Self-similarity and the beauty of Fractals

A fractal is generally "a rough or fragmented geometric shape that can be split into parts, each of which is (at least approximately) a reduced-size copy of the whole,"[1] a property called self-similarity. The term was coined by Benoît Mandelbrot in 1975 and was derived from the Latin fractus meaning "broken" or "fractured." A mathematical fractal is based on an equation that undergoes iteration, a form of feedback based on recursion.

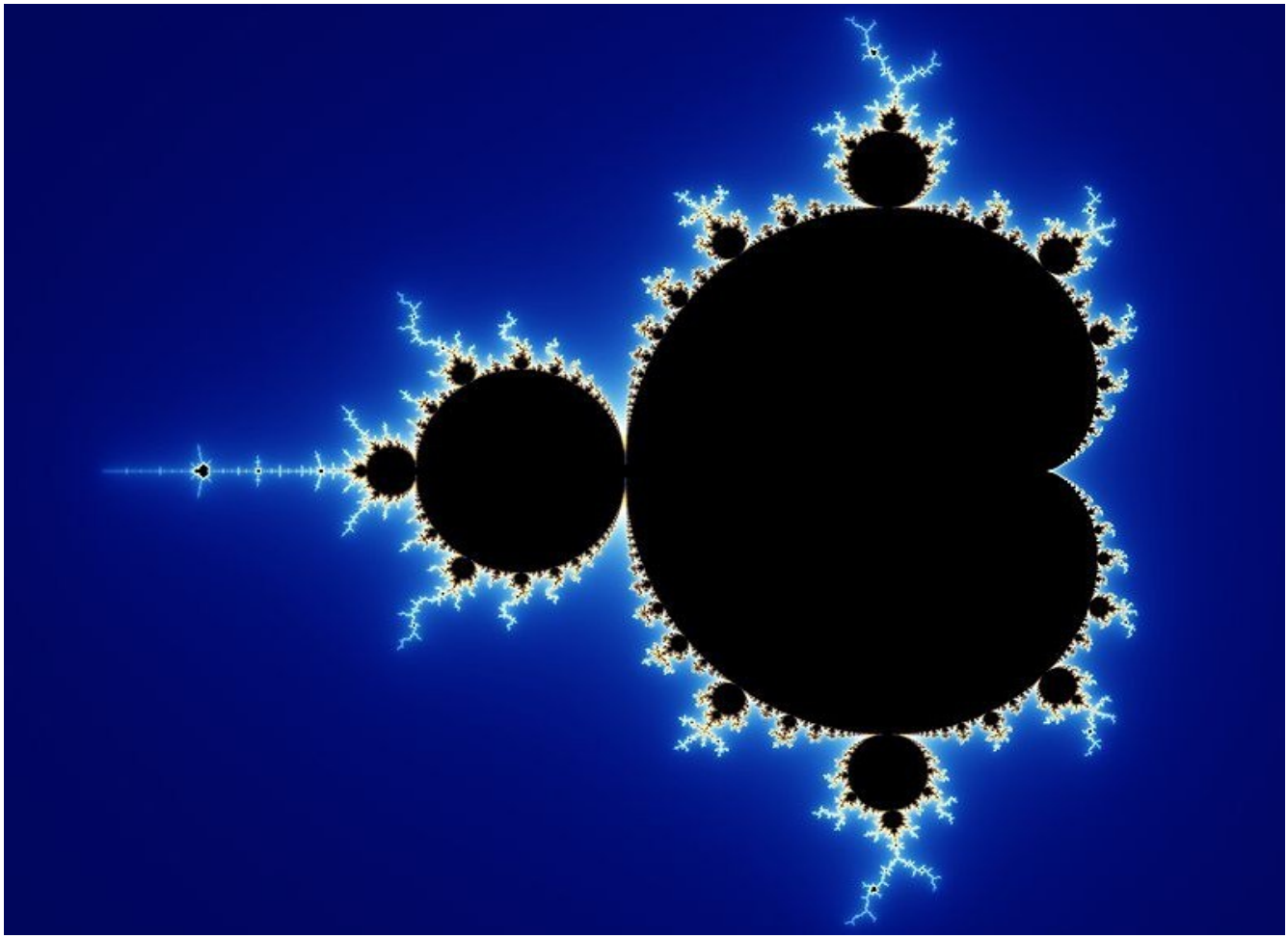
fractals, Wikipedia

A fractal often has the following features:[3]

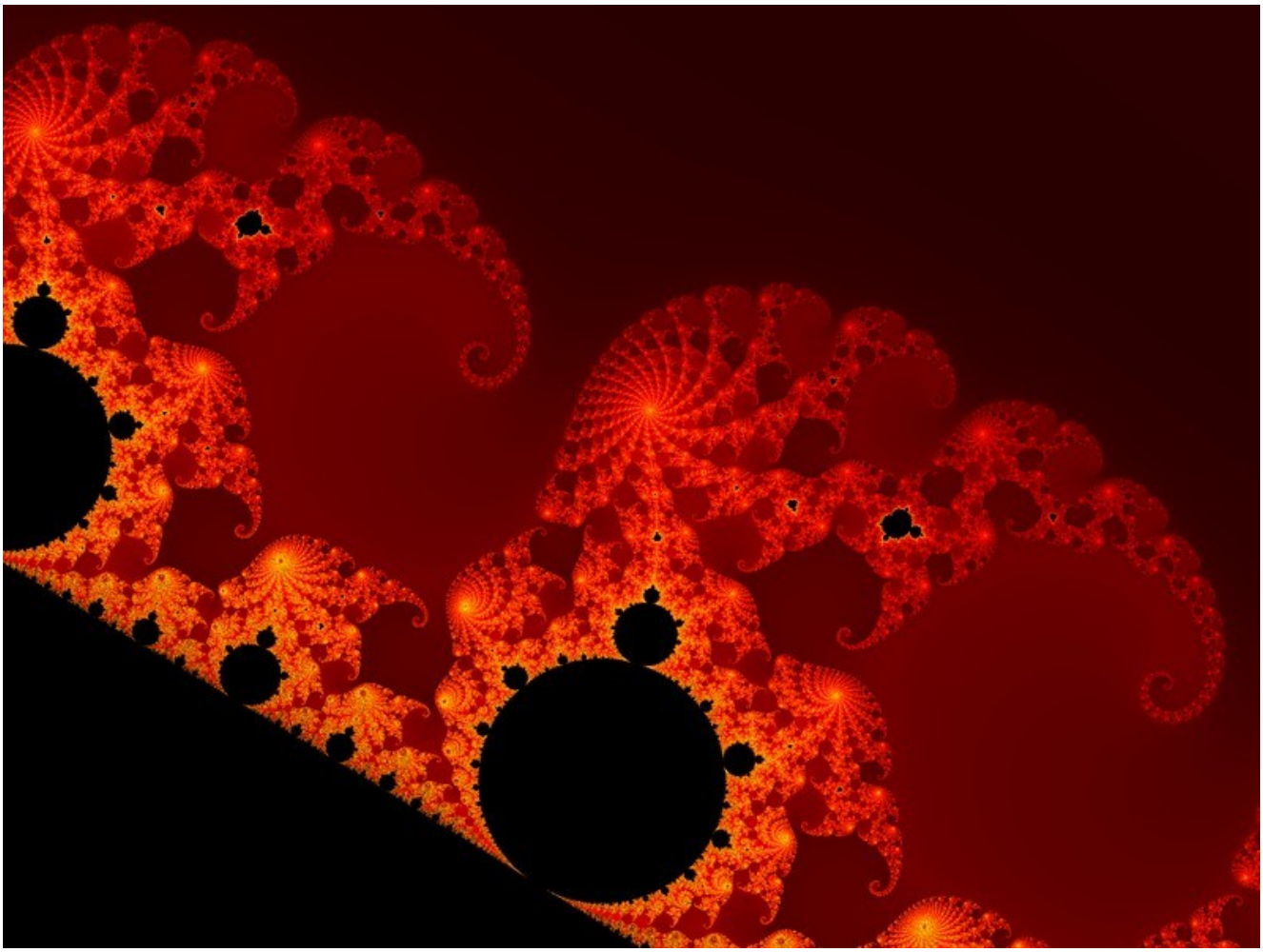
- It has a fine structure at arbitrarily small scales.
- It is too irregular to be easily described in traditional Euclidean geometric language.
- It is self-similar (at least approximately or stochastically).
- It has a Hausdorff dimension which is greater than its topological dimension (although this requirement is not met by space-filling curves such as the Hilbert curve).
- It has a simple and recursive definition.

Because they appear similar at all levels of magnification, fractals are often considered to be infinitely complex (in informal terms). Natural objects that approximate fractals to a degree include clouds, mountain ranges, lightning bolts, coastlines, and snow flakes. However, not all self-similar objects are fractals—for example, the real line (a straight Euclidean line) is formally self-similar but fails to have other fractal characteristics; for instance, it is regular enough to be described in Euclidean terms.

Images of fractals can be created using fractal generating software. Images produced by such software are normally referred to as being fractals even if they do not have the above characteristics, as it is quite possible to zoom into a region of the image that does not exhibit any fractal properties.



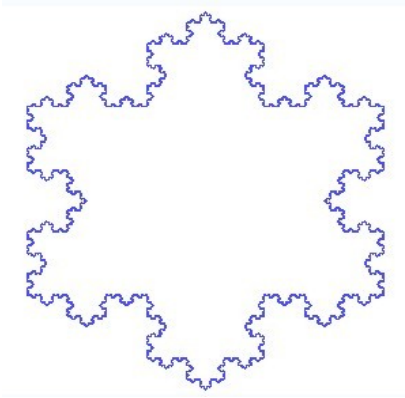
The Mandelbrot set is a famous example of a fractal.



A closer view of the Mandelbrot set

History

Animated construction of a Sierpiński Triangle, only going four generations of infinite



To create a Koch snowflake, one begins with an equilateral triangle and then replaces the middle third of every line segment with a pair of line segments that form an equilateral "bump." One then performs the same replacement on every line segment of the resulting shape, ad infinitum. With every iteration, the perimeter of this shape increases by one third of the previous length. The Koch snowflake is the result of an infinite number of these iterations, and has an infinite length, while its area remains finite. For this reason, the Koch snowflake and similar constructions were sometimes called "monster curves."

The mathematics behind fractals began to take shape in the 17th century when mathematician and philosopher Leibniz considered recursive self-similarity (although he made the mistake of thinking that only the straight line was self-similar in this sense).

It took until 1872 before a function appeared whose graph would today be considered fractal, when Karl Weierstrass gave an example of a function with the non-intuitive property of being everywhere continuous but nowhere differentiable. In 1904, Helge von Koch, dissatisfied with Weierstrass's very abstract and analytic definition, gave a more geometric definition of a similar function, which is now called the Koch snowflake. In 1915, Waclaw Sierpinski constructed his triangle and, one year later, his carpet. Originally these geometric fractals were described as curves rather than the 2D shapes that they are known as in their modern constructions. In 1918, Bertrand Russell had recognized a "supreme beauty" within the mathematics of fractals that was then emerging.[2] The idea of self-similar curves was taken further by Paul Pierre Lévy, who, in his 1938 paper *Plane or Space Curves and Surfaces Consisting of Parts Similar to the Whole* described a new fractal curve, the Lévy C curve. Georg Cantoralso gave examples of subsets of the real line with unusual properties—these Cantor sets are also now recognized as fractals.

Iterated functions in the complex plane were investigated in the late 19th and early 20th centuries by Henri Poincaré, Felix Klein, Pierre Fatouand Gaston Julia. However, without the aid of modern computer graphics, they lacked the means to visualize the beauty of many of the objects that they had discovered.

In the 1960s, Benoît Mandelbrot started investigating self-similarity in papers such as *How Long Is the Coast of Britain? Statistical Self-Similarity and Fractional Dimension*, which built on earlier work by Lewis Fry Richardson. Finally, in 1975 Mandelbrot coined the word "fractal" to denote an object whose Hausdorff-Besicovitch dimension is greater than its topological dimension. He illustrated this mathematical definition with striking computer-constructed visualizations. These images captured the popular imagination; many of them were based on recursion, leading to the popular meaning of the term "fractal".

Examples

A class of examples is given by the Cantor sets, Sierpinski triangle and carpet, Menger sponge, dragon curve, space-filling curve, and Koch curve. Additional examples of fractals include the Lyapunov fractal and the limit sets of Kleinian groups. Fractals can be deterministic (all the above) or stochastic(that is, non-deterministic). For example, the trajectories of the Brownian motion in the plane have a Hausdorff dimension of 2.

Chaotic dynamical systems are sometimes associated with fractals. Objects in the phase space of a dynamical system can be fractals (see attractor). Objects in the parameter space for a family of systems may be fractal as well. An interesting example is the Mandelbrot set. This set contains whole discs, so it has a Hausdorff dimension equal to its topological dimension of 2—but what is truly surprising is that the boundary of the Mandelbrot set also has a Hausdorff dimension of 2 (while the topological dimension of 1), a result proved by Mitsuhiro Shishikura in 1991. A closely related fractal is the Julia set.

Generating fractals

Four common techniques for generating fractals are:

- **Escape-time fractals** — (also known as "orbits" fractals) These are defined by a formula or recurrence relation at each point in a space (such as the complex plane). Examples of this type are the Mandelbrot set, Julia set, the Burning Ship fractal, the Nova fractal and the Lyapunov fractal. The 2d vector fields that are generated by one or two iterations of escape-time formulae also give rise to a fractal form when points (or pixel data) are passed through this field repeatedly.
- **Iterated function systems** — These have a fixed geometric replacement rule. Cantor set, Sierpinski carpet, Sierpinski gasket, Peano curve, Koch snowflake, Harter-Heighway dragon curve, T-Square, Menger sponge, are some examples of such fractals.
- **Random fractals** — Generated by stochastic rather than deterministic processes, for example, trajectories of the Brownian motion, Lévy flight,fractal landscapes and the Brownian tree. The latter yields so-called mass- or dendritic fractals, for example, diffusion-limited aggregation orreaction-limited aggregation clusters.
- **Strange attractors** — Generated by iteration of a map or the solution of a system of initial-value differential equations that exhibit chaos.

Classification of fractals

Fractals can also be classified according to their self-similarity. There are three types of self-similarity found in fractals:

- **Exact self-similarity** — This is the strongest type of self-similarity; the fractal appears identical at different scales. Fractals defined by iterated function systems often display exact self-similarity.
- **Quasi-self-similarity** — This is a loose form of self-similarity; the fractal appears approximately (but not exactly) identical at different scales. Quasi-self-similar fractals contain small copies of the entire fractal in distorted and degenerate forms. Fractals defined by recurrence relations are usually quasi-self-similar but not exactly self-similar.
- **Statistical self-similarity** — This is the weakest type of self-similarity; the fractal has numerical or statistical measures which are preserved across scales. Most reasonable definitions of "fractal" trivially imply some form of statistical self-similarity. (Fractal dimension itself is a numerical measure which is preserved across scales.) Random fractals are examples of fractals which are statistically self-similar, but neither exactly nor quasi-self-similar.

Fractals in nature

Approximate fractals are easily found in nature. These objects display self-similar structure over an extended, but finite, scale range. Examples include clouds, snow flakes, crystals, mountain ranges, lightning, river networks, cauliflower or broccoli, and systems of blood vessels and pulmonary vessels. Coastlines may be loosely considered fractal in nature.

Figure. A fractal fern and Photograph of a cauliflower, showing naturally a occuring fractal

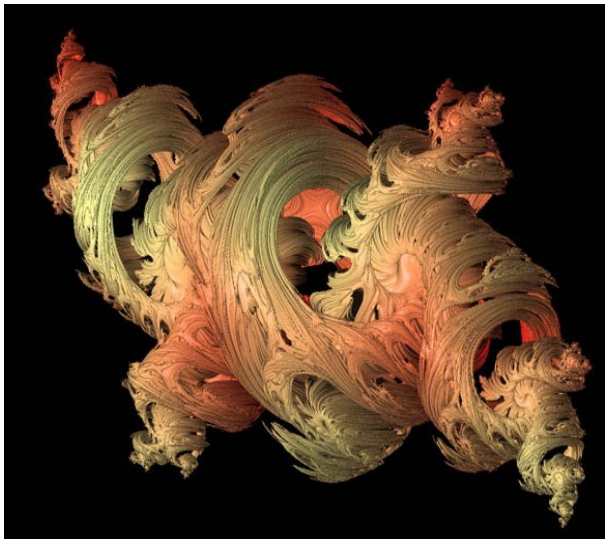


Figure. Fractal shell and fractal tree

Trees and ferns are fractal in nature and can be modeled on a computer by using a recursive algorithm. This recursive nature is obvious in these examples — a branch from a tree or a frond from a fern is a miniature replica of the whole: not identical, but similar in nature. The connection between fractals and leaves are currently being used to determine how much carbon is really contained in trees. This connection is hoped to help determine and solve the environmental issue of carbon emission and control.

