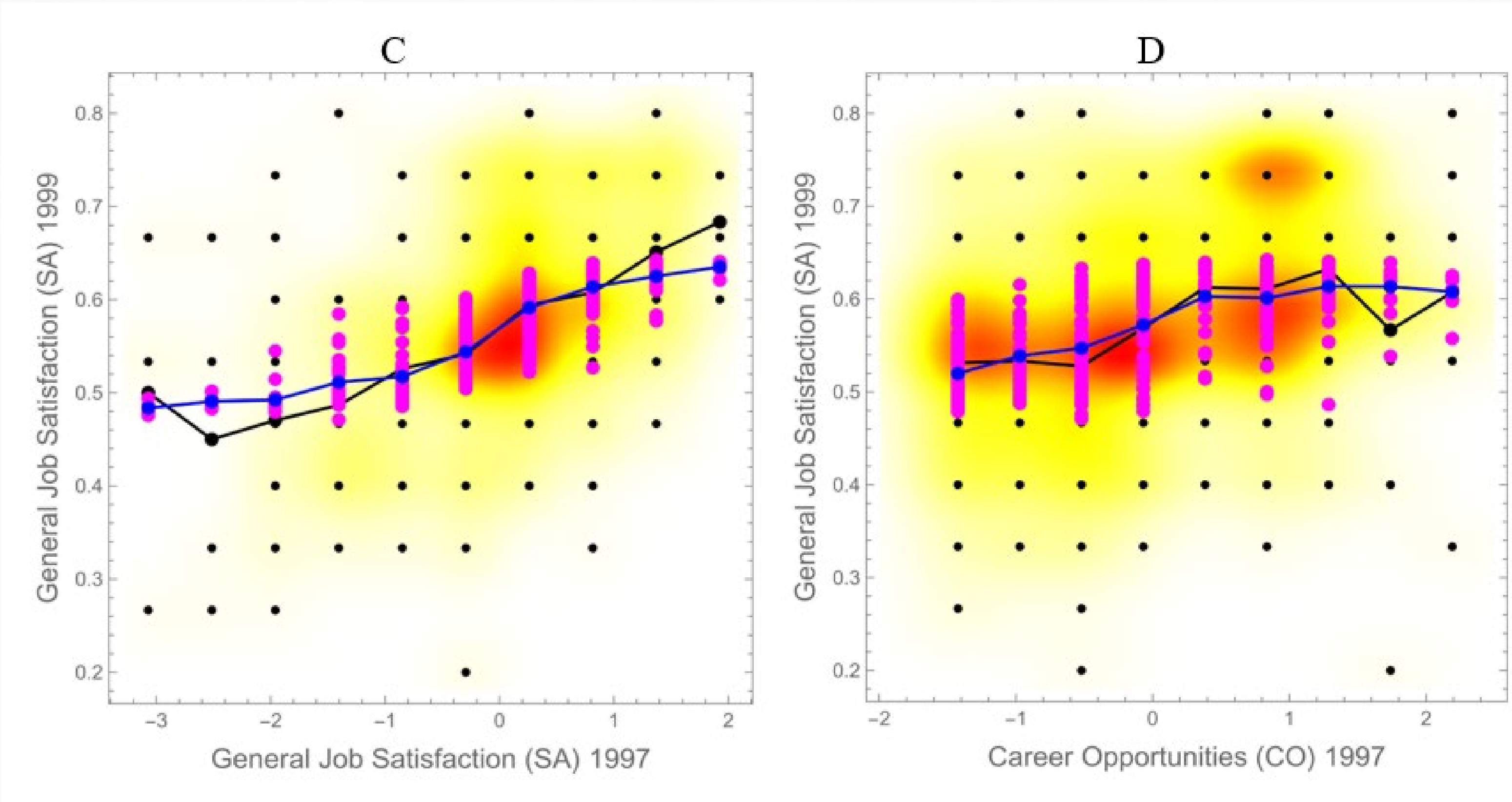


Figure 9. Forecasting General Job Satisfaction (SA) in 1999 after one WTA epoch followed by one distributed training epoch. **A** and **B**. The best result, R = 0.5036, is achieved by a 100-neuron forecast. **C** and **D**. A tiny bit worse, yet visually more compelling result is R = 0.5017, by a 200-neuron forecast.

