

DATA FORMATS IN MULTI-NEURONAL SYSTEMS AND BRAIN REVERSE ENGINEERING

Witali L. Dunin-Barkowski,

*Department of Neuroinformatics,
Center for Optical Neural Technologies
Scientific Research Institute for System Analysis,
Russian Academy of Sciences,
Moscow, Russia*

wldbar@gmail.com

*David C. Marr Memorial Internet Laboratory
on Brain Reverse Engineering*

<http://rebrain.2045.com>

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The main claim in this communication is that now we are close to understanding data formats in neuronal systems.

Understanding comes from multiple recent contributions to the field from many labs in the world. We will show our old results, which are relevant to this problem.

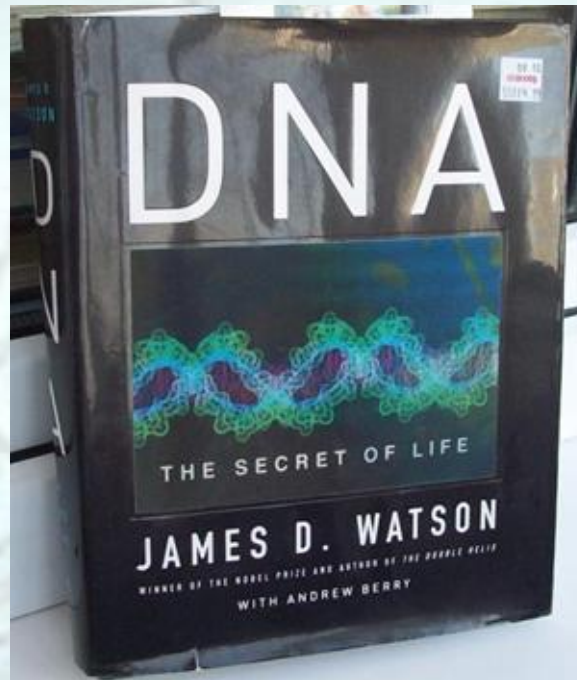
Then I will speculate on general importance of the data formats for understanding informational systems.

And, finally, the arguments will be given in favor of hope for success of our project:

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which was first publicized in Boston on September 5th at Neuroinformatics 2011:





INTRODUCTION
THE SECRET OF LIFE

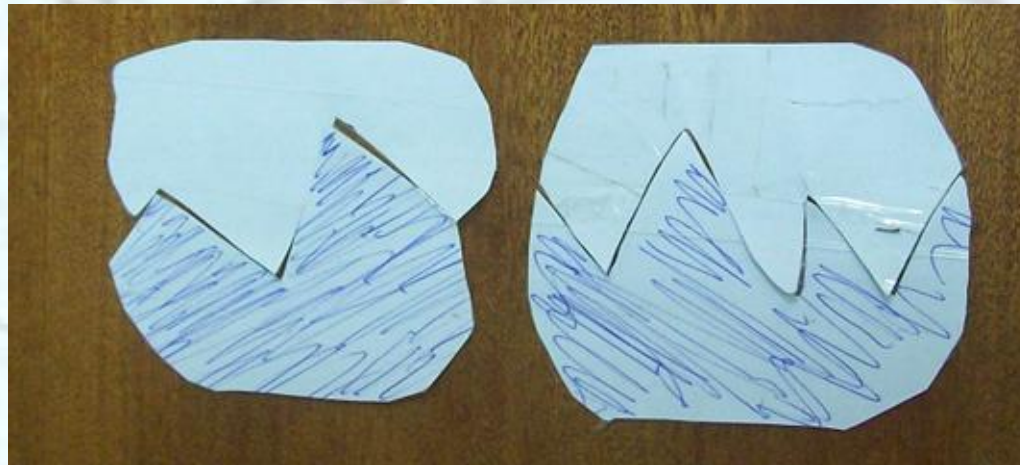
As was normal for a Saturday morning, I got to work at Cambridge University's Cavendish Laboratory earlier than Francis Crick on February 28, 1953. I had good reason for being up early. I knew that we were

basic unit, the nucleotide, which comes in four varieties: adenine (A), thymine (T), guanine (G), and cytosine (C). I had spent the previous afternoon making cardboard cutouts of these various components, and now, undisturbed on a quiet Saturday morning, I could shuffle around the pieces of the 3-D jigsaw puzzle. How did they all fit together? Soon I realized that a simple pairing scheme worked exquisitely well. **A** fitted neatly with **T** and **G** with **C**. Was this

So the code came in threes, and the links from DNA to protein were RNA-mediated. But we still had to crack the code. What pair of amino acids was specified by a stretch of DNA with, say, sequence ATA TAT or GGT CAT? The first glimpse of the solution came in a talk given by Marshall Nirenberg at the International Congress of Biochemistry in Moscow in 1961.