Applications of fractals

Main article: Fractal analysis

As described above, random fractals can be used to describe many highly irregular real-world objects. Other applications of fractals include:[10]

- Classification of histopathology slides in medicine
- Fractal landscape or Coastline complexity
- Enzyme/enzymology (Michaelis-Menten kinetics)
- Generation of new music
- Generation of various art forms
- Signal and image compression
- Creation of digital photographic enlargements
- Seismology
- Fractal in soil mechanics
- Computer and video game design, especially computer graphics for organic environments and as part of procedural generation
- Fractography and fracture mechanics
- Fractal antennas — Small size antennas using fractal shapes
- Small angle scattering theory of fractally rough systems
- T-shirts and other fashion
- Generation of patterns for camouflage, such as MARPAT
- Digital sundial
- Technical analysis of price series (see Elliott wave principle)

Fractal dynamics

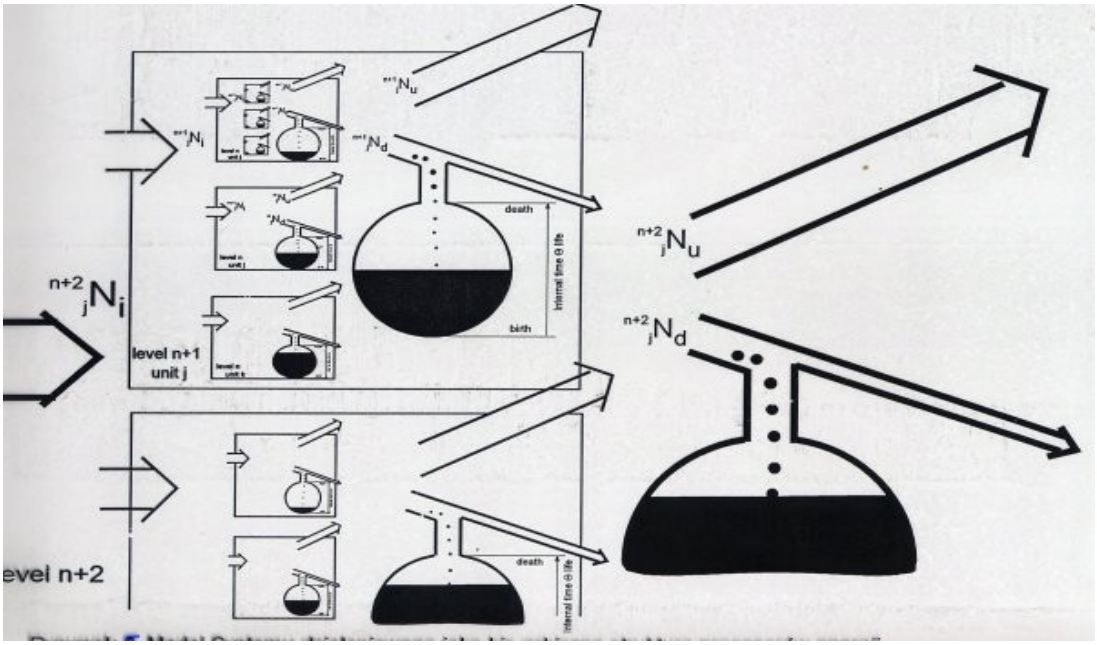
Almost all fractals with the exception of attractors in chaotic dynamical systems are topological fractals, where the geometry of the structure reveals a self-similarity.

In the chapter on theory we will also have a look at self-similar fractal like processes like the self-similar hierarchy of energy transformation processors called birth and death processors and the self-similar structure of feed forward Artificial Neural Networks with backpropagation called Perceptrons.

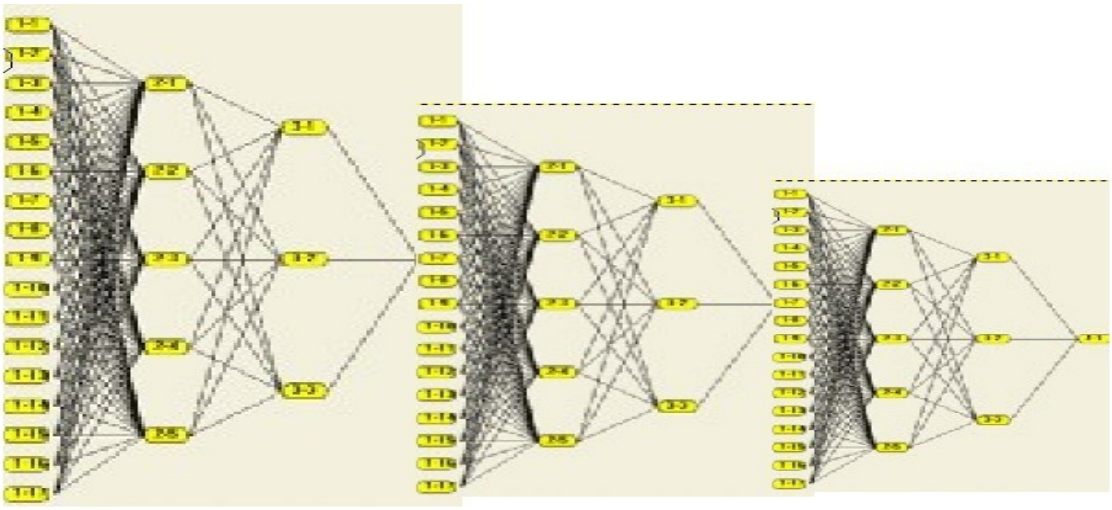
In these fractal hierarchies we observe a **self-similar process** of energy / information transformation on each level of the hierarchy when zooming in or zooming out.

A birth and death processor accumulates internal dissipation energy until its death or breakdown.

This process takes place on any level of the hierarchy.



The self-similar hierarchy of energy / information transformation processors [Winiwarter 1992]



The self-similar hierarchy of information transformation processors (multilayer perceptrons)

In the case of a formal neuron, each neuron accumulates weighted inputs until it fires at threshold.

This process takes place on any level of the hierarchy.

The approach of self-similar recursion is called recursionism and is at the basis of the metaphysical background of this book.

Networks everywhere

Networks are ubiquitous. They serve to model any type of physical realm. A network in general is an interconnected group or system, or a fabric or structure of fibrous elements attached to each other at regular intervals, or formally: a graph. The network approach is at the core of the ideas put forward in this book.

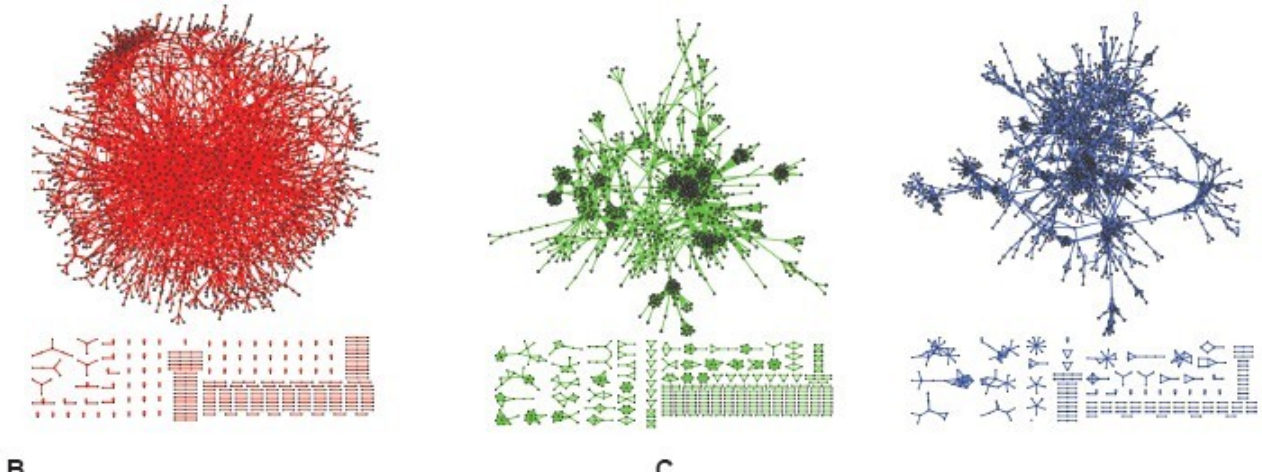


Figure. Network analysis of different data sets

Networks, Wikipedia

A network diagrams is a special kind of cluster diagram, which even more general represents any cluster or small group or bunch of something, structured or not. Both the flow diagram and the tree diagram can be seen as a specific type of network diagram.

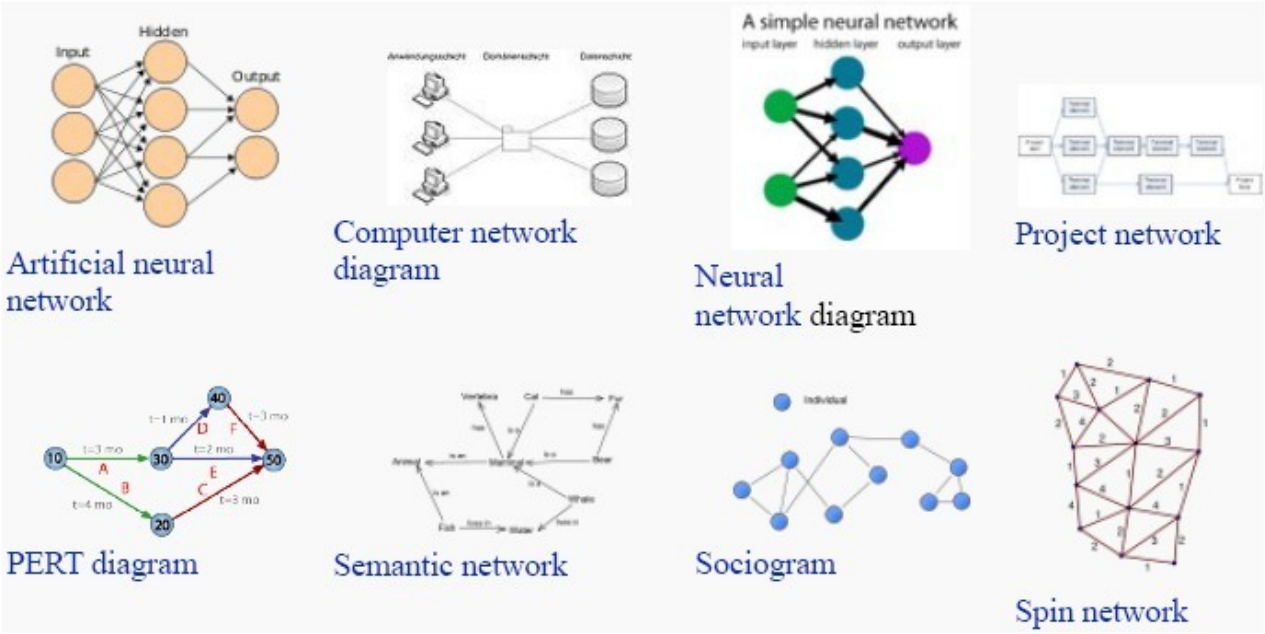
Types of network diagrams

There are different types network diagrams:

- Artificial neural network or "neural network" (NN), is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation.

- Computer network diagram is a schematic depicting the nodes and connections amongst nodes in a computer network or, more generally, any telecommunications network.
- In project management a network diagram is the logical representation of activities, that defines the sequence or the work of a project. It shows the path of a project, lists starting and completion dates , and names the responsibilities for each task. At a glance it explains how the work of the project goes together. A network for a simple project might consist one or two pages, and on a larger project several network diagrams may exist.[1] Specific diagrams here are
    - Project network: a general flow chart depicting the sequence in which a project's terminal elements are to be completed by showing terminal elements and their dependencies.
    - PERT network
- Neural network diagram: is a network or circuit of biological neurons or artificial neural networks, which are composed of artificial neurons or nodes.
- A semantic network is a network or circuit of biological neurons. The modern usage of the term often refers to artificial neural networks, which are composed of artificial neurons or nodes]].[2]
- A sociogram is a graphic representation of social links that a person has. It is a sociometric chart that plots the structure of interpersonal relations in a group situation.

Gallery



Network topologies

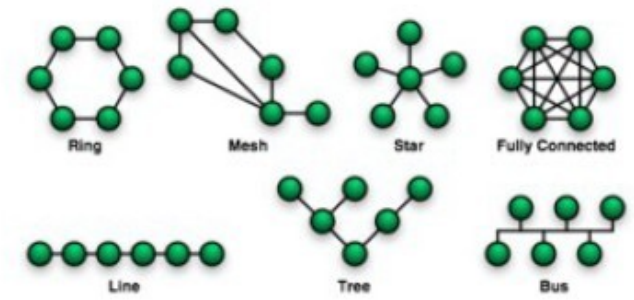


Figure. Diagram of different network topologies.

In computer science the elements of a network are arranged in certain basic shapes (see figure):

- Ring: The ring network connects each node to exactly two other nodes, forming a circular pathway for activity or signals - a ring. The interaction or data travels from node to node, with each node handling every packet.

- Mesh is a way to route data, voice and instructions between nodes. It allows for continuous connections and reconfiguration around broken or blocked paths by "hopping" from node to node until the destination is reached.
- Star: The star network consists of one central element, switch, hub or computer, which acts as a conduit to coordinate activity or transmit messages.
- Fully connected: Self Explanatory
- Line - Everything connected in a single line.
- Tree: This consists of tree-configured nodes connected to switches/concentrators, each connected to a linear bus backbone. Each hub rebroadcasts all transmissions received from any peripheral node to all peripheral nodes on the network, sometimes including the originating node. All peripheral nodes may thus communicate with all others by transmitting to, and receiving from, the central node only.
- Bus: In this network architecture a set of clients are connected via a shared communications line, called a bus.

Network theory

Network theory is an area of applied mathematics and part of graph theory. It has application in many disciplines including particle physics, computer science, biology, economics, operations research, and sociology. Network theory concerns itself with the study of graphs as a representation of either symmetric relations or, more generally, of asymmetric relations between discrete objects. Examples of which include logistical networks, the World Wide Web, gene regulatory networks, metabolic networks, social networks, epistemological networks, etc.

Network optimization

Network problems that involve finding an optimal way of doing something are studied under the name of combinatorial optimization. Examples include network flow, shortest path problem,transport problem, transshipment problem, location problem, matching problem, assignment problem, packing problem, routing problem, Critical Path Analysis and PERT (Program Evaluation & Review Technique).

Centrality measures

Information about the relative importance of nodes and edges in a graph can be obtained through centrality measures, widely used in disciplines like sociology. For example, eigenvector centrality uses the eigenvectors of the adjacency matrix to determine nodes that tend to be frequently visited.

Social network analysis maps relationships between individuals in social networks.[1] Such individuals are often persons, but may be groups (including cliques), organizations, nation-states,web sites, or citations between scholarly publications (scientometrics).

Network analysis, and its close cousin traffic analysis, has significant use in intelligence. By monitoring the communication patterns between the network nodes, its structure can be established. This can be used for uncovering insurgent networks of both hierarchical and leaderless nature.

Link analysis is a subset of network analysis, exploring associations between objects. An example may be examining the addresses of suspects and victims, the telephone numbers they have dialed and financial transactions that they have partaken in during a given timeframe, and the familial relationships between these subjects as a part of police investigation. Link analysis here provides the crucial relationships and associations between very many objects of different types that are not apparent from isolated pieces of information. Computer-assisted or fully automatic computer-based link analysis is increasingly employed by banks and insurance agencies in fraud detection, by telecommunication operators in telecommunication network analysis, by medical sector in epidemiology and pharmacology, in law enforcement investigations, by search engines for relevance rating (and conversely by the spammers for spamdexing and by business owners for search engine optimization), and everywhere else where relationships between many objects have to be analyzed.

Web link analysis

Several Web search ranking algorithms use link-based centrality metrics, including (in order of appearance) Marchiori's Hyper Search, Google's PageRank, Kleinberg's HITS algorithm, and theTrustRank algorithm. Link analysis is also conducted in information science and communication science in order to understand and extract information from the structure of collections of web pages. For example the analysis might be of the interlinking between politicians' web sites or blogs.

Spread of content in networks

Content in a complex network can spread via two major methods: conserved spread and non-conserved spread. In conserved spread, the total amount of content that enters a complex network remains constant as it passes through. The model of conserved spread can best be represented by a pitcher containing a fixed amount of water being poured into a series of funnels connected by tubes. Here, the pitcher represents the original source and the water is the content being spread. The funnels and connecting tubing represent the nodes and the connections between nodes, respectively. As the water passes from one funnel into another, the water disappears instantly from the funnel that was previously exposed to the water. In non-conserved spread, the amount of content changes as it enters and passes through a complex network. The model of non-conserved spread can best be represented by a continuously running faucet running through a series of funnels connected by tubes. Here, the amount of water from the original source is infinite. Also, any funnels that have been exposed to the water continue to experience the water even as it passes into successive funnels. The non-conserved model is the most suitable for explaining the transmission of most [[infectious diseases].

The origins: the seven bridges of Königsberg

The Seven Bridges of Königsberg is a famous historical problem in mathematics. Its 1736 negative resolution by Leonhard Euler laid the foundations of graph theory and presaged the idea of topology.

Description

The city of Königsberg in Prussia (now Kaliningrad, Russia) was set on both sides of the Pregel River, and included two large islands which were connected to each other and the mainland by seven bridges.

The problem was to find a walk through the city that would cross each bridge once and only once. The islands could not be reached by any route other than the bridges, and every bridge must have been crossed completely every time (one could not walk halfway onto the bridge and then turn around to come at it from another side).

Euler's analysis

It turns out that the problem has no solution.

To start with, Euler pointed out that the choice of route inside each landmass is irrelevant. The only important feature of a route is the sequence of bridges crossed. This allowed him to reformulate the problem in abstract terms (laying the foundations of graph theory), eliminating all features except the list of landmasses and the bridges connecting them. In modern terms, one replaces each landmass with an abstract "vertex" or node, and each bridge with an abstract connection, an "edge", which only serves to record which pair of vertices (landmasses) is connected by that bridge. The resulting mathematical structure is called a graph.

Figure. The seven bridges of Königsberg

Since only the connection information is relevant, the shape of pictorial representations of a graph may be distorted in any way without changing the graph itself. Only the existence (or lack) of an edge between each pair of nodes is significant. For example, it does not matter whether the edges drawn are straight or curved, or whether one node is to the left or right of another.

Next, Euler observes that (except at the endpoints of the walk) whenever one enters a vertex by a bridge, one leaves the vertex by a bridge. In other words, during any walk in the graph, the number times one enters a non-terminal vertex equals the number of times one leaves it. Now if every bridge is traversed exactly once it follows that for each landmass (except possibly for the ones chosen for the start and finish), the number of bridges touching that landmass is **even** (half of them will be traversed "toward" the landmass, the other half "away" from it). On the other hand, all the four landmasses in the original problem are touched by an **odd** number of bridges (one is touched by 5 bridges and the other three by 3). Since at most two landmasses can serve as the endpoints of a putative walk, the existence of a walk traversing each bridge once leads to a contradiction.

In modern language, Euler shows that the existences of a walk in a graph which traverses each edge once depends on the degrees of the nodes. The degree of a node is the number of edges touching it. Euler's argument shows that a walk of the desired form exists if and only if the graph is connected, and there are exactly zero or two nodes of odd degree. Such a walk is now called an *Eulerian path* or *Euler walk* in his honor. Further, if there are nodes of odd degree, all Eulerian paths start at one of them and end at the other. Since the graph corresponding to historical Königsberg has four nodes of odd degree, it cannot have an Eulerian path.

An alternative form of the problem asks for a path that traverses all bridges and also has the same starting and ending point. Such a walk is called an *Eulerian circuit* or an *Euler tour*. Such a circuit exists if and only if the graph is connected and there are no nodes of odd degree at all. Clearly Eulerian circuits are also Eulerian paths.

