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Recurrent and multi-layer neural networks playing "Even-Odd": reflection against regression

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Abstract. Reflection understood as an internal representation of the external world by the subject is the key property of consciousness. In a refined form this property is manifested in reflective games. To win a reflective game a player has to use reflection of strictly one rank higher than the opponent. So it can be assumed that there are only two game modes - when only one player uses reflection and wins and when both players use reflection but one of them chooses incorrect reflection rank. The option of random move selection is not considered since firstly, starting the game for a draw is strange, and secondly, it is technically impossible to make random moves without a special device. Experiments with recurrent neural networks playing with each other showed that the entire set of game patterns (time series of the game score) is split into two sharply different groups that can be associated with two modes mentioned above. Experiments, in which a multilayer neural network, which is basically incapable of reflection, played against a recurrent neural network, showed that a recurrent neural network has a clear advantage winning confidently in more than 90% of the games. At the same time game patterns demonstrate splitting into two sharply different groups as was observed in experiments with the game of two recurrent neural networks and in the reflexive game of living people.

1. Introduction

The nature of consciousness is the one of the fundamental problems of science and philosophy. The long-term goal of cognitive neurobiology is to identify the neural correlates that underlie cognitive phenomena, and to determine which neurological events correlate with one or another state and content of consciousness. This approach is based on the concept of “neural correlates of consciousness” (NCC) [1, 2]. Orientation of NCC concept to the identification of minimal neural structures that accompany some conscious experience gives rise to move away from studying the complex functions of the human brain [3-8] to the study of individual phenomena of consciousness realized by simple systems.

According to V. Lefebvre [9] subjectivity (consciousness, mind) is associated with the presence of an internal representation of the external world including the image of the subject itself. Lefebvre called this type of inner representation "reflection." Reflection is possible to be the key attribute of consciousness.

Obviously the most effective approach is to study such behavior which in addition to reflection contains the minimum contribution of other cognitive functions, such as logical reasoning, pattern recognition, memory, etc. Reflexive games almost completely meet these requirements.

In the course of the previous research [10] two groups of similar patterns of “Even-Odd” reflexive game dynamics was revealed. Significant difference observed in these patterns indicates qualitatively different dynamic patterns of neuron excitations of the playing networks. We have made an assumption the difference is the manifestation of two game modes - when only one player uses reflection and wins and when both players use reflection, but one of them chooses incorrect reflection rank. Let’s consider it in more detail.

From obvious considerations it is clear that reflection is a kind of interaction of external signals with the internal representation of the external world and the intentions of the subject, which, ultimately is also a combination of signals generated by the neural network (NN) itself. Therefore, recurrent neural networks (RNNs) seem to be a natural candidate for modeling reflection.

A steady win in any reflective game including the simplest one – "even-odd" is a sign of a player using a reflection that is exactly one rank higher than the playmate reflection level. In the study of reflection it seems important to find out how the “hardware” characteristics of a RNN affect the quality of the playing and therefore the ability to the reflection of the desired rank.

However, when two RNNs are playing some complex situations may arise when both neural networks turn to reflection, but of different ranks. To study the simplest case, it would be useful to turn to a system that can reveal patterns, but cannot possess reflection, in principle. As such a system, multilayer (feed-forward) neural networks (MNNs) can be used.

But if the processing of temporary patterns is natural for the RNN then for the MNN the temporal pattern of the opponent’s moves can be set using the shift register in which the next opponent’s move is entered in the left place and the content of the register is shifted by one position. Unlike RNN where reflection may occur, in the case of MNN we are guaranteed to deal only with non-linear regression - the MNN goal is to predict the next move of the playmate on the base of the found regression dependence. Starting a reflective game between the RNN and the MNN we can evaluate the effectiveness of reflection and regression for this type of non-cooperative interaction. In addition if reflection does not occur in every RNN then one should expect splitting of all game patterns into two typical groups as was observed in [10].

So the aim of the work is to compare the capabilities of systems potentially capable of reflective information processing and systems without reflection in the situation of non-cooperative strategic interactions.