... according to procedures developed at New York University ... by the French biochemist Marianne Grunberg-Manago. She had discovered an RNA-specific enzyme that could produce strings like AAAAAA or GGGGGG. And because one key chemical difference between RNA and DNA is RNA's substitution of uracil, "U," for thymine, "T," this enzyme would also produce strings of U, UUUUU . . . —poly-U, in the biochemical jargon. It was poly-U

Just look, what **Watson** writes in 2005, at the jubilee of the discovery. They found the secret of life! But what they found in fact, was the data format in heredity (or, say, in phylogenesis). And these data are coded in sequences of four "letters": A, G, T, C. That's it! In eight years after 1953, in 1961, in Moscow, the first element of data format in ontogenesis was publicized: the nucleotide sequence UUU means phenylalanine (discovered by **Nirenberg**). These events started the growth and glory of the modern molecular biology. So, the data formats in concrete informational processes are important.



In this discovery, I would stress one major point: there was no need for “new math language” to find, what they did.

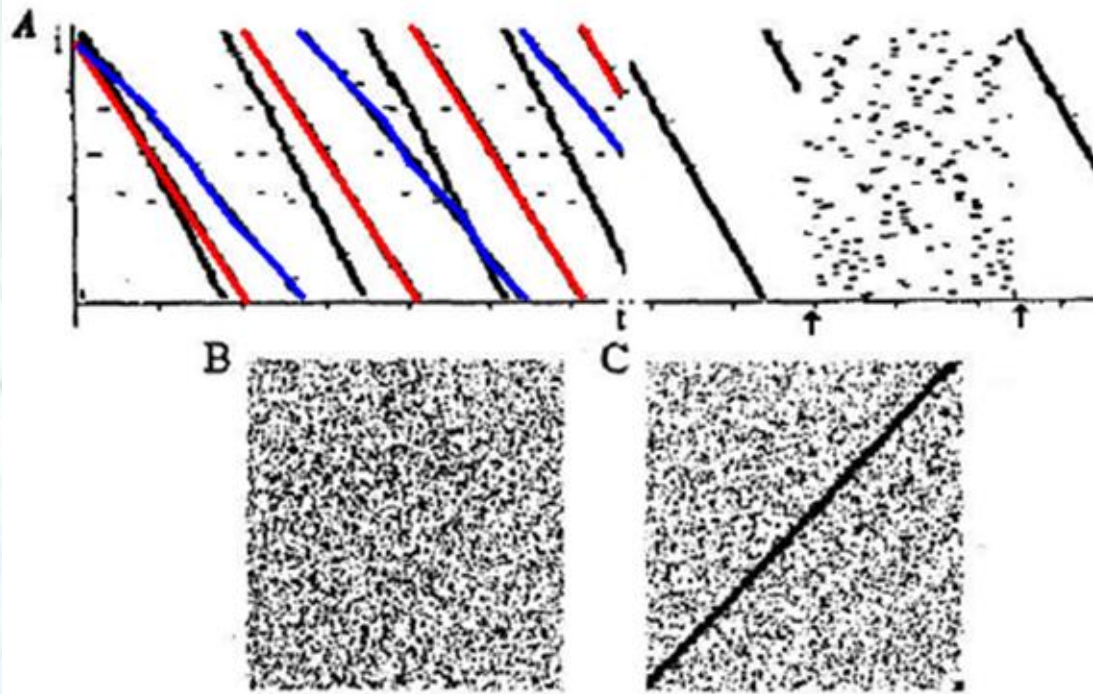
The key properties of the “heredity letters” were revealed by simple manipulations with the simple cardboard cutouts of nucleotide models.

Back to neural data format:

My presence at the bica 2011 is due to the fact, that one of really important data formats in multineuronal systems has been revealed by the bica co-founder Alexei Samsonovich. I mean the insemminating paper of Samsonovich and McNoughton, (1997) on so called path integration. The developments, preceding Samsonovich's results (e.g. Sun-ichi Amari, 1971, 1974, Dunin-Barkowski et al., 1984 – 1995) and following them (Tsodyks, 2010, Izhikevich, 2010; and many others) constitute the bulk of my talk.