Euler's work was presented to the St. Petersburg Academy on August 26, 1735, and published as *Solutio problematis ad geometriam situs pertinentis* (The solution of a problem relating to the geometry of position) in the journal *Commentarii academiae scientiarum Petropolitanae* in 1741.[1] It is available in English in The World of Mathematics.

Significance in the history of mathematics

In the history of mathematics, Euler's solution of the Königsberg bridge problem is considered to be the first theorem of graph theory, a subject now generally regarded as a branch of combinatorics. Combinatorial problems of other types had been considered since antiquity.

In addition, Euler's recognition that the key information was the number of bridges and the list of their endpoints (rather than their exact positions) presaged the development of topology. The difference between the actual

layout and the graph schematic is a good example of the idea that topology is not concerned with the rigid shape of objects.

Present state of the bridges

Two of the seven original bridges were destroyed by bombs during World War II. Two others were later demolished by the Russians and replaced by a modern highway. The three other bridges remain, although only two of them are from Euler's time (one was rebuilt by the Germans in 1935). Thus, in all, there are five bridges in modern-day Königsberg (modern name Kaliningrad).

In terms of graph theory, two of the nodes now have degree 2, and the other two have degree 3. Therefore, an Eulerian path is now possible, but since it must begin on one island and end on the other, it is impractical for tourists.

The random Networks of Erdős and Rényi

Paul Erdős (occasionally spelled Erdos or Erdös; Hungarian: Erdős Pál; March 26, 1913 – September 20, 1996) was an immensely prolific (and famously eccentric) Hungarian mathematician. With hundreds of collaborators, he worked on problems in combinatorics, graph theory, number theory, classical analysis, approximation theory, set theory, and probability theory.
His colleague Alfréd Rényi said, "a mathematician is a machine for turning coffee into theorems", and Erdős drank copious quantities. (This quotation is often attributed incorrectly to Erdős.) After 1971 he also took amphetamines, despite the concern of his friends, one of whom (Ron Graham) bet him $500 that he could not stop taking the drug for a month. Erdős won the bet, but complained during his abstinence that mathematics had been set back by a month: "Before, when I looked at a piece of blank paper my mind was filled with ideas. Now all I see is a blank piece of paper." After he won the bet, he promptly resumed his amphetamine habit.
Because of his prolific output, friends created the **Erdős number** as a humorous tribute; Erdős alone was assigned the Erdős number of 0 (for being himself), while his immediate collaborators could claim an Erdős number of 1, their collaborators have Erdős number at most 2, and so on. Some have estimated that 90% of the world's active mathematicians have an Erdős number smaller than 8 (not surprising in the light of the small world phenomenon). It is jokingly said that Baseball Hall of Famer Hank Aaron has an Erdős number of 1 because they both autographed the same baseball when Emory University awarded them honorary degrees on the same day. Erdős numbers have also been humorously assigned to an infant, a horse and several actors. For details see the "Extended Erdős Number Project".

Complex networks describe a variety of systems found in nature and society. Traditionally these systems have been modeled as random graphs, a relatively primitive and brutal approach. These traditional models do not produce topological and structural properties featured in real network examples. In recent years many new models have been developed, to correctly describe the scale- free structure of real networks.
Traditionally the study of complex networks has been the territory of mathematics, especially the graph theory. Initially the graph theory focused on regular graphs, with no apparent design principles were described as random graphs, proposed as the simplest and most straightforward realization of a complex network.
The pioneer of the theory was Leonhard Euler, who studied first regular graphs in 18th century. In the 20th century the theory became much more statistically and algorithmically oriented.
Later in 1950's graph theory was used to describe large networks, with no particular distributions of nodes and link, whose organization principles were not easily definable. These networks were first studied by Paul Erdős and Alfred Rényi and were called "random graphs", due to their generating method: we start with N nodes and connect every pair of them with probability p. Obtained graph has on average p (N(N 1)) 2 edges distributed randomly. The degree distribution of such graph is Poisson with peak at $P($ k $)$. This model has guided our thinking for decades after it has been presented.
The topology of **real world** large networks (i.e. Internet, WWW, telephone networks, ecological networks) substantially differs from the topology of random graphs produced by the simple Erdős-Rényi (ER) model, therefore new methods, tools and models needed to be developed.

In past years we witnessed dramatic advances in this direction. The computerisation of data acquisition has led to the emergence of large databases on the topology of various real networks. Wide availability of computer power allows to investigate networks containing millions of nodes, exploring questions that could not be answered before as well as the slow but noticeable breakdown between different science disciplines allows scientists to access different databases, allowing to uncover the generic properties of large networks.
Networks found in nature show degree distribution that greatly differs from the Poisson degree distribution of random graphs. Because of existence of a few vertices with high degree, the distribution of real networks has a power-law tail $P(k)$ k , which indicates scale free properties.

The small Worlds of Watts and Strogatz, the six degrees of separation

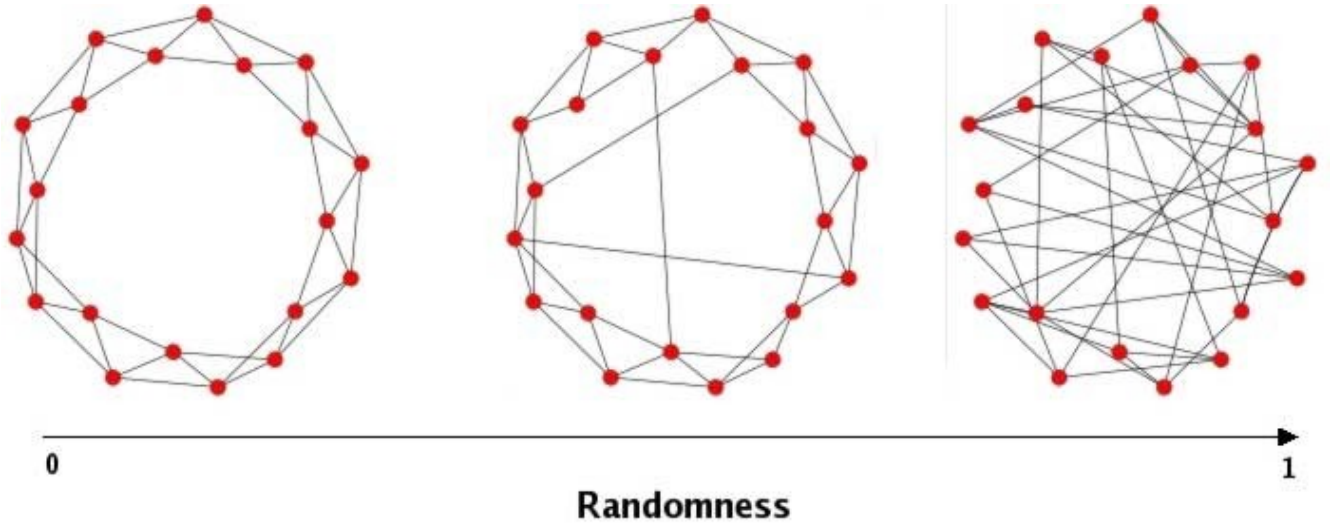


Figure. *Small worlds*, between perfect order and chaos;
the first graph is completely ordered, the graph in the middle is a "small world" graph,
the graph at the right is complete random.

A network is called a small-world network by analogy with the small-world phenomenon (popularly known as six degrees of separation). The small world hypothesis, which was first described by the Hungarian writer Frigyes Karinthy in 1929, and tested experimentally by Stanley Milgram (1967), is the idea that two arbitrary people are connected by only six degrees of separation, i.e. the diameter of the corresponding graph of social connections is not much larger than six. In 1998, Duncan J. Watts and Steven Strogatz published the first small-world network model, which through a single parameter smoothly interpolates between a random graph to a lattice. Their model demonstrated that with the addition of only a small number of long-range links, a regular graph, in which the diameter is proportional to the size of the network, can be transformed into a "small world" in which the average number of edges between any two vertices is very small (mathematically, it should grow as the logarithm of the size of the network), while the clustering coefficient stays large. It is known that a wide variety of abstract graphs exhibit the small-world property, e.g., random graphs and scale-free networks. Further, real world networks such as the World Wide Web and the metabolic network also exhibit this property.

In the scientific literature on networks, there is some ambiguity associated with the term "small world." In addition to referring to the size of the diameter of the network, it can also refer to the co-occurrence of a small

diameter and a high clustering coefficient. The clustering coefficient is a metric that represents the density of triangles in the network. For instance, sparse random graphs have a vanishingly small clustering coefficient while real world networks often have a coefficient significantly larger. Scientists point to this difference as suggesting that edges are correlated in real world networks.

Despite the large network size, it commonly happens that there is relatively short distance among any pair of nodes. Path length is defined by minimum number of edges needed to pass from first point to the other (in case of weighted edges, the path length is defined by minimal sum of weights). This phenomena is called the small world effect and can be observed in society and nature: all chemicals inside a living cell are at average 3 reactions away from each other, there is a path of acquaintances between most pairs of people in USA with typical length of about six and the actors in Hollywood are on average within three costars from each other.
All networks of the chapter 'illustrated regularities of the Pareto-Zipf-Mandelbrot (PZM) type' reveal small world properties. As shown below, any small world graph can be mapped on an Artificial Neural Network of the multilayer Perceptron with hidden layers and links arranged properly.
This allows us to put forward our main hypothesis, the equivalence between energy transformation systems (Birth and Death processor networks) and information transformation systems (networks of multilayer Perceptrons).

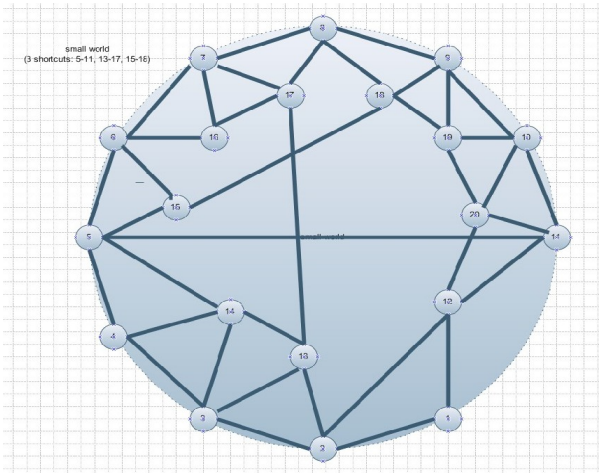


Figure. Example of a small world network mapped on a multilayer Perceptron see graph below.

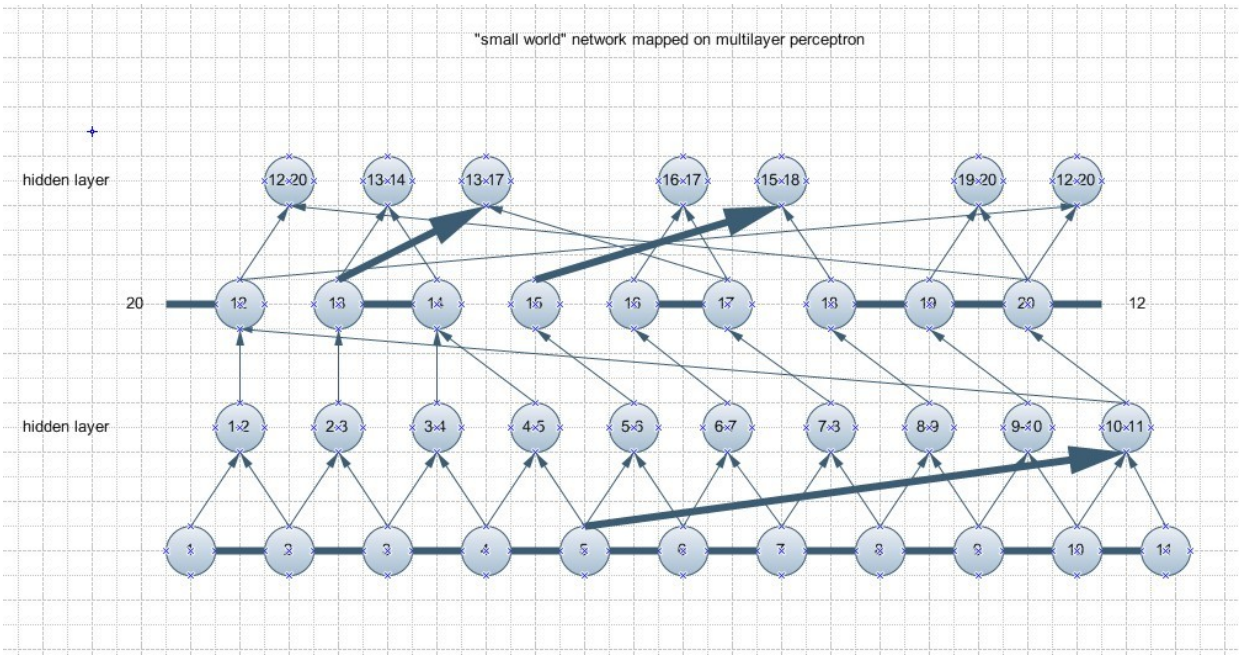


Figure. The shortcuts of the small world graph are mapped as fat arrow links in the multilayer Perceptron.

Barabási's scalefree networks from cells to the Internet

A network is named scale-free if its degree distribution, i.e., the probability that a node selected uniformly at random has a certain number of links (degree), follows a particular mathematical function called a power law. The power law implies that the degree distribution of these networks has no characteristic scale. In contrast, network with a single well-defined scale are somewhat similar to a lattice in that every node has (roughly) the same degree. Examples of networks with a single scale include the Erdős–Rényi random graph and hypercubes. In a network with a scale-free degree distribution, some vertices have a degree that is orders of magnitude larger than the average - these vertices are often called "hubs", although this is a bit misleading as there is no inherent threshold above which a node can be viewed as a hub. If there were, then it wouldn't be a scale-free distribution!

Interest in scale-free networks began in the late 1990s with the apparent discovery of a power-law degree distribution in many real world networks such as the World Wide Web, the network of Autonomous systems (ASs), some network of Internet routers, protein interaction networks, email networks, etc. Although many of these distributions are not unambiguously power laws, their breadth, both in degree and in domain, shows that networks exhibiting such a distribution are clearly very different from what you would expect if edges existed independently and at random (aPoisson distribution). Indeed, there are many different ways to build a network with a power-law degree distribution. The Yule process is a canonical generative process for power laws, and has been known since 1925. However, it is known by many other names due to its frequent reinvention, e.g., The Gibrat principle by Herbert Simon, the Matthew effect, cumulative advantage and, most recently, preferential attachment by Barabási and Albert for power-law degree distributions.

Networks with a power-law degree distribution can be highly resistant to the random deletion of vertices, i.e., the vast majority of vertices remain connected together in a giant component. Such networks can also be quite sensitive to targeted attacks aimed at fracturing the network quickly. When the graph is uniformly random except for the degree distribution, these critical vertices are the ones with the highest degree, and have thus been implicated in the spread of disease (natural and artificial) in social and communication networks, and in the spread of fads (both of which are modeled by a percolation or branching process).

Clustering

In many real examples of networks or graphs fully connected subgraphs emerge. Such structures are called cliques. A typical example of such feature are circles of friends or acquaintances in social networks where every member of a clique knows every other member. This inherent tendency of clustering is quantified by the clustering coefficient [Watts and Strogatz, 1998] and is defined for a single node in the network.
$_i E$ is the number of all edges that actually exist among all first neighbor of selected node. If all the neighbors were connected, there would be $(1) / 2 _{ii} k k$ edges among them. The ratio

between the actual number of edges $_i E$ and maximum number of edges is the clustering coefficient of a node.
The clustering coefficient of all the network is the average of all individual Ci's:
For random graphs the clustering coefficient is equal to graph generating connection probability ($C p$), since the probability of first neighbors being connected is constant for all nodes.
In real networks the clustering coefficient is much larger than in case of random graphs of equal size (equal number of nodes and edges).

Degree distribution

The number of edges a node has is called node degree. The spread of node degrees is characterized by a distribution function *P(k*), which gives the probability that randomly selected node has exactly k edges. Since in the random graph the edges are placed randomly, the majority of nodes have approximately the same degree, close to the average *k* of the network. The degree distribution of a random graph is a Poisson distribution with a peak at $P k$. On the other hand the empirical results for most large networks show distribution that significantly deviates from Poisson distribution. This degree distribution has a power-law tail.
Such network are called **scale free**. While some real networks still display an exponential tail, often the functional form of *P(k*) still deviates from Poisson distribution expected for a random graph.

Scale free model

Many large networks are scale free: their degree distribution follows a power law for large *k*. Even for those real networks for which *P(k)* has an exponential tail, the degree distribution significantly deviates from a Poisson. Random graph theory and the WS model are unable to reproduce this feature.
What is the mechanism responsible for the emergence of scale free networks?
A shift from modeling network topology to modeling the **network assembly and evolution** is required to get insight into mechanisms responsible to create scale-free networks.
While the goal of the other models (random graphs and small - world models) is to construct a graph with correct topological features, modeling scale free networks puts the emphasis on capturing the **network dynamics.** The assumption behind evolving or dynamic networks is that if we capture correctly the processes that assembled the networks that we see today, then we will obtain their topology correctly as well. Dynamics takes the driving role, topology being only a by product of this modeling philosophy.

Scale-free networks, Wikipedia

A **scale-free network** is a network whose degree distribution follows a power law, at least asymptotically. That is, the fraction $P(k)$ of nodes in the network having k connections to other nodes goes for large values of k as $P(k) \sim k^{-\gamma}$ where γ is a constant whose value is typically in the range $2 < \gamma < 3$, although occasionally it may lie outside these bounds.

Scale-free networks are noteworthy because many empirically observed networks appear to be scale-free, including the world wide web, protein networks, citation networks, and some social networks.

- Scale-free networks show a power law degree distribution like many real networks.
- The mechanism of preferential attachment has been proposed as a mechanism to explain power law degree distributions in some networks.

History

In studies of the networks of citations between scientific papers, Derek de Solla Price showed in 1965 that the number of links to papers—i.e., the number of citations they receive—had a heavy-tailed distribution following a Pareto distribution or power law, and thus that the citation network was scale-free. He did not however use the term "scale-free network" (which was not coined until some decades later). In a later paper in 1976, Price also proposed a mechanism to explain the occurrence of power laws in citation networks, which he called "cumulative advantage" but which is today more commonly known under the name preferential attachment.