2. Methods and materials

We used fully-connected RNN and three-layer MNN with different numbers of neurons. In addition we used different depths of error propagation for the RNN, and the length of the shift register displaying the previous moves of the playmate for the MNN.

NN played with each other in "even-odd" game. Let’s recall the rules of the game. Each player secretly selects “0” or “1”, and then their choice is presented and summed. An "even" amount means that one player receives one point, while an "odd" amount means that the point is received by another player. "Even-odd" is an example of a reflexive game in which there is no fixed winning strategy, and a draw strategy is a random choice. If players cannot choose randomly or try to avoid a draw the game becomes non-trivial: the one who better predicts opponent's moves becomes the winner.

The functioning and training of the used RNN is described in details in the previous work [10]. In order to single out only the effect of the structure on the playing abilities of NNs, the transition function of the MNN was chosen the same as for the RNN:

$$\alpha_i^{n+1} = \frac{\rho_i^n}{a + \left|\rho_i^n\right|}, \quad \rho_i^n = \sum_j w_{ij}\alpha_j^n + A_i^n, \tag{1}$$

where α_i^n is the output signal of the *i*-th neuron at the *n*-th moment of time; w_{ij} is the matrix of weight coefficients (for a RNN this matrix is single, and for a layered network there are several of them); $A^n{}_i$ is the input signal arriving at the *i*-th neuron at the *n*-th moment of time.

Information about the move of the partner is fed through two input neurons of the RNN and to the first place of the MNN shift register. The ratio of signals of two output neurons determines the move of the neural network - “0” or “1”. The objective functions for the NNs differ because one NN wins when its move coincides with the move of the second NN, and the second NN wins when it makes a move different from the opponent’s move:

$$H_1(\alpha_i^n, n) = \frac{1}{2}\left[(\alpha_3^n - move2)^2 + (\alpha_4^n - (1 - move2))^2\right] \text{ and}$$
$$H_2(\alpha_i^n, n) = \frac{1}{2}\left[(\alpha_3^n - (1 - move1))^2 + (\alpha_4^n - move1)^2\right]. \quad (2)$$

The synapses of the RNN and the MNN were modified after each move according to the well-known algorithm of back propagation of the error.

Open soft, ‘Lazarus’ (https://www.lazarus-ide.org/) was used for the simulation. For statistic analyses of experimental data, MS Excel (Fourier transform) and open soft ‘Tanagra’ (http://eric.univ-lyon2.fr/~ricco/tanagra/en/tanagra.html) (cluster analyses) were used.

3. Results

A comparison of the playing abilities of the RNN and the MNN showed that with the same number of neurons (10) and the depth of memory (5 moves to the past) the MNNs as a whole demonstrate a significantly worse playing quality than the RNNs.

It is important to note about one feature of the used RNN. The fact is that information about the opponent’s move received at the current step of the game will only be available to other RNN neurons in the next step, then the response of internal neurons will only be available to output neurons in the second step, and therefore, the RNN reaction to this opponent’s move can only appear on third step after the move. Then it turns out the RNN used in the work wins by planning the opponent's move two steps forward.

In contrast to the RNN the state of the shift register is accessible to the MNN immediately after the opponent moves, and the calculations for all layers occur in one clock cycle. Then "honestly" we need to introduce a temporary delay in the submission of information about the playmate's move to the shift register. The share of MNN wins in the game with RNN depending on the value of the time delay is shown in table 1.

Table 1. The share of MNN wins in the game with RNN depending on the value of the time delay.

Delay	0	1	2
MNN win percentage	10.9%	8.8%	5.4%

White's nonparametric T-test showed that the difference between the quality of the game for different delay values differ at the 5% significance level.

At the same time the appearance of the curves of RNN-MNN game patterns looks quite variable (figure 1B), but visually they are not essentially different from the game patterns of RNN-RNN games (figure 1A).