Naturally, I will describe the basic phenomena in the form, in which we have seen them, when they came to our eyes.

First, we have repeated the phenomenon, first described by Amari. He noticed that N neurons, put in a line, with local excitatory and non-local inhibitory connection ("Mexican Hat" connection matrix) have N stable excitation states, in each of which L successive neurons are active, while all the rest neurons are inhibited. We have just changed a line into a ring.



Dunin-Barkowski, Osovets, 1994, 1995

Then we have introduced neuron accommodation. This change did help us to switch from static stable states to dynamics of states. We were able to observe a kind of a generator of rhythms as there was a wave propagation in the ring. The speed of propagation depends on neurons' threshold and a (random) direction of propagation is determined by symmetry violation. Matrix (and activity) looks random, when the neuron enumeration does not match the activity pattern.

Another NN activity paradigm arise in the explored networks, when we introduce neuron threshold, $\pi_i(t)$ dependence on neuron activity state:

$$\pi_i(t) = \pi_0 + \lambda \int_0^t V_i(t) \cdot h(t - \tau) d\tau,$$

where $h(\theta)$ is a unite function of the duration W and π_0 and λ are constants.



Activity propagates over ring in either direction

Next step was also simple, but very important. We have randomly permuted the order on neurons and again formed “Mexican Hat” connections. The states in the new ring behave in the same way as in the first. And in the network, which hosted two rings, the activity could propagate in either of them, with either of two directions in each. We have managed to put up to *five* full independent rings with $N=256$ neurons.

And we also made the next step. We put the snake into the neural network. What is snake? Here is the formal definition. Informally: “Snake-in-a-Box” (SIB) code is a model of half-hard bike inner tube, smashed into box.

Snake-in-a-box code

$$\rho_{ij} = \begin{cases} |i - j|, & \text{if } |i - j| \leq \delta, \\ \geq \delta, & \text{if } |i - j| > \delta, \end{cases}$$

Code definition

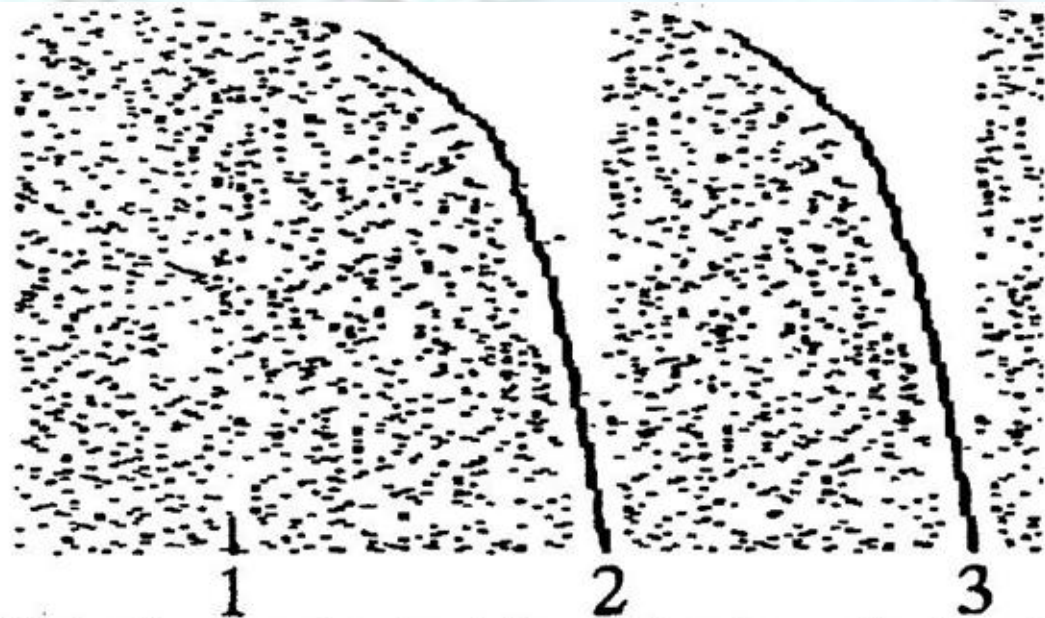
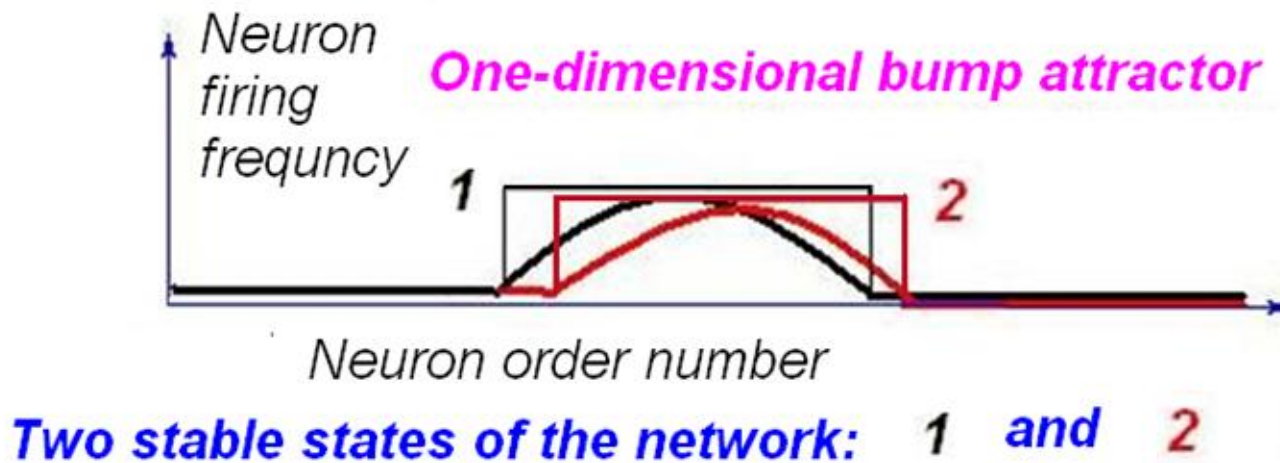