Recent interest in scale-free networks started in 1999 with work by Albert-László Barabási and colleagues at the University of Notre Dame who mapped the topology of a portion of the Web (Barabási and Albert 1999), finding that some nodes, which they called "hubs", had many more connections than others and that the network as a whole had a power-law distribution of the number of links connecting to a node.

After finding that a few other networks, including some social and biological networks, also had heavy-tailed degree distributions, Barabási and collaborators coined the term "scale-free network" to describe the class of networks that exhibit a power-law degree distribution. Soon after, Amaral et al. showed that most of the real-world networks can be classified into two large categories according to the decay of P(k) for large k.

Barabási and Albert proposed a mechanism to explain the appearance of the power-law distribution, which they called "preferential attachment" and which is essentially the same as that proposed by Price. Analytic solutions for this mechanism (also similar to the solution of Price) were presented in 2000 by Dorogovtsev, Mendes and Samukhin and independently by Krapivsky, Redner, and Leyvraz, and later rigorously proved by mathematician Béla Bollobás. Notably, however, this mechanism only produces a specific subset of networks in the scale-free class, and many alternative mechanisms have been discovered since.

Although the scientific community is still debating the usefulness of the scale-free term in reference to networks, Li et al. (2005) recently offered a potentially more precise "scale-free metric". Briefly, let g be a graph with edge-set ε, and let the degree (number of edges) at a vertex i be di. Define

$$s(g) = \sum_{(i,j)\in\epsilon} d_i d_j.$$

This is maximised when high-degree nodes are connected to other high-degree nodes. Now define

$$S(g) = \frac{s(g)}{s_{max}}$$

where S_{max} is the maximum value of $s(h)$ for h in the set of all graphs with an identical degree distribution to g. This gives a metric between 0 and 1, such that graphs with low $S(g)$ are "scale-rich", and graphs with $S(g)$ close to 1 are "scale-free". This definition captures the notion of self-similarity implied in the name "scale-free".

Characteristics and examples

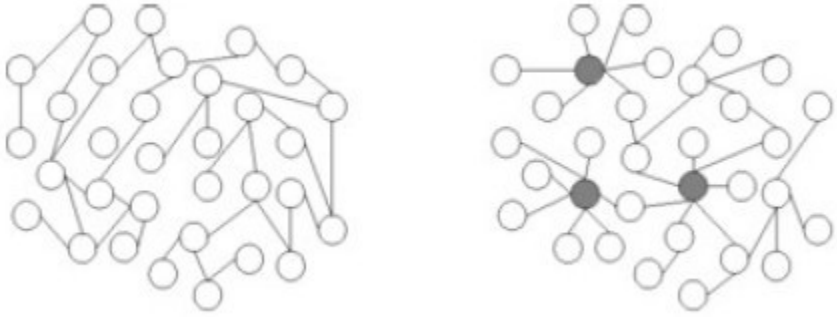


Figure. Random network left, scale-free network right. In the scale-free network, the larger hubs are highlighted.

As with all systems characterized by a power law distribution, the most notable characteristic in a scale-free network is the relative commonness of vertices with a degree that greatly exceeds the average. The highest-degree nodes are often called "hubs", and are thought to serve specific purposes in their networks, although this depends greatly on the domain.

The power law distribution highly influences the network topology. It turns out that the major hubs are closely followed by smaller ones. These ones, in turn, are followed by other nodes with an even smaller degree and so on. This hierarchy allows for a fault tolerant behavior. Since failures occur at random and the vast majority of

nodes are those with small degree, the likelihood that a hub would be affected is almost negligible. Even if such event occurs, the network will not lose its connectedness, which is guaranteed by the remaining hubs. On the other hand, if we choose a few major hubs and take them out of the network, it simply falls apart and is turned into a set of rather isolated graphs. Thus hubs are both the strength of scale-free networks and their Achilles' heel.

Another important characteristic of scale-free networks is the clustering coefficient distribution, which decreases as the node degree increases. This distribution also follows a power law. That means that the low-degree nodes belong to very dense sub-graphs and those sub-graphs are connected to each other through hubs. Consider a social network in which nodes are people and links are acquaintance relationships between people. It is easy to see that people tend to form communities, i.e., small groups in which everyone knows everyone (one can think of such community as a complete graph). In addition, the members of a community also have a few acquaintance relationships to people outside that community. Some people, however, are so related to other people (e.g., celebrities, politicians) that they are connected to a large number of communities. Those people may be considered the hubs responsible for the small world phenomenon.

At present, the more specific characteristics of scale-free networks can only be discussed in either the context of the generative mechanism used to create them, or the context of a particular real-world network thought to be scale-free. For instance, networks generated by preferential attachment typically place the high-degree vertices in the middle of the network, connecting them together to form a core, with progressively lower-degree nodes making up the regions between the core and the periphery. Many interesting results are known for this subclass of scale-free networks. For instance, the random removal of even a large fraction of vertices impacts the overall connectedness of the network very little, suggesting that such topologies could be useful for security, while targeted attacks destroys the connectedness very quickly. Other scale-free networks, which place the high-degree vertices at the periphery, do not exhibit these properties; notably, the structure of the Internet is more like this latter kind of network than the kind built by preferential attachment. Indeed, many of the results about scale-free networks have been claimed to apply to the Internet, but are disputed by Internet researchers and engineers.

As with most disordered networks, such as the small world network model, the average distance between two vertices in the network is very small relative to a highly ordered network such as a lattice. The clustering coefficient of scale-free networks can vary significantly depending on other topological details, and there are now generative mechanisms that allow one to create such networks that have a high density of triangles.

It is interesting that Cohen and Havlin proved that uncorrelated power-law graph having $2 < \gamma < 3$ will also have ultrasmall diameter $d \sim \ln \ln N$. So from the practical point of view, the diameter of a growing scale-free network might be considered almost constant.

Although many real-world networks are thought to be scale-free, the evidence remains inconclusive, primarily because the generative mechanisms proposed have not been rigorously validated against the real-world data. As such, it is too early to rule out alternative hypotheses. A few examples of networks claimed to be scale-free include:

- Social networks, including collaboration networks. An example that has been studied extensively is the collaboration of movie actors in films.
- Protein-Protein interaction networks.
- Sexual partners in humans, which affects the dispersal of sexually transmitted diseases.
- Many kinds of computer networks, including the World Wide Web.
- Semantic networks. [1]

Generative models

These scale-free networks do not arise by chance alone. Erdős and Rényi (1960) studied a model of growth for graphs in which, at each step, two nodes are chosen uniformly at random and a link is inserted between them. The properties of these random graphs are not consistent with the properties observed in scale-free networks, and therefore a model for this growth process is needed.

The scale-free properties of the Web have been studied, and its distribution of links is very close to a power law, because there are a few Web sites with huge numbers of links, which benefit from a good placement in search engines and an established presence on the Web. Those sites are the ones that attract more of the new links. This has been called the winner takes allphenomenon.

The mostly widely known generative model for a subset of scale-free networks is Barabási and Albert's (1999) rich get richer generative model in which each new Web page creates links to existing Web pages with a probability distribution which is not uniform, but proportional to the current in-degree of Web pages. This model was originally discovered by Derek J. de Solla Pricein 1965 under the term **cumulative advantage**, but did not reach popularity until Barabási rediscovered the results under its current name (BA Model). According to this process, a page with many in-links will attract more in-links than a regular page. This generates a power-law but the resulting graph differs from the actual Web graph in other properties such as the presence of small tightly connected communities. More general models and networks characteristics have been proposed and studied (for a review see the book by Dorogovtsev and Mendes).

A different generative model is the **copy** model studied by Kumar et al. (2000), in which new nodes choose an existent node at random and copy a fraction of the links of the existent node. This also generates a power law.

However, if we look at communities of interests in a specific topic, discarding the major hubs of the Web, the distribution of links is no longer a power law but resembles more a normal distribution, as observed by Pennock et al. (2002) in the communities of the home pages of universities, public companies, newspapers and scientists. Based on these observations, they propose a generative model that mixes preferential attachment with a baseline probability of gaining a link.

The growth of the networks (adding new nodes) is not a necessary condition for creating a scale-free topology. Dangalchev (2004) gives examples of generating static scale-free networks. Another possibility (Caldarelli et al.

2002) is to consider the structure as static and draw a link between vertices according to a particular property of the two vertices involved. Once specified the statistical distribution for these vertices properties (fitnesses), it turns out that in some circumstances also static networks develop scale-free properties.

Recently, Manev and Manev (Med. Hypotheses, 2005) proposed that small world networks may be operative in adult brain neurogenesis. Adult neurogenesis has been observed in mammalian brains, including those of humans, but a question remains: how do new neurons become functional in the adult brain? It is proposed that the random addition of only a few new neurons functions as a maintenance system for the brain's "small-world" networks. Randomly added to an orderly network, new links enhance signal propagation speed and synchronizability. Newly generated neurons are ideally suited to become such links: they are immature, form more new connections compared to mature ones, and their number but not their precise location may be maintained by continuous proliferation and dying off. Similarly, it is envisaged that the treatment of brain pathologies by cell transplantation would also create new random links in small-world networks and that even a small number of successfully incorporated new neurons may be functionally important.

Real Networks: Empirical results

The study of most complex networks has been initiated by a desire to understand various real systems.

Complex systems that have been studied are:

1. **World Wide Web (WWW)**: Nodes are web pages and link are hyperlinks. The network is directed, but in some researches is made undirected Some of the researches are made on site level: All the pages in a site are merged into a supernode.
2. **Internet**: topology is studied at two different levels: at the router level the nodes are routers and edges are physical connections between them; at the interdomain level each domain, containing hundreds of routers, is represented as a single node. This is an undirected network.
3. **Cellular networks**: metabolisms of different species from all three domains of life are studied and organized into networks in which the substrates (ATP, ADP, H2O) are nodes and edges represent the predominantly directed chemical reactions in which these substrates can participate.
4. **Ecological networks or food webs**: the nodes are species and the edges represent predator-prey relationships among them. Food webs are directed networks.
5. **Protein folding**: Different states of single protein are represented by different nodes. Conformations are linked if they can be obtained from each other by an elementary move. This is an undirected network.
6. **Citation networks**: Published articles are represented by nodes and a directed edge represents a reference to a previously published article. This is an undirected network.
7. **Co authorship networks**: Collaboration network exists of scientists represented by nodes

and two nodes are connected if two scientists have written an article together.
8. **Movie actor collaboration networks**: In this network the nodes are actors and two nodes have a common edge if two actors have acted in a movie together. This is an undirected network.
9. **The web of human sexual contacts**: Many sexually transmitted diseases spread on a network of sexual relationships. This is an undirected network.
10. **Phone-call networks**: A large directed graph can be constructed using telephone numbers as nodes and completed phone calls as edges, directed from caller to receiver.
11. **Networks in linguistics**: The complexity of human language offers several possibilities to define and study complex networks. One way of building a network is to describe words as nodes and connect them with edges if they appear one word form each other inside sentences of the literature of certain language. This is an undirected network. The other way to construct a network is to link words bases on their meaning: words are represented as nodes and are linked by an edge id they are known to be synonyms. This is an undirected network as well.
12. **Power networks**: Power grid is described as an undirected network where nodes are generators, transformers and substations and the edges are high-voltage transmission lines.
13. **Neural networks**: Nerve systems of different animal species are studied. An undirected network nodes are neurons joined together by an edge if connected by either synapse or gap-junction.
Studies of complex systems stated above were performed by different scientists on different datasets of different network sizes, ranging from small networks with only few hundred nodes (ecological networks) to large networks with as many as 10^9 nodes like WWW. Studied networks are of both directed and undirected type. In researches the average path length among the nodes of a graph, clustering coefficient and degree distribution were measured and compared to the same properties of random graphs. For a estimation of clustering coefficient the directed networks need to be turned into undirected, since coefficient can only be calculated for undirected webs.
All the real networks mentioned in this section feature short average path lengths, large clustering coefficients and many of them have power-tail degree distribution and are scale free (WWW, cellular networks, Internet, some social networks and the citation networks). However, others like the power grid or the neural network appear to feature exponential or a coherent mixture of scale-free and exponential degree distributions. As it is shown these networks are far from being random like ER random graphs, these systems are best described by evolving networks and can therefore develop both power law and exponential degree distributions or a mixture of them. While the power law regime appears to be robust, sublinear preferential attachment, aging effects, growth constraints lead to crossovers to exponential decay.

The mysteries of Artificial Neural Networks

An artificial neural network (ANN), often just called a "neural network" (NN), is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase.

Artificial Neural Networks have developed in a highly specialized technical field with thousands of publications. Below the rather technical article from Wikipedia. If you have to retain a single feature of ANNs its the one the Artificial Neural Networks can **learn**.

In more practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data.

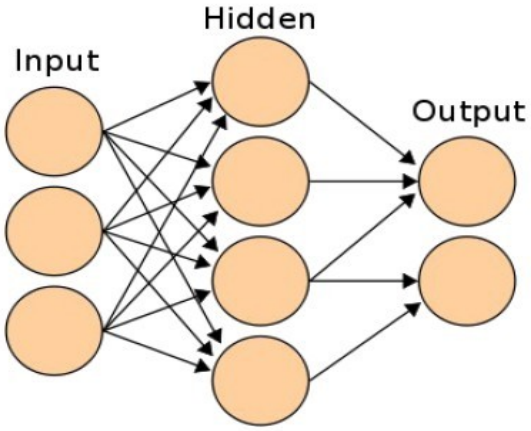


Figure. A neural network is an interconnected group of nodes, akin to the vast network of neurons in the human brain.

Background

There is no precise agreed-upon definition among researchers as to what a neural network is, but most would agree that it involves a network of simple processing elements (neurons), which can exhibit complex global behavior, determined by the connections between the processing elements and element parameters. The original inspiration for the technique was from examination of the central nervous system and the neurons (and

their axons, dendrites and synapses) which constitute one of its most significant information processing elements (see Neuroscience). In a neural network model, simple nodes (called variously "neurons", "neurodes", "PEs" ("processing elements") or "units") are connected together to form a network of nodes — hence the term "neural network." While a neural network does not have to be adaptive per se, its practical use comes with algorithms designed to alter the strength (weights) of the connections in the network to produce a desired signal flow.

These networks are also similar to the biological neural networks in the sense that functions are performed collectively and in parallel by the units, rather than there being a clear delineation of subtasks to which various units are assigned (see also connectionism). Currently, the term Artificial Neural Network (ANN) tends to refer mostly to neural network models employed in statistics, cognitive psychology and artificial intelligence. Neural network models designed with emulation of the central nervous system (CNS) in mind are a subject of theoretical neuroscience (computational neuroscience).

In modern software implementations of artificial neural networks the approach inspired by biology has more or less been abandoned for a more practical approach based on statistics and signal processing. In some of these systems neural networks, or parts of neural networks (such as artificial neurons) are used as components in larger systems that combine both adaptive and non-adaptive elements. While the more general approach of such adaptive systems is more suitable for real-world problem solving, it has far less to do with the traditional artificial intelligence connectionist models. What they do, however, have in common is the principle of non-linear, distributed, parallel and local processing and adaptation.

Models

Neural network models in artificial intelligence are usually referred to as artificial neural networks (ANNs); these are essentially simple mathematical models defining a function $f : X \rightarrow Y$. Each type of ANN model corresponds to a *class* of such functions.

The *network* in *artificial neural network*

$$f(x) = K\left(\sum_i w_i g_i(x)\right)$$

The word *network* in the term 'artificial neural network' arises because the function $f(x)$ is defined as a composition of other functions $gi(x)$, which can further be defined as a composition of other functions. This can be conveniently represented as a network structure, with arrows depicting the dependencies between variables. A widely used type of composition is the *nonlinear weighted sum*, where , where K is some predefined function, such as the hyperbolic tangent. It will be convenient for the following to refer to a collection of functions gi as simply a vector $g = (g_1, g_2, \ldots g_n)$.

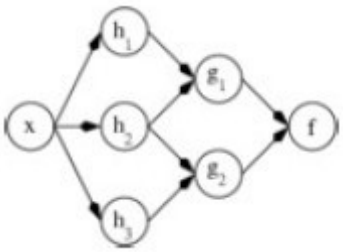


Figure. ANN dependency graph

This figure depicts such a decomposition of f, with dependencies between variables indicated by arrows. These can be interpreted in two ways.

The first view is the functional view: the input x is transformed into a 3-dimensional vector h, which is then transformed into a 2-dimensional vector g, which is finally transformed into f. This view is most commonly encountered in the context of optimization.

The second view is the probabilistic view: the random variable $F = f(G)$ depends upon the random variable $G = g(H)$, which depends upon $H = h(X)$, which depends upon the random variable X. This view is most commonly encountered in the context of graphical models.

The two views are largely equivalent. In either case, for this particular network architecture, the components of individual layers are independent of each other (e.g., the components of g are independent of each other given their input h). This naturally enables a degree of parallelism in the implementation.

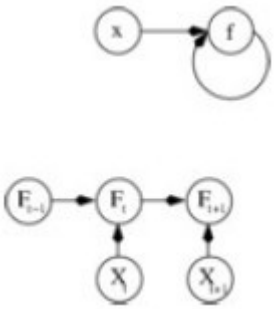


Figure. Recurrent ANN dependency graph

Networks such as the previous one are commonly called feedforward, because their graph is a directed acyclic graph. Networks with cycles are commonly called recurrent. Such networks are commonly depicted in the manner

shown at the top of the figure, where f is shown as being dependent upon itself. However, there is an implied temporal dependence which is not shown.

Learning

However interesting such functions may be in themselves, what has attracted the most interest in neural networks is the possibility of ***learning***, which in practice means the following:

Given a specific *task* to solve, and a *class* of functions F, learning means using a set of *observations*, in order to find a function which solves the task in an *optimal sense*.

The cost function C is an important concept in learning, as it is a measure of how far away we are from an optimal solution to the problem that we want to solve. Learning algorithms search through the solution space in order to find a function that has the smallest possible cost.

$$\hat{C} = \frac{1}{N}\sum_{i=1}^{N}(f(x_i) - y_i)^2$$

For applications where the solution is dependent on some data, the cost must necessarily be a *function of the observations*, otherwise we would not be modeling anything related to the data. It is frequently defined as a statistic to which only approximations can be made. As a simple example consider the problem of finding the model f which minimizes C, for data pairs (x,y) drawn from some distribution D. In practical situations we would only have N samples from D and thus, for the above example, we would only minimize . Thus, the cost is minimized over a sample of the data rather than the true data distribution.