Before a more detailed comparison of the RNN and MNN playing abilities the dependency of the RNN playing abilities on their parameters — the number of neurons and the depth of error propagation to the past — were studied (figure 2). Each point on the graph is the result of averaging from 1,500 to 3,000 games (depending on the severity of the result). The gain of NN is the deviation of score from the case of equal playmates when the expected score is zero. Each game was of 500 moves. The reference RNN was of 10 neurons and the error propagation depth was 5 clock cycles. These parameters happened historically – a minimal neural network that successfully played against a human had such parameters [11].

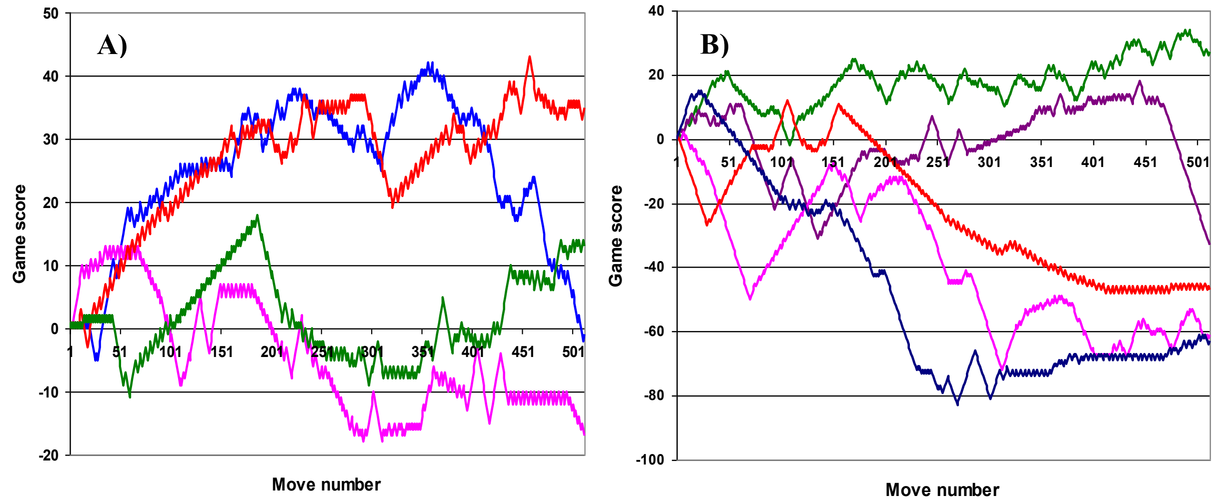

Figure 1. Examples of game patterns of two recurrent NNs (A) and recurrent and multilayer NNs (B).