Fig.4. Work of a neural network in which a hyper-ring is written.
1) Phase-ordering of neurons;
2), 3) times of accomplishment of the complete activity cycles.

The code represents a dense homogeneous sequence of points, which are put on the axis of this inner tube. And it happened that activity could propagate along the snake axis in neural network. The latter fact can be easily revealed as is shown at the figure. One should just put order numbers of neurons corresponding to the time of the their last previous (to the current moment t) excitation . The figure shows, that we will see that indeed “snake IS in the box”, when in course of the periodic dynamics, the neural network activity will come back to the point, where ordering was performed.

The resulting quasi-continuous attractor of the neural network dynamics is called bump attractor.

Why “bump”? Because for each stable state of the network there exists such an enumeration of neurons that all excited neurons are enumerated in succession and the states, with small shifts of order numbers of excited neurons, are also stable. So, for the stable states, locally, with appropriate enumeration, there are “bumps” of activity in the network.



In the last two years it became clear that the bump attractors might be PREFORMED in the neural networks, obviously with some kinds of molecular markers.

The exact mechanisms of attractor network formation are not yet known, but there are reasonable speculations, which show, how they might be formed.

Let us consider one-dimensional cyclic attractor. Here the following mechanism might work.

Let us take an attractor with M states in the network of N neurons. We select M molecular marks, which are put at equal distances on some ring so that there exists a function of distance between the marks along the ring. Then for each of N neurons we randomly select (M/N) marks, so, that among the marks of one neuron the distance between any two marks is no less, than Δ . Afterwards, we connect all neurons with excitatory connections to all other neurons, which have marks at distances not more, than δ with marks of a given neuron. All the rest connections in the network are inhibitory. With appropriate M , N , Δ and δ (we tested the numbers 5632, 512, 150 and 10) in this network exists a SIB-type cyclic bump attractor.

The set of the snake-in-a-box states can make a one-dimensional grid for representation of one-dimensional variables.

The procedure of mapping of oligo-dimensional ($d=0, 1, 2, 3$) variables onto the finite neural grid (neural analog-into-discrete converter) , based on learning, has been elaborated in detail by Teuvo Kohonen, starting in 1980-ies (self-organizing maps, SOM). The same technique even better works for bump attractors. Probably, there exist more efficient than Kohonen's methods of obtaining mappings.

There are restrictions on variable representation, based on bump attractor-based grids. The typical size of the neural networks, which are available in brains for preformed attractors, is about $N=10000$. The number of states in the bump attractor is about $100N = 1000000$. For one dimensional variable it can be a good dynamical range.