When N $\rightarrow \infty$ some form of on line learning must be used, where the cost is partially minimized as each new example is seen. While on line learning is often used when D is fixed, it is most useful in the case where the distribution changes slowly over time. In neural network methods, some form of online learning is frequently also used for finite datasets.

Choosing a cost function

While it is possible to arbitrarily define some ad hoc cost function, frequently a particular cost will be used either because it has desirable properties (such as convexity) or because it arises naturally from a particular formulation of the problem (i.e., In a probabilistic formulation the posterior probability of the model can be used as an inverse cost). **Ultimately, the cost function will depend on the task we wish to perform.** The three main categories of learning tasks are over viewed below.

Learning paradigms

There are three major learning paradigms, each corresponding to a particular abstract learning task. These are supervised learning, unsupervised learning and reinforcement learning. Usually any given type of network architecture can be employed in any of those tasks.

1. Supervised learning

In supervised learning, we are given a set of example pairs (x,y) with $x \in X$ and $y \in Y$ and the aim is to find a function $f : X \rightarrow Y$ in the allowed class of functions that matches the examples. In other words, we wish to *infer* the mapping implied by the data; the cost function is related to the mismatch between our mapping and the data and it implicitly contains prior knowledge about the problem domain.

A commonly used cost is the mean-squared error which tries to minimize the average squared error between the network's output, f(x), and the target value y over all the example pairs. When one tries to minimise this cost using gradient descent for the class of neural networks called Multi-Layer Perceptrons, one obtains the common and well-known backpropagation algorithm for training neural networks.

Tasks that fall within the paradigm of supervised learning are pattern recognition (also known as classification) and regression (also known as function approximation). The supervised learning paradigm is also applicable to sequential data (e.g., for speech and gesture recognition). This can be thought of as learning with a "teacher," in the form of a function that provides continuous feedback on the quality of solutions obtained thus far.

2. Unsupervised learning

In unsupervised learning we are given some data x, and the cost function to be minimized can be any function of the data x and the network's output, f.

The cost function is dependent on the task (what we are trying to model) and our *a priori* assumptions (the implicit properties of our model, its parameters and the observed variables).

As a trivial example, consider the model $f(x) = a$, where a is a constant and the cost $C = E[(x - f(x))2]$. Minimizing this cost will give us a value of a that is equal to the mean of the data. The cost function can be much more complicated. Its form depends on the application: For example in compression it could be related to the mutual information between x and y. In statistical modeling, it could be related to the posterior probability of the model given the data. (Note that in both of those examples those quantities would be maximized rather than minimized).

Tasks that fall within the paradigm of unsupervised learning are in general estimation problems; the applications include clustering, the estimation of statistical distributions, compression and filtering.

3. Reinforcement learning

In reinforcement learning, data x is usually not given, but generated by an agent's interactions with the environment. At each point in time t, the agent performs an action yt and the environment generates an observation xt and an instantaneous cost ct, according to some (usually unknown) dynamics. The aim is to discover a *policy* for selecting actions that minimizes some measure of a long-term cost, i.e. the expected cumulative cost. The environment's dynamics and the long-term cost for each policy are usually unknown, but can be estimated.

ANNs are frequently used in reinforcement learning as part of the overall algorithm.

Tasks that fall within the paradigm of reinforcement learning are control problems, games and other sequential decision making tasks.

Learning algorithms

Training a neural network model essentially means selecting one model from the set of allowed models (or, in a Bayesian framework, determining a distribution over the set of allowed models) that minimises the cost criterion. There are numerous algorithms available for training neural network models; most of them can be viewed as a straightforward application of optimization theory and statistical estimation.

Most of the algorithms used in training artificial neural networks are employing some form of gradient descent. This is done by simply taking the derivative of the cost function with respect to the network parameters and then changing those parameters in a gradient-related direction.

Evolutionary methods, simulated annealing, and expectation-maximization and non-parametric methods are among other commonly used methods for training neural networks. See alsomachine learning.

Temporal perceptual learning relies on finding temporal relationships in sensory signal streams. In an environment, statistically salient temporal correlations can be found by monitoring the arrival times of sensory signals. This is done by the perceptual network.

Employing artificial neural networks

Perhaps the greatest advantage of ANNs is their ability to be used as an arbitrary function approximation mechanism which 'learns' from observed data. However, using them is not so straightforward and a relatively good understanding of the underlying theory is essential.

- Choice of model: This will depend on the data representation and the application. Overly complex models tend to lead to problems with learning.
- Learning algorithm: There are numerous tradeoffs between learning algorithms. Almost any algorithm will work well with the *correct hyperparameters* for training on a particular fixed dataset. However selecting and tuning an algorithm for training on unseen data requires a significant amount of experimentation.

- Robustness: If the model, cost function and learning algorithm are selected appropriately the resulting ANN can be extremely robust.

With the correct implementation ANNs can be used naturally in online learning and large dataset applications. Their simple implementation and the existence of mostly local dependencies exhibited in the structure allows for fast, parallel implementations in hardware.

Applications

The utility of artificial neural network models lies in the fact that they can be used to infer a function from observations. This is particularly useful in applications where the complexity of the data or task makes the design of such a function by hand impractical.

Real life applications

The tasks to which artificial neural networks are applied tend to fall within the following broad categories:

- Function approximation, or regression analysis, including time series prediction and modelling.
- Classification, including pattern and sequence recognition, novelty detection and sequential decision making.
- Data processing, including filtering, clustering, blind source separation and compression.

Application areas include system identification and control (vehicle control, process control), game-playing and decision making (backgammon, chess, racing), pattern recognition (radar systems, face identification, object recognition and more), sequence recognition (gesture, speech, handwritten text recognition), medical diagnosis, financial applications (automated trading systems), data mining (or knowledge discovery in databases, "KDD"), visualization and e-mail spam filtering.

Neural network software

Neural network software is used to simulate, research, develop and apply artificial neural networks, biological neural networks and in some cases a wider array of adaptive systems. See also logistic regression.

Types of neural networks

Feedforward neural network

The feedforward neural network was the first and arguably simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network.

A multilayer feedforward network –also called multilayer Perceptron –with gradient descent for error backpropagation has been used in our case study on the ecosystem of lake Constance.

There exists a panoply of other network types to cite just a few:

Radial basis function (RBF) network, Kohonen self-organizing network or SOMs (self-organizing maps), Recurrent network, Hopfield network, Echo state network, Long short term memory network, Stochastic neural networks, Boltzmann machine, Modular neural networks, Committee of machines, Associative neural network (ASNN), Holographic associative memory, Instantaneously trained networks, Spiking neural networks, Dynamic neural networks, Cascading neural networks, Neuro-fuzzy networks, Compositional pattern-producing networks, One-shot associative memory ...

Theoretical properties

Computational power, universal Turing Machine

The multi-layer perceptron （MLP） is a **universal function approximator**, as proven by the Cybenko theorem. However, the proof is not constructive regarding the number of neurons required or the settings of the weights.

Work by Hava Siegelmann and Eduardo D. Sontag has provided a proof that a specific recurrent architecture with rational valued weights （as opposed to the commonly used floating point approximations） has the full power of a Universal Turing Machine[2] using a finite number of neurons and standard linear connections. They have further shown that the use of irrational values for weights results in a machine with trans-Turing power.

Capacity

Artificial neural network models have a property called 'capacity', which roughly corresponds to their ability to model any given function. It is related to the amount of information that can be stored in the network and to the notion of complexity.

Convergence

Nothing can be said in general about convergence since it depends on a number of factors. Firstly, there may exist many local minima. This depends on the cost function and the model. Secondly, the optimization method used might not be guaranteed to converge when far away from a local minimum. Thirdly, for a very large amount of data or parameters, some methods become impractical. In general, it has been found that theoretical guarantees regarding convergence are an unreliable guide to practical application.

Generalization and statistics

In applications where the goal is to create a system that generalizes well in unseen examples, the problem of overtraining has emerged. This arises in overcomplex or overspecified systems when the capacity of the network significantly exceeds the needed free parameters. There are two schools of thought for avoiding this problem: The first is to use cross-validation and similar techniques to check for the presence of overtraining and optimally select hyperparameters such as to minimize the generalization error. The second is to use some form of regularization. This is a concept that emerges naturally in a probabilistic (Bayesian) framework, where the regularization can be performed by selecting a larger prior probability over simpler models; but also in statistical learning theory, where the goal is to minimize over two quantities: the 'empirical risk' and the 'structural risk', which roughly correspond to the error over the training set and the predicted error in unseen data due to overfitting.

We have cited the whole “zoo” of neural networks just to illustrate how rich this field of research is.

In our case study of the ecosystem of lake Constance we used only the first mentioned type of neural network, a multilayer feed forward network with gradient descent error backpropagation also called multilayer Perceptron.

The **multilayer Perceptron** is also the main paradigm when mapping energy transformation networks of a trophic web to information transformation networks of an ANN.

To map hypercycle structure networks, complex network theory has not much to say on the subject. The models are limited to networks growing under the mechanisms of preferential linking. In the field of artificial neural networks Kohonen's self-organizing maps (SOMs) might be a way to get hypercycle structure into a harder grip.

Theoretical attempts to explain the PZM regularities: Birth and Death processors and Artificial Neural Networks

"We are all agreed that your theory is crazy. The question which divides us is whether it is crazy enough to have a chance of being correct. My own feeling is that is not crazy enough. "

Niels Bohr on Pauli's theory of elementary particles
from Arne A. Wyller's *The Planetary Mind*

In every discipline, for example in geography there exist a great number of theoretical models to "explain" the observed PZM regularities. There are almost as many models as there are authors and many of them arrive at a Pareto-Zipf distribution. However the model's assumptions are specific to the field. One speaks of spatial fields, central place hierarchy and so on, but these concepts can not be transposed to other fields for which we observe PZM regularities.

We therefor constrained ourself to speak only about general models which cover a variety of different fields of science.

Self-organized critically, Wikipedia

I cite "Evolution of Networks" by [Dorogovtsev and Mendes, 2003] the bible of network theory.
"Thus the architecture that is based on fat-tailed degree distributions, with the key role of strongly connected vertices (hubs), is very important.
Where does it come from? Is it a result of the imposition of some external will, a lucky product of special design? Does somebody create intentionally such an architecture?
The answer is no.
These structures are the direct result of the self-organization of networks. Hence, the evolution of networks turns out to be among numerous growth processes which have been studied by phycisists for many years. One can say, by definition, that scalefree networks are in a critical state. so, the problems of the network growth are directly related to self-oranized critically."

Self-organized criticality is one of a number of important discoveries made in statistical physics and related fields over the latter half of the 20th century, discoveries which relate particularly to the study of complexity in nature. For example, the study of cellular automata, from the early discoveries of Stanislaw Ulam and John von Neumann through to John Conway's Game of Life and the extensive work of Stephen Wolfram, made it clear that complexity could be generated as an emergent feature of extended systems with simple local interactions. Over a similar period of time, Benoît Mandelbrot's

large body of work on fractals showed that much complexity in nature could be described by certain ubiquitous mathematical laws, while the extensive study of phase transitions carried out in the 1960s and '70s showed how scale invariant phenomena such as fractals and power laws emerged at the critical point between phases.

Bak, Tang and Wiesenfeld's 1987 paper linked together these factors: a simple cellular automaton was shown to produce several characteristic features observed in natural complexity (fractal geometry, 1/f noise and power laws) in a way that could be linked to critical-point phenomena. Crucially, however, the paper demonstrated that the complexity observed emerged in a robust manner that did not depend on finely-tuned details of the system: variable parameters in the model could be changed widely without affecting the emergence of critical behavior (hence, *self-organized* criticality). Thus, the key result of BTW's paper was its discovery of a mechanism by which the emergence of complexity from simple local interactions could be *spontaneous* — and therefore plausible as a source of natural complexity — rather than something that was only possible in the lab (or lab computer) where it was possible to tune control parameters to precise values. The publication of this research sparked considerable interest from both theoreticians and experimentalists, and important papers on the subject are among the most cited papers in the scientific literature.

Due to BTW's metaphorical visualization of their model as a "sandpile" on which new sand grains were being slowly sprinkled to cause "avalanches", much of the initial experimental work tended to focus on examining real avalanches in granular matter, the most famous and extensive such study probably being the Oslo rice pile experiment. Other experiments include those carried out on magnetic-domain patterns, the Barkhausen effect and vortices in superconductors. Early theoretical work included the development of a variety of alternative SOC-generating dynamics distinct from the BTW model, attempts to prove model properties analytically (including calculating the critical exponents), and examination of the necessary conditions for SOC to emerge. One of the important issues for the latter investigation was whether conservation of energy was required in the local dynamical exchanges of models: the answer in general is no, but with (minor) reservations, as some exchange dynamics (such as those of BTW) do require local conservation at least on average. In the long term, key theoretical issues yet to be resolved include the calculation of the possible universality classes of SOC behaviour and the question of whether it is possible to derive a general rule for determining if an arbitrary algorithm displays SOC.

Alongside these largely lab-based approaches, many other investigations have centered around large-scale natural or social systems that are known (or suspected) to display scale-invariant behavior. Although these approaches were not always welcomed (at least initially) by specialists in the subjects examined, SOC has nevertheless become established as a strong candidate for explaining a number of natural phenomena, including: earthquakes (which, long before SOC was discovered, were known as a source of scale-invariant behavior such as the Gutenberg-Richter law describing the statistical distribution of earthquake sizes, and the Omori law describing the frequency of aftershocks); solar

flares; fluctuations in economic systems such as financial markets (references to SOC are common in econophysics); landscape formation; forest fires; landslides; epidemics; and biological evolution (where SOC has been invoked, for example, as the dynamical mechanism behind the theory of "punctuated equilibria" put forward by Niles Eldredge and Stephen Jay Gould). Worryingly, given the implications of a scale-free distribution of event sizes, some researchers have suggested that another phenomenon that should be considered an example of SOC is the occurrence of wars. These "applied" investigations of SOC have included both attempts at modelling (either developing new models or adapting existing ones to the specifics of a given natural system), and extensive data analysis to determine the existence and/or characteristics of natural scaling laws.

The recent excitement generated by scale-free networks has raised some interesting new questions for SOC-related research: a number of different SOC models have been shown to generate such networks as an emergent phenomenon, as opposed to the simpler models proposed by network researchers where the network tends to be assumed to exist independently of any physical space or dynamics.

West's MinMax priciple for scaling laws

Geoffrey West from the Santa Fee Institute studied scaling laws during an entire life time, see his book Scaling in Biology [Brown, West, 2000].

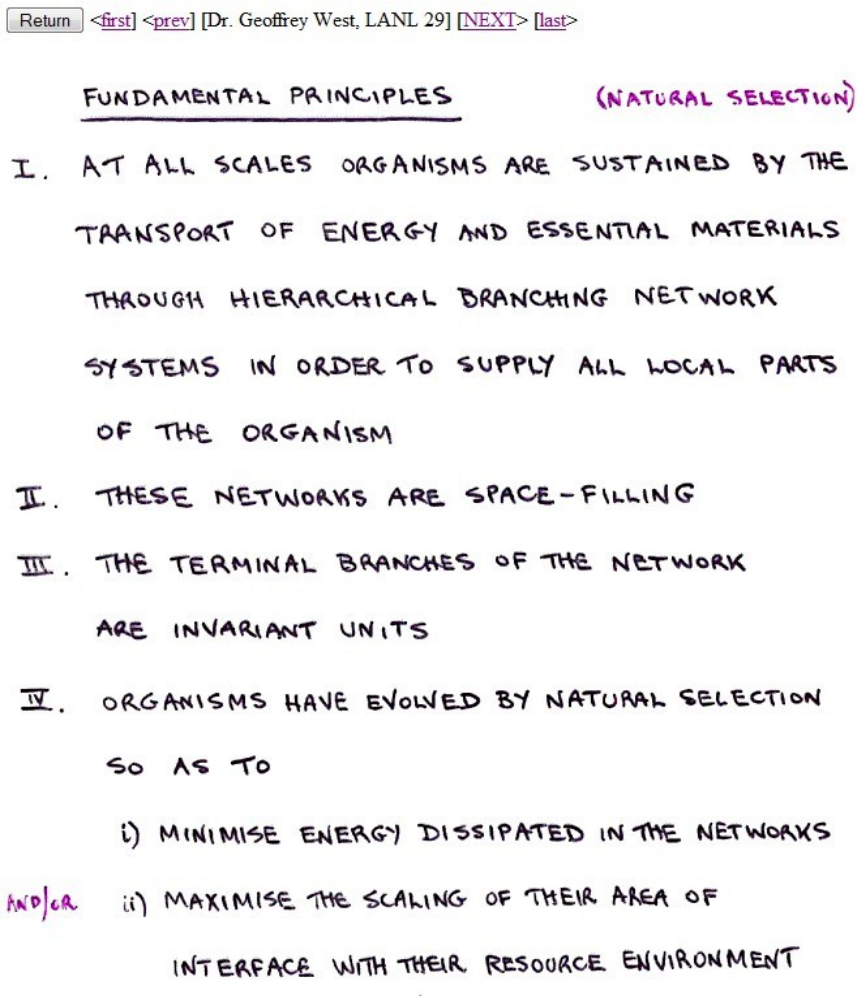
The first accurate measurements of body mass versus metabolic rate in 1932 shows that the metabolic rate R for all organisms follows exactly the 3/4 power-law of the body mass, i.e., $R \propto M^{3/4}$. This is known as the Kleiber's Law. It holds good from the smallest bacterium to the largest animal. The relation remains valid even down to the individual components of a single cell such as the mitochondrion, and the respiratory complexes (a subunit of the mitochondrion). It works for plants as well. This is one of the few all-encompassing principles in biology. But the law's universality is baffling: Why should so many species, with their variety of body plans, follow the same rules?
An explanation for this kind of relationship was proposed further back in 1883:

- Suppose the organism has a size of L, then the surface area $A \propto L^2$, while the volume $V \propto L^3$ assuming that it is in the shape of a sphere.
- If the density in the organism $\rho \propto M / L^3$ is constant, then $L \propto M^{1/3}$, where M is the total mass of the organism.
- Since the heat dissipation from an organism is proportional to its surface area, the total metabolic rate $R \propto L^2 \propto M^{2/3}$, which is close but not quite the same as the 3/4 power-law.