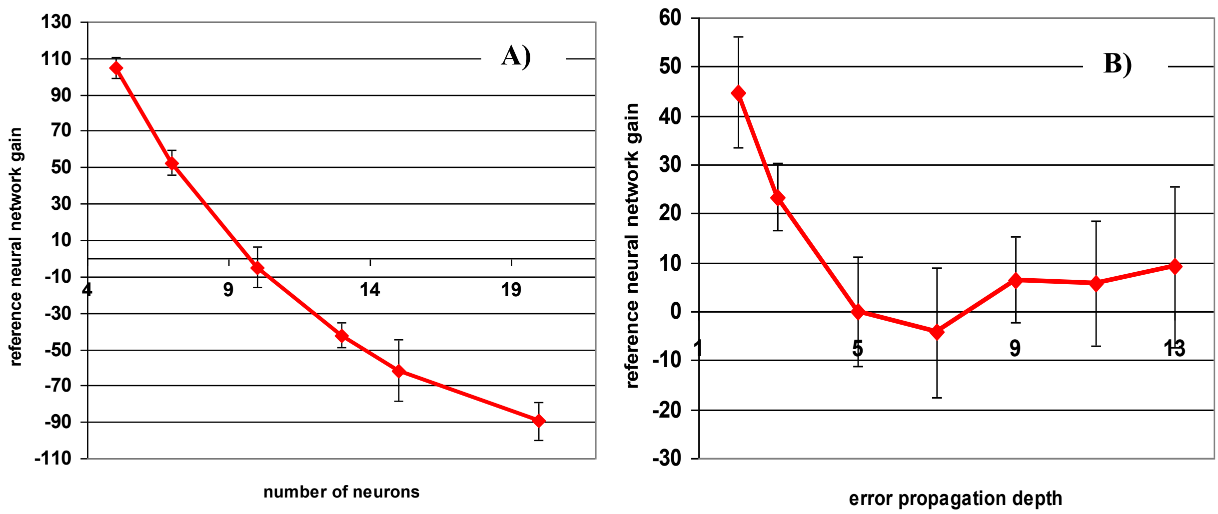

Figure 2. Dependence of the quality of NN playing on the number of neurons (A), and the depth of error propagation (B).

In principle the results presented were not unexpected, because if we associate success in a reflective game with the presence of reflection of the corresponding rank (one more than the opponent's one) then a larger number of neurons allows to organize better reflection – reflection need brains. And the optimum of the depth of error propagation can be explained: for effective game in the situation when a partner can quickly change strategies extremely deep back propagation of errors into the past reduces the possibility of fast response to changes in the opponent's strategy.

The results of RNN against MNN game (reflection against regression) turned out to be quite unexpected (figure 3). MNN with three layers (4; 4; 2) and a shift register length of 5 was initially played against RNN. Formally, the number of neurons of this MNN coincided with the number of neurons of the referent RNN, and the memory depth coincided with the depth of error propagation. However, it turned out that RNNs triumphed even with a minimum number of neurons - 4 (two input and two output neurons) (figure 3A). The dependence on the depth of error propagation is also quite unusual - RNN loses only at a depth of 1, i.e. when only the synapses of the output neurons change (figure 3B). It turned out that the MNN can outperform four neuron RNN with a propagation depth of error 2, if the number of MNN neurons is increased, for example, in the second layer (figure 3C).

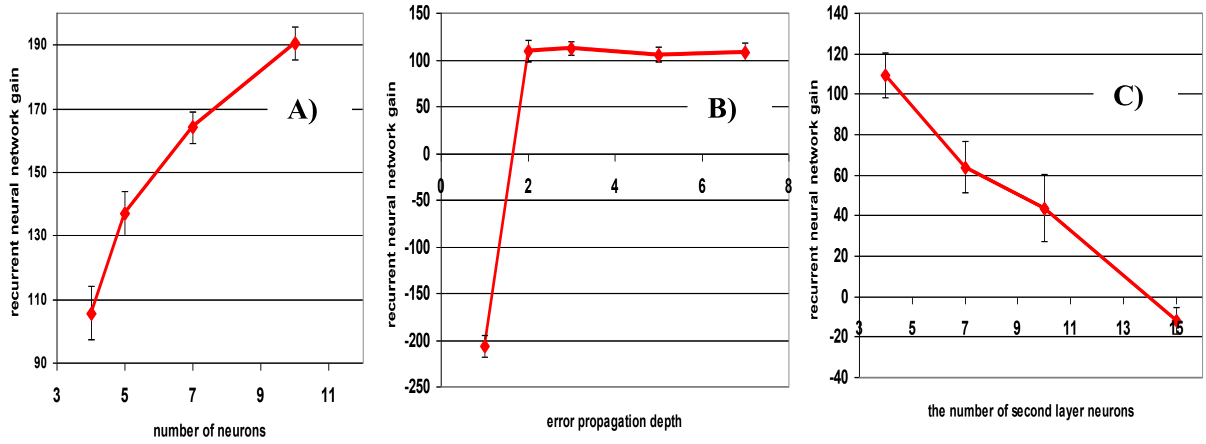

Figure 3. Dependences of the gain of the referent RNN on the number of neurons (A) in it, the depth of error propagation (B), and on the number of neurons in the second layer of MNN (C) (the RNN was of 4 neurons and the error propagation depth was 2).