For two-dimensional variables, we will have 1000 grades per dimension, which is fair. For three-dimensional -100 grades, which is probably the least tolerable. Thus, direct representation in one neural network of variables with the number of dimensions exceeding $d=3$ is hardly possible.

A special case of Kohonen's SOMs presents $d=0$. We will treat this case in more detail.

First – the procedure of network pre-formation. Again, we have M marks for distribution between N neurons. In this case, however, we will have only n types of marks. So, after random distribution, each neuron will have M/N marks, all of different types. Then, all neurons, having the same type of marks, should establish excitatory connections between them. The rest of connections should be inhibitory.

The dynamics of the neural network with such connections is the classical Hopfield dynamics with fast convergence from any state to one of the n stable states. The important point is that there is no simple deterministic rule for selection of neuron interconnection matrix, which can provide a homogeneous distribution of n states of activity among all possible states of activity. However, the RANDOM choice, provided by the described above procedures, yields very good approximations to a homogeneous distribution. This fact is well-known from information theory and its “neural” meaning was first noted by Cowan and Winograd (1963) and Brindley (1969).

And, the next point in attractor dynamics is acquisition of meaning by the attractor points. This is achieved by tuning of the external connections of the attractor network. Of course, both, afferent and efferent connections should be established.

On the afferent part, tuning of the connections provides “grandma cell” properties. Probably, they are acquired by the process resembling the perceptron learning. The efferent part of the process makes attractor states having properties of “command neurons”. Most probably, a special role in attractor states learning might play feedback loops, which include convergence properties of attractor dynamics.

It would be interesting to speculate on the features of one special case of grandma cells. I mean grandma cells for words. What is clear from the stated earlier, is the fact that words have their representing attractors not depending on their semantics (I mean meaning). This is very much like the well-known poetic metaphor that the words exist by their own, not depending upon their sense. This naturally leads us to language problems.

It is obvious that all words of natural languages have their separate representing attractors. These attractors technically are of the same type as general grandma cells (GMC). But, unlike primordial GMCs, which represent natural objects (say, thunder and lightning), they represent artificial human-made artifacts.

There are serious reasons to believe that initially, many combinations of sounds, used by people, were just toys, transferred from one generation into the next.

But once, one of our great ancestors – really the greatest person in human history – has INVENTED the way to transfer universal-type thoughts from people to people, using these tongue-made toys.

Of course, the limited set of thoughts (less than a hundred in total number) are transmitted between individual members of many animal species. I mean alarm cries, aggressive roaring, barking, howling, purring, etc.

But universal thoughts have not one hundred, but a very large, virtually infinite, number of versions of possible communications.

In spite of the fact that we do not know for sure, who was this first speaking person, we should acknowledge this person's greatness.

Of course, that happened long time ago. From the hints of paleontological findings we know that it was about 75000 years ago. Most probably, nobody remembers the fact itself and the name of the inventor. However, I would try to guess that there exist the ancient written evidences of the fact of the language invention (“... in the beginning was the word...”) and of the name of the Inventor. Yes! Her name was Eve! That is why she is known as the mother of all humans.

And I would propose to honor that person with the title of
Eve of Lingua.

We can celebrate her 75000-th birthday, today, on November 6, 2011.

Please excuse me for being a little emphatique. I just want to argue that now it is a good time to think through many details of brain architecture and physiology, and that that can be the shortest way to understand our mind.

One final comment. In 1970-ies I was often told by my friends, non-neural physicists:

-Why do you think that you will understand anything about the brain, inserting into it few electrodes?

Just imaging, what can you find about the processes in computer just measuring the electric field in few points inside it!

Now in the XXI-st century we do know that we shouldn't let our enemy (and, might be, even our friend) to measure the electric field at any point close to our computer – the bulk of our private information can be stolen this way. Why?

Because we know the principles of computer functioning.

So, if we are going to understand the brain, the first thing to do is to understand basic TECHNICAL principles of its functioning.

And that is exactly, what we are going to do in the Russian project of brain reverse engineering. And I hope that I have demonstrated here that we are now close to understanding the most basic principles – the neural data format, the neural code. That is the basis for our confidence that we can do the job in four years. Of course, should we will be lucky enough.