Then in 1997, a couple of physicist and biologists successfully derive the 3/4 power-law using the concept of fractal. The theory considers the fact that the tissues of large organisms have a supply problem. That is what blood systems in animals and vascular plants are all about: transporting materials to and from tissues. Small organisms don't face the problem to the same extent. A very small organism

has such a large surface area compared to its volume that it can get all the oxygen it needs through its body wall. Even if it is multicellular, none of its cells are very far from the outside body wall. But a large organism has a transport problem because most of its cells are far away from the supplies they need. Insects literally pipe air into their tissues in a branching network of tubes called tracheae. Mammals have richly branched air tubes, but they are confined to special organs, the lungs. Fish do a similar thing with gills. Trees use their richly dividing branches to supply their leaves with water and pump sugars back from the leaves to the trunk.
The 3/4-power law is derived in part from the assumption that mammalian distribution networks are "fractal like" and in part from the conjecture that natural selection has tended to maximize metabolic capacity "by maintaining networks that occupy a fixed percentage (6 - 7%) of the volume of the body". Effort has been made to derive the 3/4 power-law for a broader category that includes plants, animals, and even one-celled organisms lacking a vascular system. The latest derivation is based mostly on geometry, particularly the hierarchical nature of circulatory networks. It is argued that an organism's "internal area" -- the total area of its capillary walls -- fills up space so efficiently that it, in effect, adds a third dimension (similar to the compactification of extra dimensions in the Superstring Theory). Therefore, the "internal volume" of all the vessels feeding the capillaries acts as an extra dimension, scaling as the fourth power of internal length.

The figure below shows West's formulation of a minimum maximum principle which is at the base of the observed power law regularities in terms of hierarchical branching networks.



Holistic Extremum principle (Mandelbrot, Winiwarter)

Mandelbrot, the inventor of Fractals [Winiwarter, 1983b], has studied in detail the theory of coding and given an explanation for the regularities of word counts in terms of an extremum principle :
within a text, the quantity to be optimized (minimized) is the "average cost per word".
Assuming that the "cost" of a word depends on the "costs" of its constituting letters, Mandelbrot showed that the resulting "optimal" distribution is of the Pareto-Zipf type.
Based on a general principal of evolution or self-organization which states, that the complexity of a self-organized system can only grow or remain constant (first law of genesis)[Winiwarter], we put forward the hypothesis, that Pareto-Zipf type distributions are common to all processes of self-

organization (second law of genesis)[Winiwarter] .
Generalizing Mandelbrot's arguments from words to energy quanta, we speculated, that the observed Pareto-Zipf regularities are the result of a general extremum principle, which maximizes what we have called the energy redundancy (binding energy or synergy) within a self-organized system.
This approach seems very general and attractive, however - besides for systems of nucleons - it is difficult or impossible to verify.
Note that Mandelbrot's approach of a holistic extremum principle is very similar the the principle of maximum entropy production.

Pareto ⊕ Pareto = Pareto , stability under addition (Roehner, Winiwarter)

The Gaussian distribution is known to be a limit distribution of random variables .
It is well known, that the random sum ⊕ of two Gaussian distributions G1 and G2 yields a new distribution G3 which is also Gaussian.
$G1 \oplus G2 = G3$
It is too generally assumed, that this property is unique for the distributions called "normal", "bell-shaped" or Gaussian.
We have shown, that Pareto distributions are possible limit distributions of sums of random variables [Roehner, Winiwarter, 1985] .
The random sum ⊕ of two Paretian distributions P1 and P2 yields a new distribution P3 which is also Paretian .
$P1 \oplus P2 = P3$
Based on this statistical stability of Pareto distributions, we have explained the stability of empirical distributions as the result of a stochastic process :
$S_{t+1} = \alpha S_t \oplus \Delta$
The distribution at time t+l depends on the distribution at time t multiplied by a factor α characterizing the total growth of the system, plus a deviation Δ added at random.
If the initial distribution is Paretian and if the distribution of fluctuations Δ is Paretian, then the resulting distribution must also be Paretian.
This statistical stability is certainly an interesting and important feature, explaining the extreme perseverance of Pareto distributions over time, but it does not explain in a satisfactory way their origins. Stating that every observed regularity is the stochastic result of prior regularities, can be mathematically correct, but is not a very satisfying explanation.

Birth and Death processor, the basic interaction unit

It is the merit of Howard Odum [Odum 1988] to have focused our attention on the energy transformation aspect of hierarchically organized ecosystems. He already stated that " observing self-organization in nature suggests how energy is related to hierarchy and information .. . The details of the energy transformation mechanisms are quite different in ecosystems, chemical reaction systems,

turbulent hydrodynamical systems, social systems, and stars, but energy and mathematical characteristics are common to all".
All levels of the evolutionary hierarchy have two things in common: energy transformation and information transformation.
In a paper entitled “Life symptoms: the Behavior of Open Systems with Limited Energy Dissipation Capacity and Evolution” [Winiwarter and Cempel 1992], departing from a very specific model - describing tribo-vibro-acoustic processes in machines - we propose a generalized theoretical framework in terms of
energy transformation with limited internal energy dissipation capacity, which is applicable to all levels of the evolutionary hierarchy.
The proposed model "unifies" a large variety of concepts and applies a coherent terminology to fields, which have at first sight nothing in common. For the observed life symptoms, theoretical predictions can be compared with past and future empirical observations .
What is most important is the model's inference power: from the observations of a set of units at a given moment of life-time (a snapshot of the system), one can predict the average behavior of a single unit over its entire life-time .
The system is built of basic energy/information transformation processors that are born and run to death in an irreversible way (*birth and death processors*)

The model is characterized by energy input, upgraded as well as degraded energy outputs and a limited internal transformation capacity (see fig. 1 below as an example). In addition to the traditional energy flows our model is based on two very simple postulates

1) the internal accumulation potential is finite and irreversibly filled up to a threshold value.
2) the internal accumulation level regulates the internal accumulation rate through positive feedback

(autocatalytic behavior of internal accumulation) .
This very simple model results in important statistical features concerning the behavior of a single processor
over its life-time and the statistical behavior of a population of similar processors.

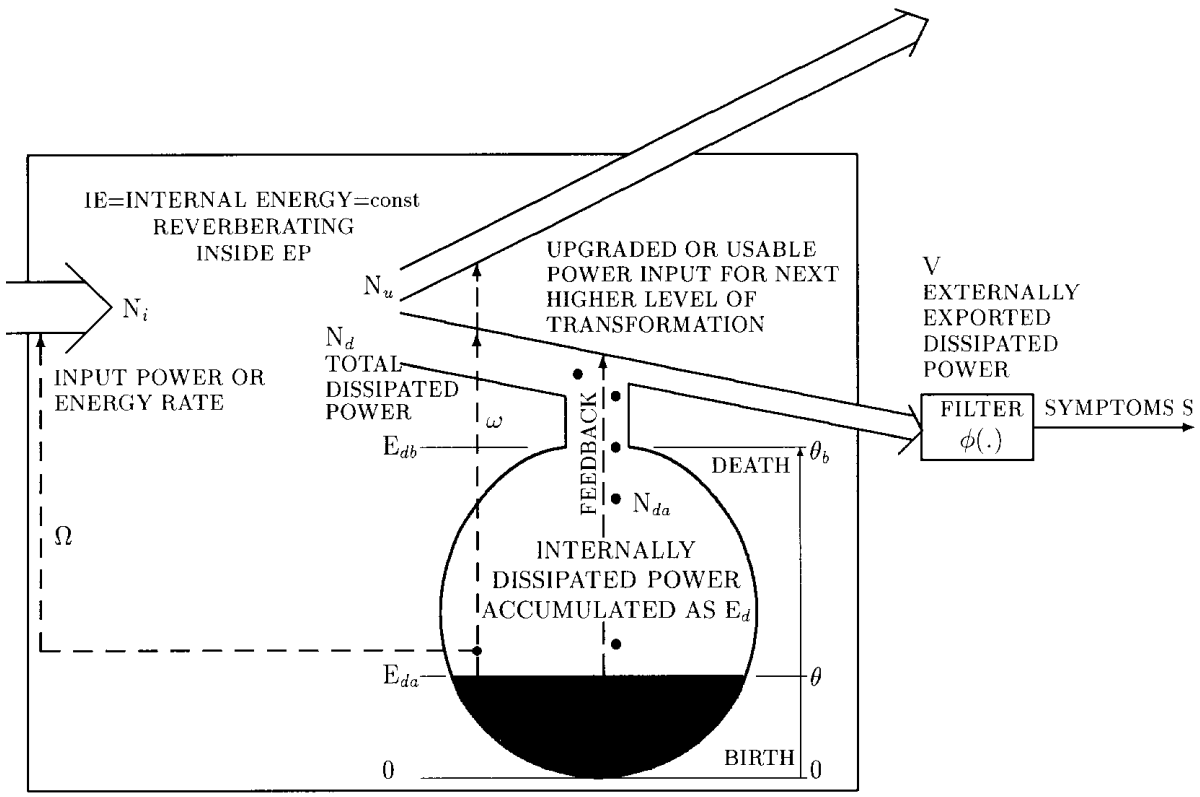
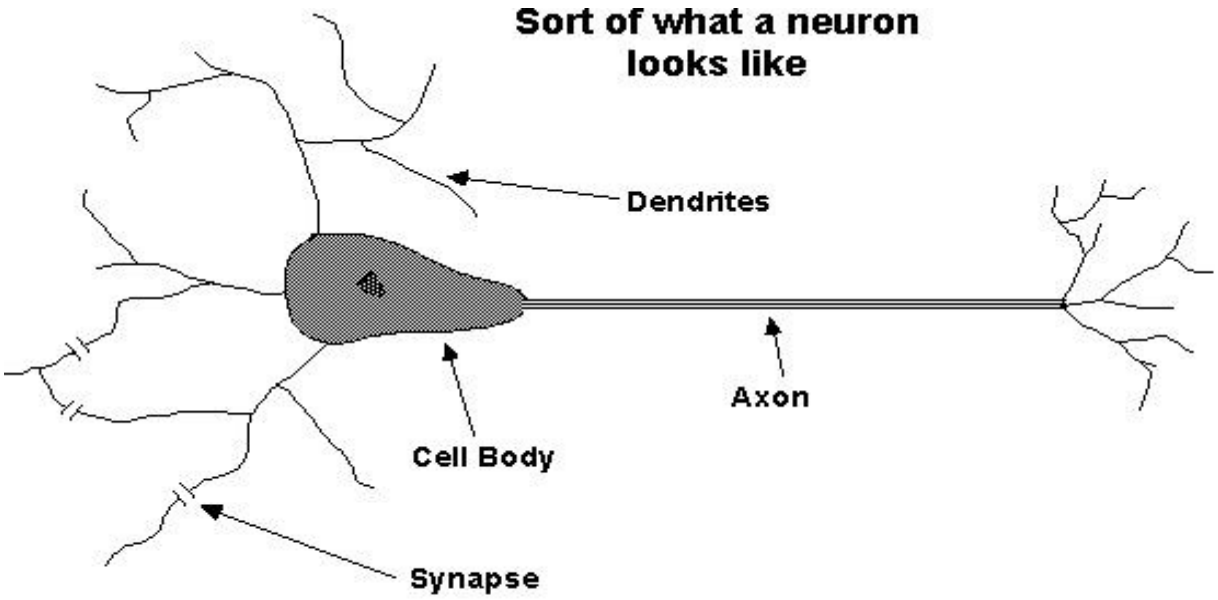


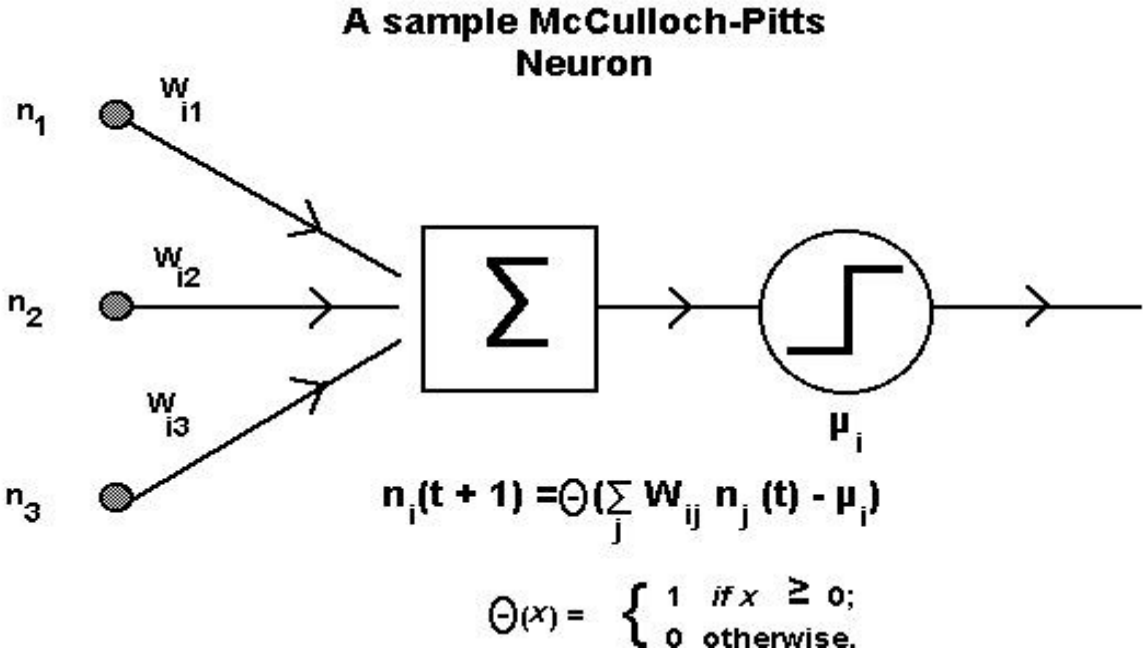
Figure . basic birth and death processor, the interaction unit of a self-organized system.
A part of the input energy rate N_i is irreversibly accumulated in an internal reservoir E_d from birth to death of the processor. Note the feedback of the internally accumulated energy and the output flow of dissipated downgraded energy observed as Symptom S. When the internal reservoir is full at E_{db}, the system brakes down (natural death).

Artificial Neuron equivalent to birth and death processor

An artificial neuron is a mathematical function conceived as a crude model, or abstraction of biological neurons. Artificial neurons are the constitutive units in an artificial neural network. Depending on the specific model used, it can receive different names, such as semi-linear unit, Nv neuron, binary neuron, linear threshold function or McCulloch-Pitts neuron. The artificial neuron receives one or more inputs (representing the one or more dendrites) and sums them to produce an output (synapse). Usually the

sums of each node are weighted, and the sum is passed through a non-linear function known as an activation function or transfer function. The transfer functions usually have a sigmoid shape.





Networks of Birth and Death processors and Artificial Neural Networks

A self-similar network of Birth and Death processors, Energy transformation

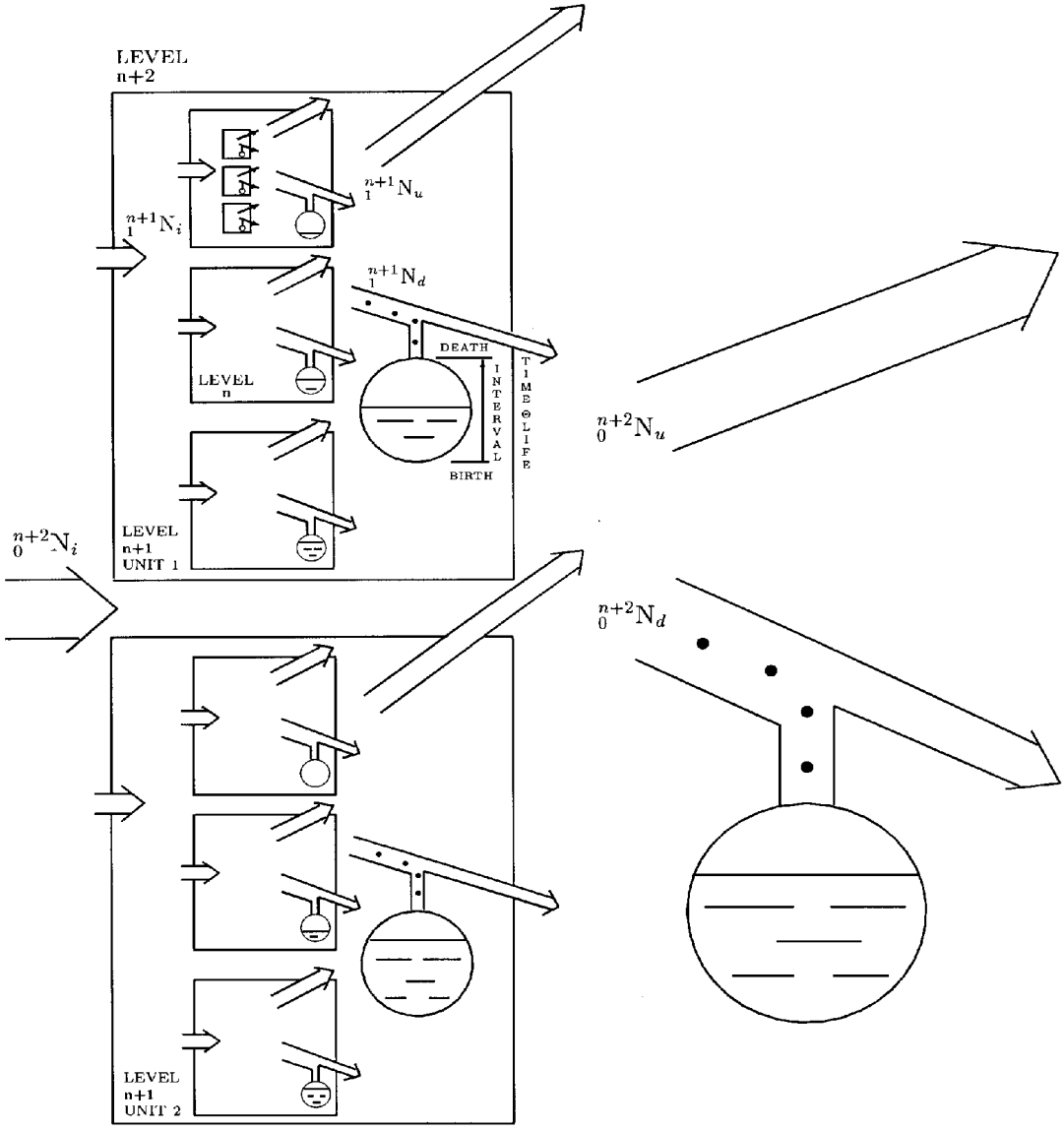


Figure. The self-similar 'fractal' hierarchy of energy transformation processors.