And the second best result



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In some cases, the NN is visually successful, numerically – not so much

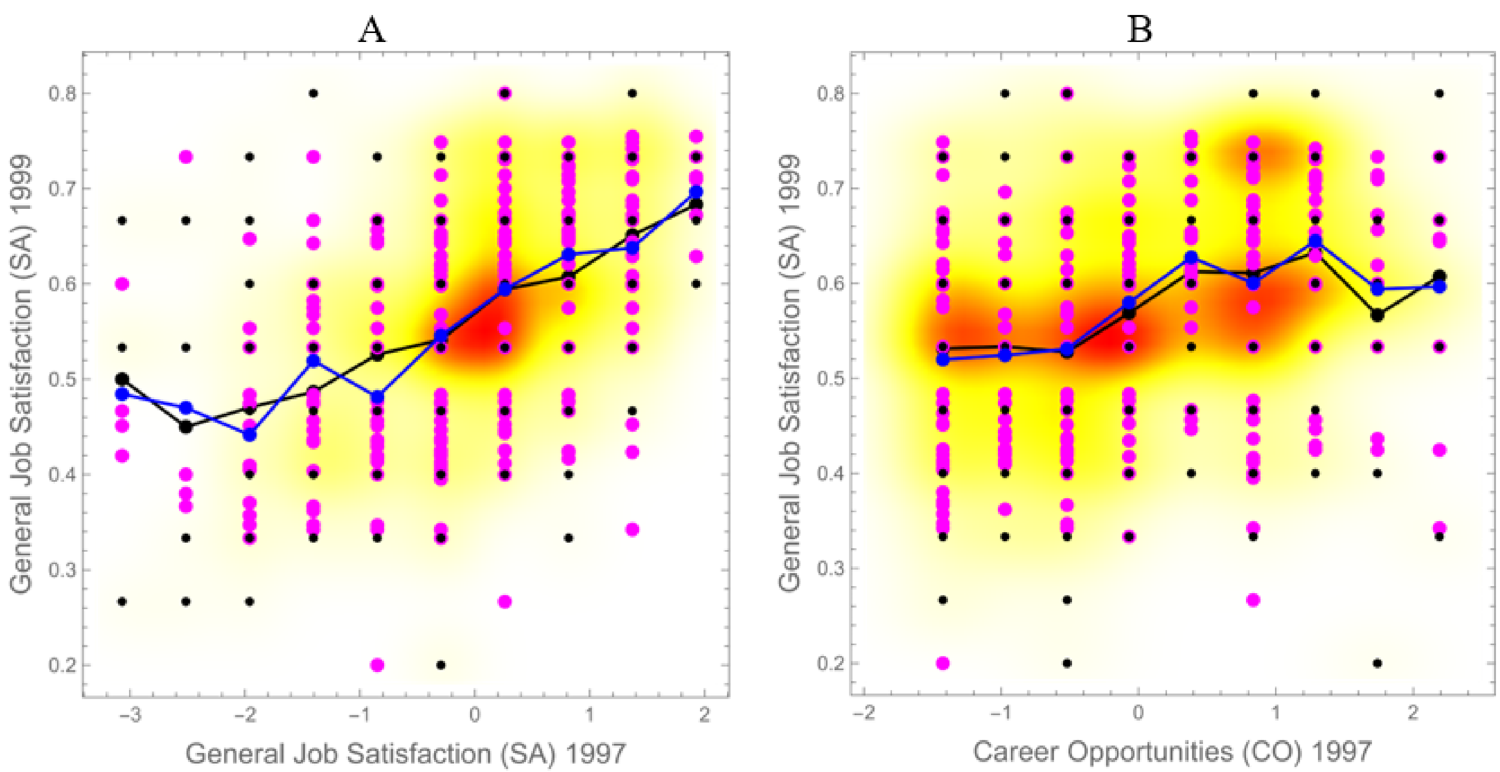

Figure 8. Forecasting General Job Satisfaction (SA) in 1999 – two predictors are shown. A single-neuron forecast after two WTA training epochs with 1994/95/97 data. Small and bigger black dots are as in Figure 5. Magenta dots are predicted observations, blue dots are column averages over predicted values. Joining lines highlight the tendencies.

- In 1999-2000, with the same data, MLP of
  - two hidden layers
  - ~0.5 mln parameters,
  - and backpropagation

(a “deep NN”) achieved forecasting precision by 1-2 p.p. above linear regression.

- The new NN achieves the same thing.

A Working Title…

A dART-Dipole neural system with error-minimization learning

A Working Title…

An efficient error-minimizing dART-Dipole neural network

A computationally efficient and explainable dART-Dipole neural network

A dART-Dipole neural network combining match-based and error-based learning

A Working Title…

dART-Dipole: A computationally efficient, explainable, and novelty-detecting function approximator

Thank you!