The analysis of patterns repeatability was carried out for an RNN with 10 neurons and an error propagation depth of 5. MNN was of "5; 5; 2" structure and the shift register length of 5. Fast Fourier transform showed a wide variety of frequency and phase spectra obtained by processing game patterns. At the same time despite the variety of frequency spectra they are not very expressive (figure 4) in comparison with phase spectra (figure 5).

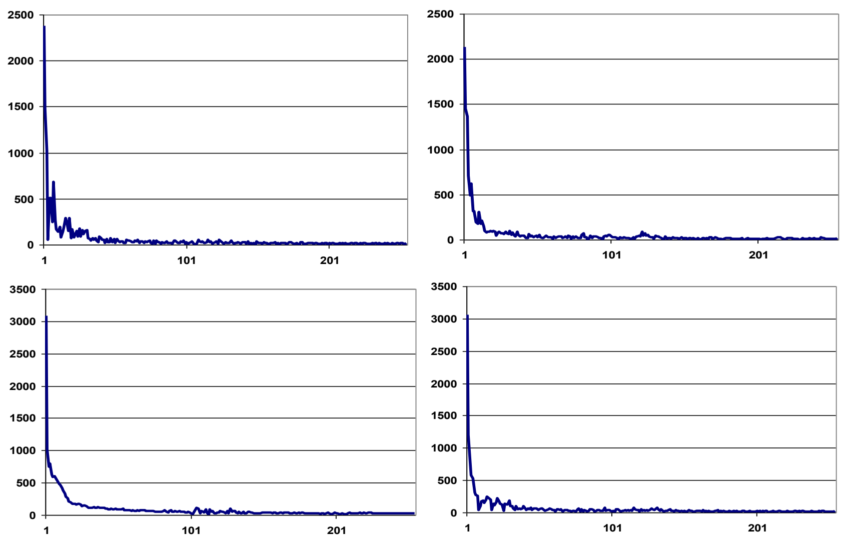

Figure 4. Some examples of frequency spectra of game patterns obtained using the Fourier transform.

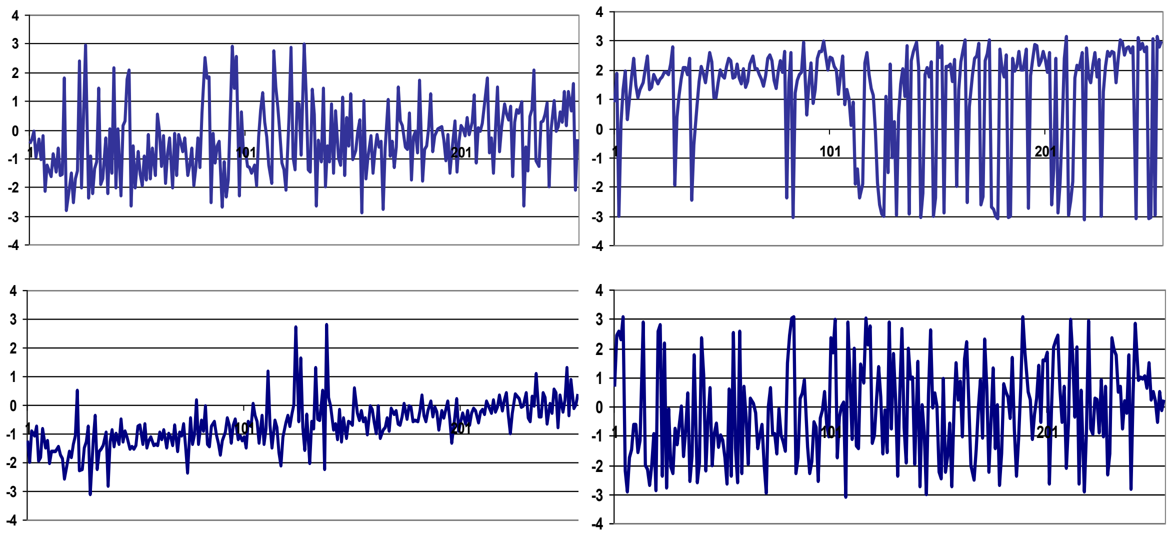

Figure 5. Some examples of phase changes in game patterns obtained by the Fourier transform.