You can zoom in or zoom out of the self-similar hierarchy of energy transformation processors (Birth and Death processors). For a unit on any level of the hierarchy you will find the structure of a basic Birth and Death processor upgrading energy to the next level of the hierarchy, downgrading energy and internally accumulating downgraded energy until a threshold, it's death. Every unit can be considered as a binary threshold automation with two possible states : 0 processing or alive and 1 dead.

A self-similar network of Artificial Neural Networks, Information transformation

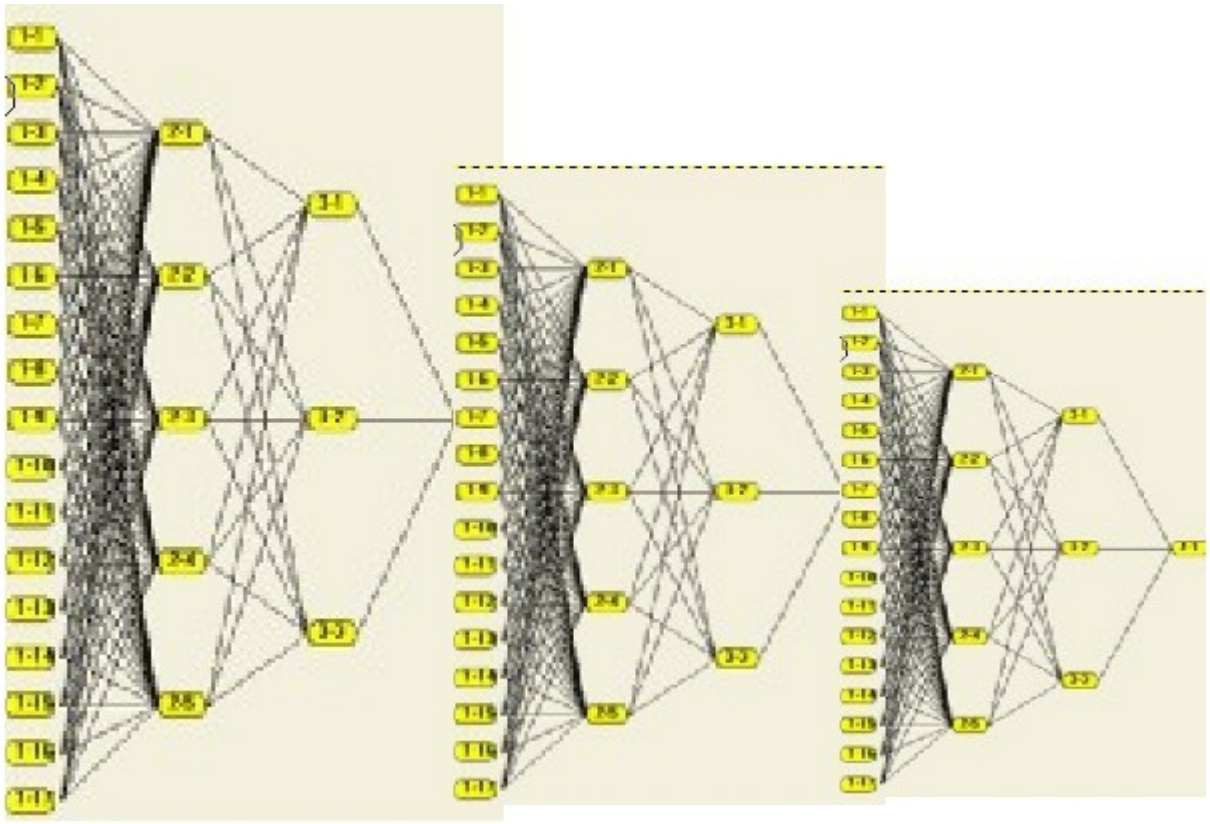


Figure. The fractal hierarchy of Neural Networks which maps the hierarchy of Energy transformation processors.

You can zoom in or zoom out of the self-similar hierarchy of information transformation processors (artificial neurons). For a unit on any level of the hierarchy you will find the structure of a basic neuron accumulating weighted incoming information pulses up to a threshold, when it fires a pulse to the next

hierarchical level. Every unit can be considered as a binary threshold automaton with two possible states : 0 accumulating and 1 firing. This maps the binary threshold automaton of a Birth and Death processor.

Multilayer Perceptron, a robust universal mapper

This class of networks consists of multiple layers of computational units, usually interconnected in a feed-forward way. Each neuron in one layer has directed connections to the neurons of the subsequent layer. In many applications the units of these networks apply a sigmoid function as an activation function.

The *universal approximation theorem* for neural networks states that every continuous function that maps intervals of real numbers to some output interval of real numbers can be approximated arbitrarily closely by a multi-layer perceptron with just one hidden layer.

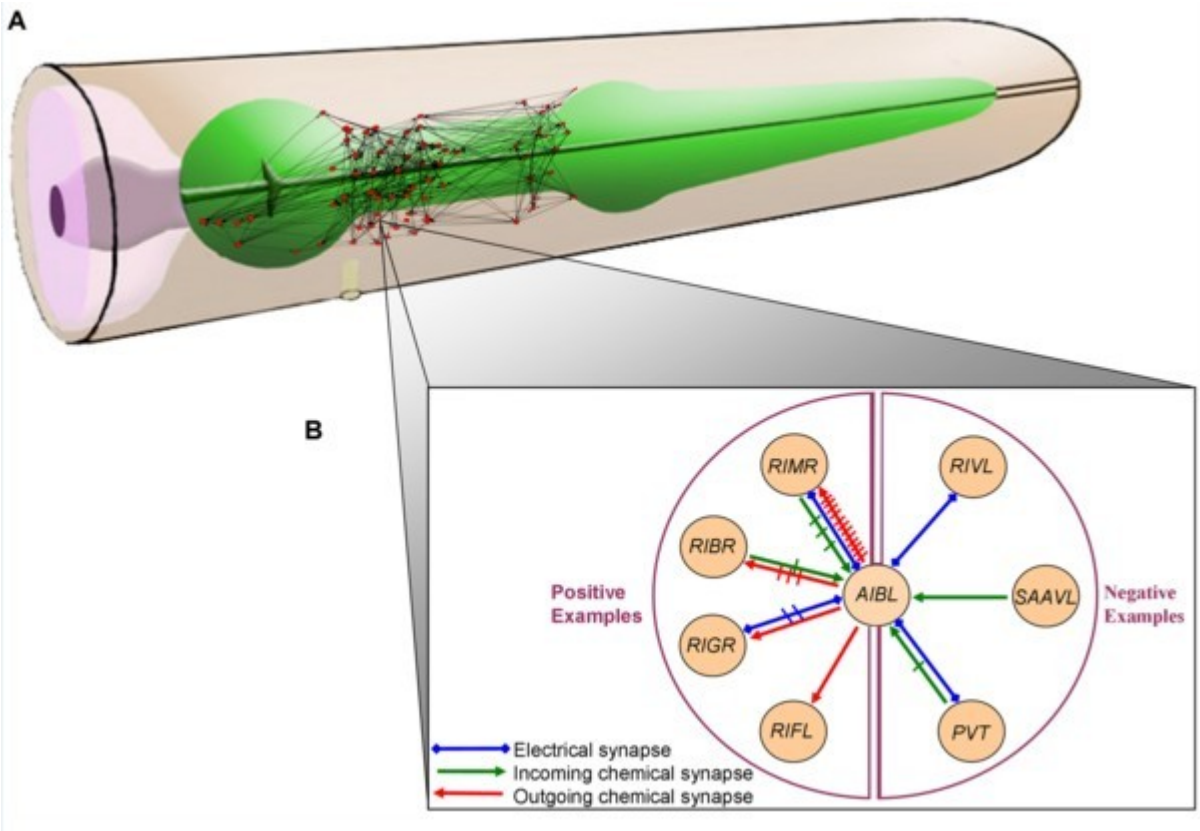
Multi-layer networks use a variety of learning techniques, the most popular being *back-propagation*. Here, the output values are compared with the correct answer to compute the value of some predefined error-function. By various techniques, the error is then fed back through the network. Using this information, the algorithm **adjusts the weights** of each connection in order to reduce the value of the error function by some small amount. After repeating this process for a sufficiently large number of training cycles, the network will usually converge to some state where the error of the calculations is small. In this case, one would say that the network has *learned* a certain target function. To adjust weights properly, one applies a general method for non-linear optimization that is called gradient descent. For this, the derivative of the error function with respect to the network weights is calculated, and the weights are then changed such that the error decreases (thus going downhill on the surface of the error function). For this reason, back-propagation can only be applied on networks with differentiable activation functions.

In general, the problem of teaching a network to perform well, even on samples that were not used as training samples, is a quite subtle issue that requires additional techniques. This is especially important for cases where only very limited numbers of training samples are available. The danger is that the network overfits the training data and fails to capture the true statistical process generating the data. Today there are practical solutions that make back-propagation in multi-layer perceptrons the solution of choice for many machine learning tasks.

Note that a major feature of an Artificial Neural Network of the perceptron type is its **robustness**. You can eliminate several or many nodes of the network, the remaining nodes will perform similar and show similar results. This feature called 'degeneracy' for biological networks can also be found within technical self-organized networks like the Internet. You can take out several nodes, but the routing will perform as prior to the incident.

Barabási [Barabási, 2003] already points out the major features of self-organized networks. “In reality, the market is nothing but a directed network. Companies, firms, corporations, financial institutions, governments, and all potential economic players are the nodes. Links quantify various interactions between these institutions, involving purchases and sales, joint research and marketing projects, and so forth. The ***weight*** of the links captures the value of the transaction, and the direction points from the provider to the receiver. The structure and evolution of this ***weighted*** and ***directed*** network determine the outcome of all macroeconomic processes.” (bold faces are ours) That is exactly the description of an artificial neural network of the perceptron type, a weighted and directed network.

Natural Neural Networks (C.elegans)



Trophic Web and Features of multilayer Perceptron (case study of lake Constance)

Box 4.1 The pelagic food web of Upper Lake Constance

Lake Constance is a large (500 km^2) and deep (z_{max} = 254 m) perialpine lake in central Europe, which has been intensively studied throughout the twentieth century. The lake consists of the more shallow Lower Lake Constance, and the deep Upper Lake Constance (Figure 4.1(a)). Due to its deep slope the latter has a truly pelagic zone, which seems to be energetically independent from littoral subsidies. Like many other temperate lakes, Lake Constance went through a period of severe eutrophication starting in the 1930s and culminating in the 1960s/1970s (Bäuerle and Gaedke 1998 and references therein). Beginning with the 1980s total phosphorus concentrations declined again. However, the response of the plankton community to oligotrophication was delayed. The pelagic food web of Upper Lake Constance during the oligotrophication period has been analyzed within several years of intensive sampling (Bäuerle and Gaedke 1998). Different food-web approaches, that is, body-mass size distributions (Gaedke 1992, 1993; Gaedke and Straile 1994*b*), binary food webs (Gaedke 1995), and mass-balanced flow networks (Gaedke and Straile 1994*a*,*b*; Straile 1995; Gaedke et al. 1996; Straile 1998; Gaedke et al. 2002) were applied to a dataset consisting of five, respectively eight (Gaedke et al. 2002) years of almost weekly sampling. A special strength of this dataset is that it encompasses both, the classical food chain as well as the microbial food web. For carbon flow models the pelagic food web was aggregated into eight different compartments (Figure 4.1(b)), of which five can be assigned to the "classical food chain," that is, phytoplankton, rotifers, herbivorous crustaceans, carnivorous crustaceans, and fish, and three to the microbial loop, that is, bacteria, heterotrophic nanoflagellates, and ciliates (Figure 4.1(b)). In addition flows between these eight compartments and the detritus/DOC (dissolved organic carbon) pool were considered (exsudation of phytoplankton, egestion and excretion of consumers, DOC uptake by bacteria). To analyze seasonal changes in carbon flows data were subdivided into up to 10 seasonal time intervals per year lasting between 14 and 102 days. For all seasonal time intervals mass-balanced carbon and phosphorous flows were established and further processed with the techniques of network analyses (Ulanowicz 1986). The results shown here are based on 44 different mass-balanced food-web diagrams for different seasonal time intervals from the study years 1987 to 1991 (Straile 1995, 1998).

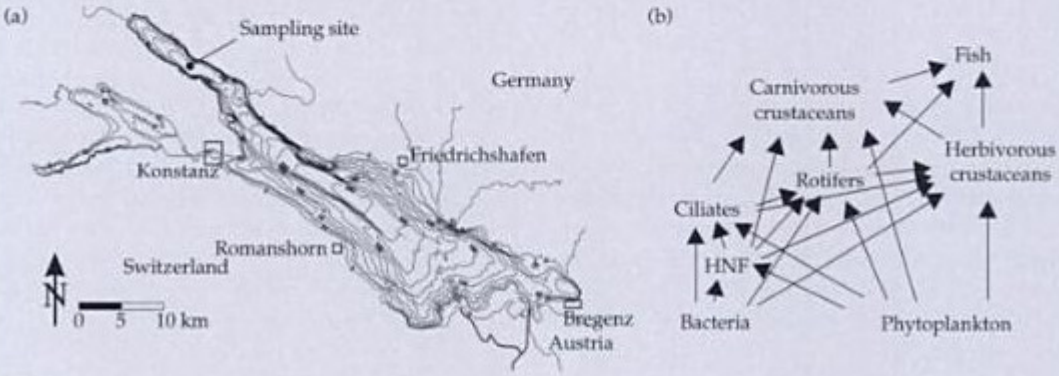


Figure 4.1 (a) Map of Lake Constance, and (b) aggregation of the Lake Constance pelagic food web into eight trophic guilds. Cannibalistic food-web interactions were considered for ciliates, rotifers, and carnivorous crustaceans, but are not shown here. Also not shown are the flows between these compartments and the detritus/DOC pool.

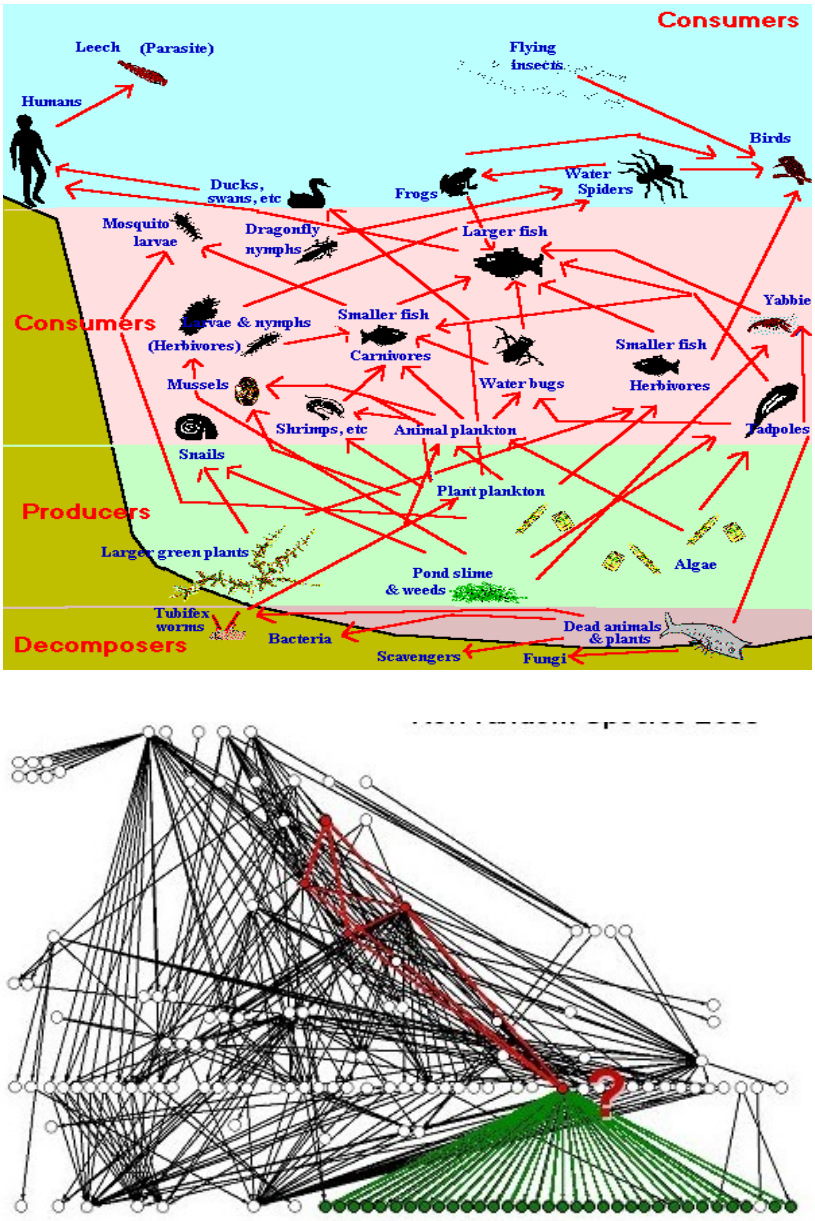


Figure. biomass-size distribution of aquatic ecosystems (trophic web or food web) Winiwarter and Vidondo modeled the ecosystem evolution of the lake Constance by a neural network of the feed forward type with back-propagation (multilayer perceptron).

To map the graph of the food web on an artificial neural networked we used a multilayer perceptron introducing an additional input layer, the time series of daily energy input from the sun (corrected for wind) day d, d-1, d-2 etc for one consecutive year. We used a single additional output layer, the coefficient alpha, slope of the observed biomass size distribution on day d.
The coefficient alpha shows strong seasonal variations which repeat each other year after year.
The model was trained with seven years of empirical data – biomass size distributions characterized by the slope alpha - yielding an excellent correlation coefficient. Forecasts with the model compared with subsequently observed data showed a high degree of coincidence between the model output and observed data.
This shows that a single parameter, the time series of daily energy input can describe the entire biodiversity of the system and its **seasonal evolution over time**.
What is remarkable is that the slope of the biomass size distribution is independent of the specific species being part of the size distribution. If one species decreases or disappears during a season or from the overall system it is replaced by other species and the slope of the distribution acts as an attractor which drives the temporal short and long term evolution of the system.
Note that the introduction of water purification stations did not alter biodiversity of the system but it did not alter its overall dynamics.
The novelty of this approach consists of mapping a complex trophic web on a simplified Artificial Neural Network (Perceptron) which allows to better understand the robustness and dynamics of the complex networks.
It is the topology of the trophic web and the weights of its interaction links which make up its memory and the consecutive daily runs – the learning process of the web – which allows its robustness.