ACKNOWLEDGEMENTS

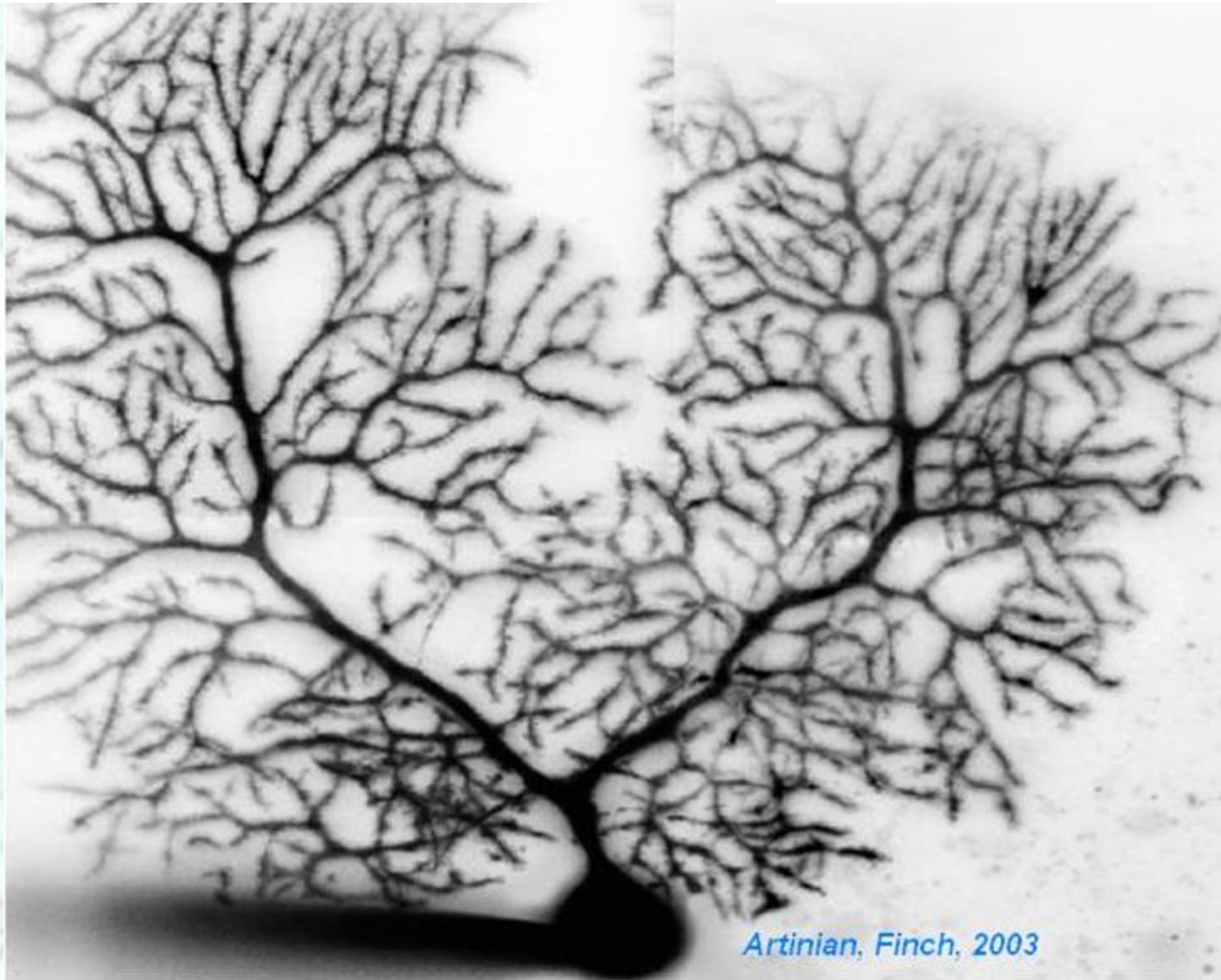
I would like to express my sincere gratitude to the founder of 'Russia 2045' movement Dmitry Itskov for hosting the website of our Brain Reverse Engineering Internet Laboratory (named after great neuro-theoretician David Marr (1945-1980)) and for sponsoring my trip here. Also, many thanks to members of the emerging team of the Russian BRE project:



And special thanks to the outstanding contemporary Russian writer *Lyudmila Ulitskaya* for reminding me the proper name of the Inventor of Human Language - *Eve of Lingua*

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wldbar@gmail.com



Artinian, Finch, 2003

THANK YOU!