Cluster analysis (hierarchical clustering, Ward's criterion) as in the case of RNN-RNN game [10] showed a similar splitting into two sharply different groups of game patterns (figure6).

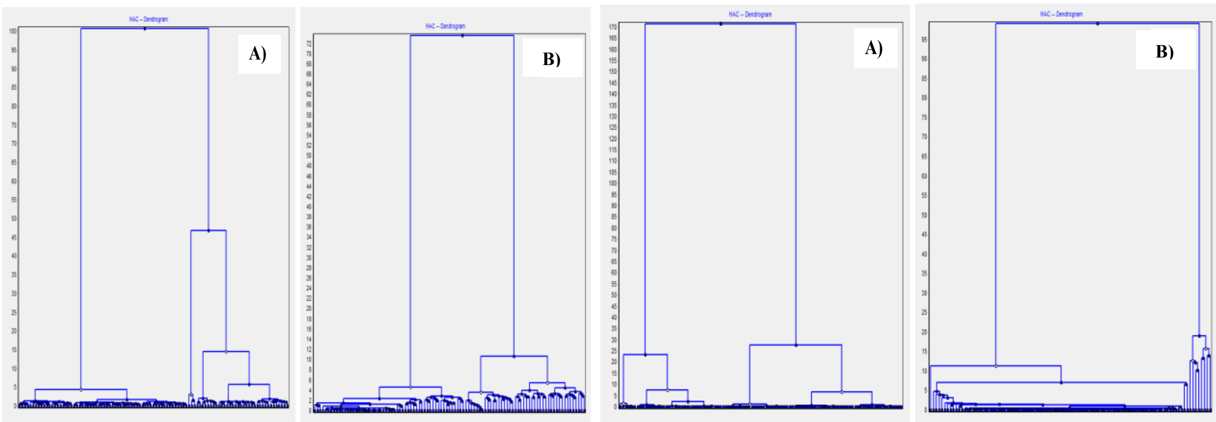

Figure 6. Hierarchical proximity tree of frequency (A) and phase (B) spectra of the Fourier transform of game patterns between recurrent (left pair) and recurrent and multilayer (right pair) NNs.

The results obtained in this work are similar to obtained before [10], and as was already noted these results are in a good agreement with the results of a massive study of decision-making in non-cooperative strategic interactions [12]. The study revealed the presence of two types of strategies in people: 1) "won - repeated, lost - changed", characteristic of most persons; 2) a strategy based on knowledge of the “typical person” strategy described above. The second strategy is to take the position of the opponent (it is a reflective action) that allows the player to prevail over the first strategy. Based on this work we can assume obtained cardinal difference in game patterns is associated with the presence or absence of reflection inside players.

According to the results of clustering the phase spectra of game patterns, it can be seen (figure 6B, right pair) that one of the groups of patterns makes up a small fraction commensurate with the share of MNN wins. Presumably these are the cases when the RNN was not able to perform the reflection mode.

4. Conclusion

In reflective games a steady gain implies the winning player has a reflection of one rank higher than opponent's one. In favor of the assumption that in the most of the analyzed game patterns the winnings were not the result of the random success, but the result of a “conscious” (reflexive) choice of the move, says the splitting of all game patterns into two groups. In the case of random outcomes of the game such clustering seems to be impossible.

It was shown the increase in the number of neurons causes the increase of the effectiveness of RNN. This effect seems quite understandable - for reflection, bigger brains are needed. But regarding the depth of error propagation, i.e. the degree of influence of past experience on the current choice situation is different - there is an optimal depth of error propagation. This effect also can be naturally explained. Indeed, in the case of a rapidly changing strategy of opponent, relying on old patterns leads to loss.

And finally, it has been demonstrated regression cannot effectively replace reflection in non-cooperative strategic interactions, which include reflexive games. From which it follows that the development of a truly powerful artificial intelligence is impossible without the reproduction of reflexive processes in intellectual systems.

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