Following the evolution of complex network theory we observe according to Barabási the stages of:

- simple random graph (Erdős and Rényi) a static viewpoint
- small world networks (Watts and Strogatz) explaining the famous six degrees between random chaos and complete order
- scale-free networks (Barabási)
  introducing dynamics explaining the existence of hubs and the observation of power laws in terms of network growth and preferential attachment.
  and finally our contribution
- artificial neural networks (Winiwarter)
  explaining the memory, learning and intelligence (robustness) of complex weighted and directed self-organized networks.

Future evolution: is the singularity near?

"Who will be man's successor? To which the answer is: We are ourselves creating our own successors. Man will become to the machine what the horse and the dog are to man; the conclusion being that machines are, or are becoming, animate."

Samuel Butler, 1863 letter "Darwin among the machines?"

Increase in complexity, the first law of genesis (Winiwarter)

There seems to be a general agreement among scientists that during the evolution from the big bang to the world wide web the complexity of the observed systems increases from atoms over molecules, unicellular and pluricellular organisms to biological neural networks etc.

However this general statement of increasing complexity is difficult, if not impossible to express in quantitative terms. So far there exists no overall agreement on a measure of complexity.

In a speculative paper [Winiwarter 1983a] we tentatively defined a quantitative measure of complexity which is measurable at least in the realm of nuclear physics. The observation of this complexity during the nuclear evolution in a massive star (building up more and more heavy elements from Hydrogen over Carbon and Oxygen to Uranium) and the natural radioactive decay of heavy elements suggests a regularity, the first law of genesis:

The complexity of a self-organized system of matter can only increase or remain constant.

To extend this law from the nuclear realm to bio-chemistry, biology and sociology is a speculation, difficult to prove, since there are no empirical measures of the "binding energy" or synergy betweeen interaction units in these fields. However we observe, that with the emergence of a new level the binding energy decreases often by orders of magnitude. Strong nuclear bonds, weak nuclear bonds, chemical bonds, bonds of the genetic network, social bonds, links between sites of the World Wide Web...

PZM power laws, the second law of genesis (Winiwarter)

As illustrated in the chapter on observed Pareto-Zipf-Mandelbrot (PZM) distributions we observe regularities of the PZM type for virtually all levels of the evolutionary hierarchy. In 1983 when most of the observations like the World Wide Web did not exist we postulated on a speculative basis a general law, the second law of genesis:

Any self-organized system reveals Pareto-Zipf regularity for its statistical structure.

Barabási pointed out that every time we observe a power law the underlying network shows a specific topology, a hierarchical organization in local modules linked to global hubs.

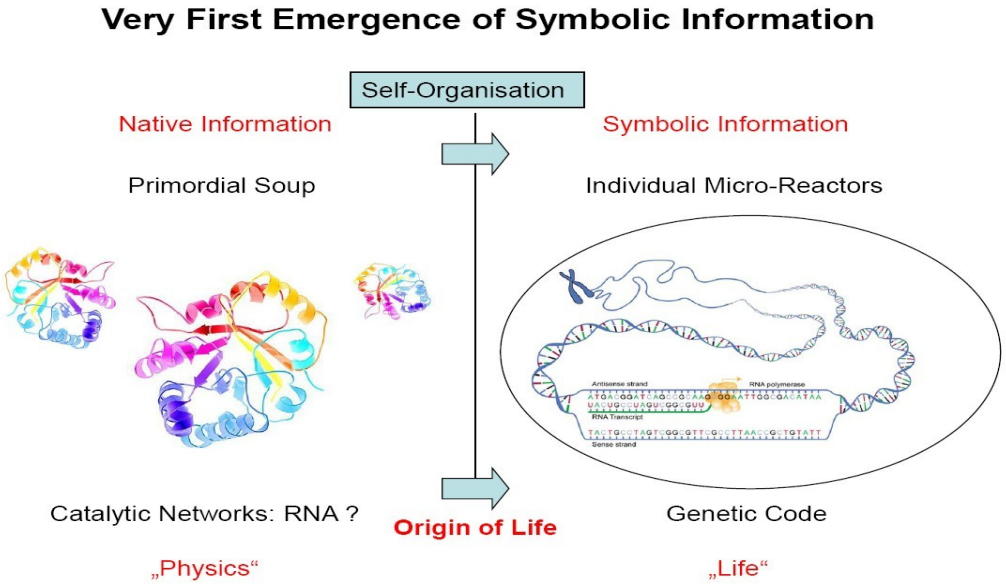
We propose the hypothesis that PZM regularities are not only characteristic for the topology of complex self-organized network but also for common processes within the network like bottom up feed forward of information and top down back-propagatio of information, which can be modeled by Artificial Neural Networks of the multilayer perceptron type.

The literature on the observation of PZM regularities of complex graphs ranges from power grid systems, natural neural networks, protein interaction maps, metabolic pathways, ecological networks, electronic circuits, Internet topology, scientific collaborations to lexical networks.

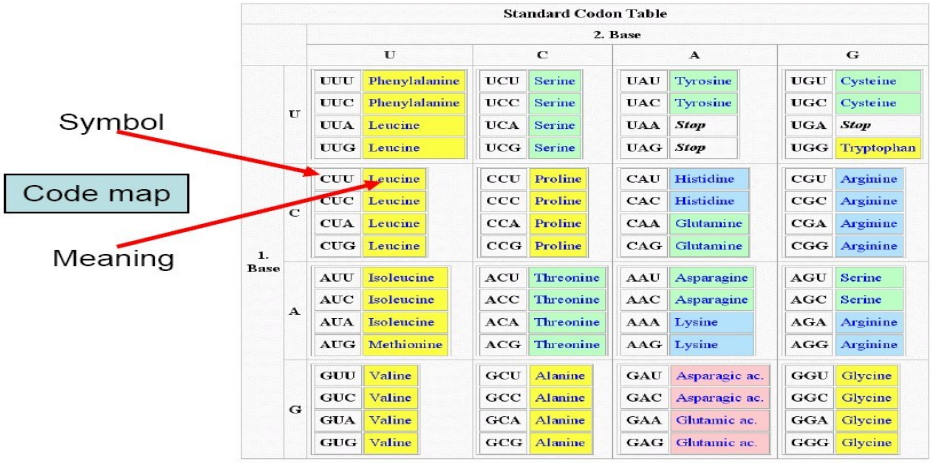
Ritualization : the Self-Organization process of symbolic information

In our evolutionary hierarchy, the Russian dolls of communication networks, each new level emerges within the prior level. The network of cellular energy communication emerges within the network of chemical bonds communication. The genetic communication network of DNA emerges within the network of RNA communication. The network of the central nervous system (neural network) emerges within the network of the genetic code.

What is remarkable is that every emergence of a new level seems like a symmetry brake in the process of evolution where the new emerging level maps in a symbolic way the communication networks from which it emerges. This is actually the case for multilayer Artificial Neural Networks, where each higher level maps the respective lower level.



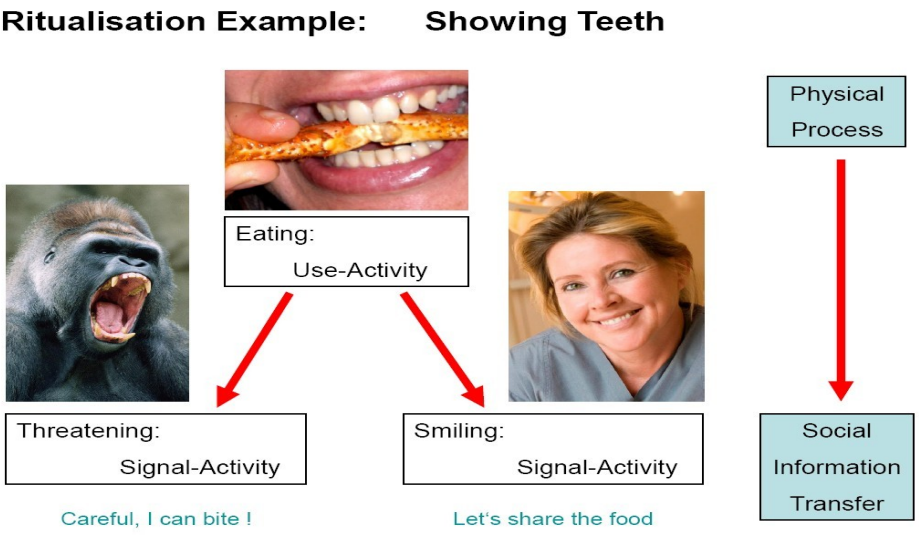
Macro-states far from Equilibrium: Life



Genetic Code:

Traces of the chemical history during Ritualisation

Feistel calls this process of the emergence of symbols “ritualization” in analogy to the emergence of behavior in ethology.



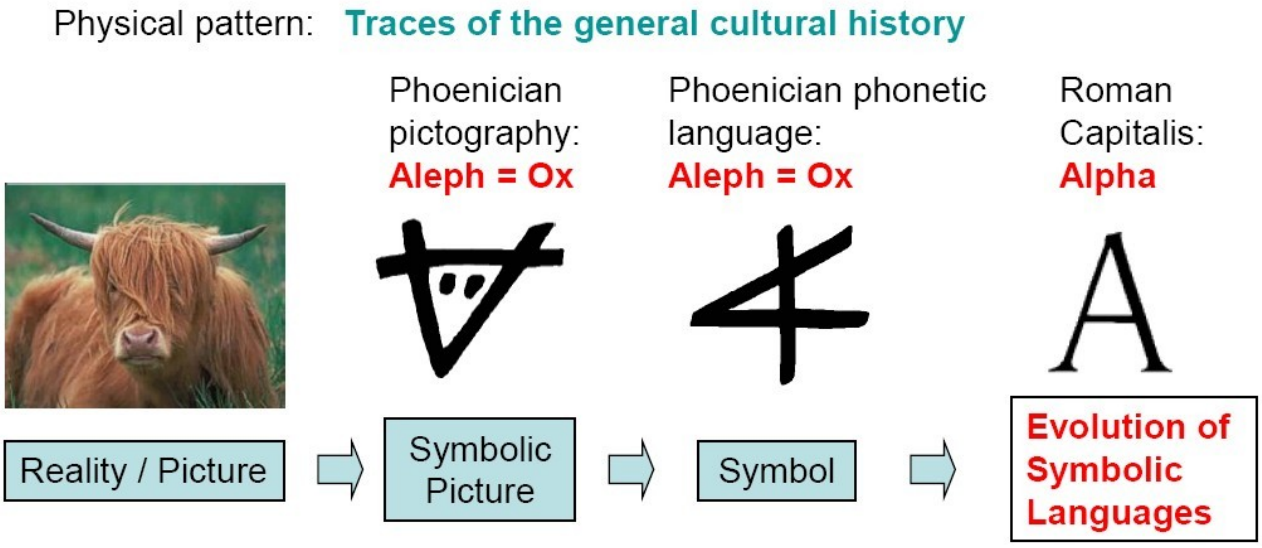
The symbol “showing teeth” stands for the communication “Let's share food”. It is only during the process of communication that the symbol acquires meaning. The symbol itself without the context is meaningless.

This phase transition takes place within the Ecosystem (central nervous system communication network) with the emergence of a semiotic communication network in social communities.

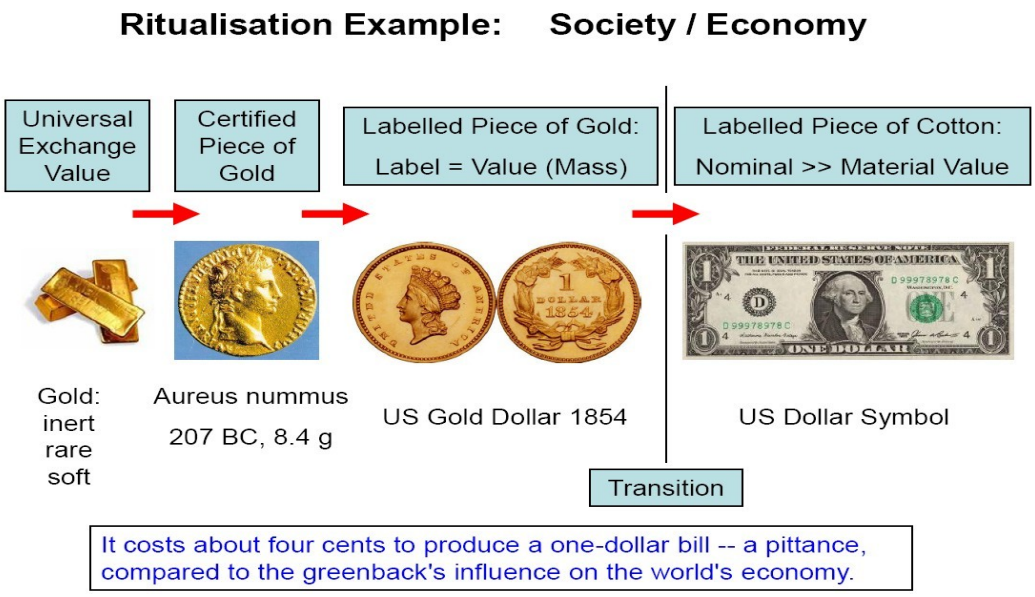
Likewise we observe the process of Ritualization during the emergence of our modern alphabet.

Within the ritual verbal symbolic communication network of culture emerges the level of mechanical tools communication network which gives rise to a written verbal communication network.

Note that the symbols of letters acquire meaning only within the context of words. The attentive reader will remember, that word frequency distributions of all languages and all time reveal a PZM regularity called Zipf's law.



If we continue to the next levels in our evolutionary hierarchy we observe the emergence of formal symbolic communication networks for economic exchange. The emerging symbols range from a piece of gold over simple certified coins to face value coins and finally to the highly abstract dollar bill which lost its link to gold value only recently.



The attentive reader will recall that the statistical structure of personal fortunes and of firm sizes expressed in monetary values reveal PZM regularities.

Extending the operator hierarchy of Gerard Jagers from the biological to the economic realm we can define the following "operators":

- **Cell** = multi-atom unit with the exchange of chemical compounds
  The closure is defined as the cell membrane.
- **Memon** = multi-cellular unit with a hardwired neural network with the exchange of perceptions
  The closure is defined by the physical organs of perception.
- **Oikos** = multi-memon unit with a hard structured home (greek 'oikos' means fireplace or home) with the exchange of basic goods like food and fuel for the fireplace
  The closure is defined by the physical walls of the home.
- **Market** = multi-oikos unit with a physical market place with the exchange of physical goods
  The closure is defined by the physical frontiers of the market .
- **Stock market** = multi-market with a virtual market place of the stock market where stocks and bonds are traded
  The closure is defined by virtual frontiers essentially the currency of the stock-market.

The singularity is near (Kurzweil)

Different sources of evidence and theoretical arguments indicate the technological innovation shares some basic traits with the patterns displayed by biological novelty. The rise and fall of technological creations also resembles the origination and extinction patterns observable in some groups of organisms and Jacques Monod actually suggested that the evolution of technology is sometimes closer to Darwinian selection than biology itself.

Foreword to The Intelligent Universe of James Gardner

by Ray Kurzweil

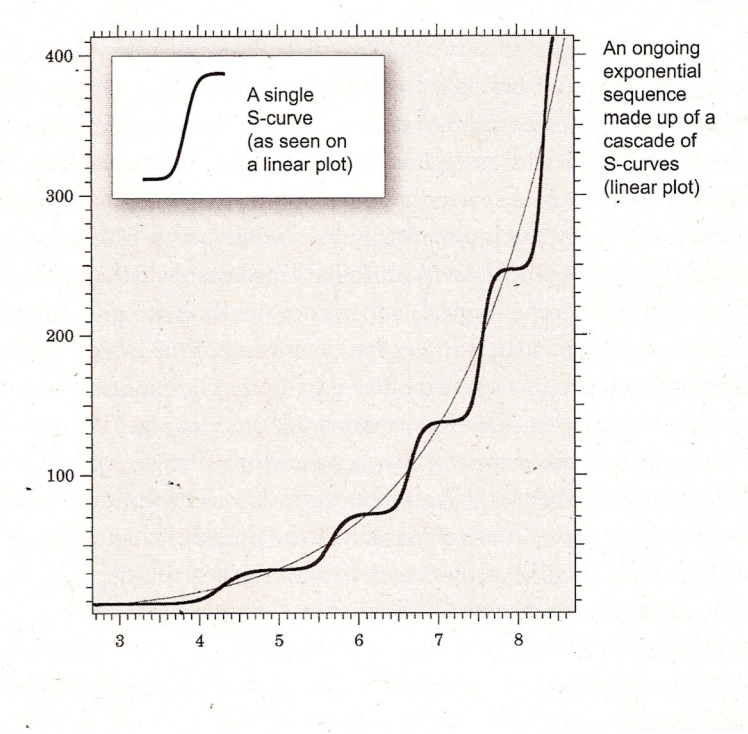
"The explosive nature of exponential growth means it may only take a quarter of a millennium to go from sending messages on horseback to saturating the matter and energy in our solar system with sublimely intelligent processes. The ongoing expansion of our future superintelligence will then require moving out into the rest of the universe, where we may engineer new universes. A new book by James Gardner tells that story.

Consider that the price-performance of computation has grown at a superexponential rate for over a century. The doubling time(of computes per dollar) was three years in 1900 and two years in the middle of the 20th century; and priceperformance is now doubling each year. This progression has been remarkably smooth and predictable through five paradigms of computing substrate: electromechanical calculators, relay-based computers, vacuum tubes, transistors, and now several decades of Moore's Law (which is based on shrinking the size of key features on a flat integrated circuit). The sixth paradigm—three-dimensional molecular computing—is already beginning to work and is waiting in the wings. We see similar smooth exponential progressions in every other aspect of information technology, a phenomenon I call the law of accelerating returns."

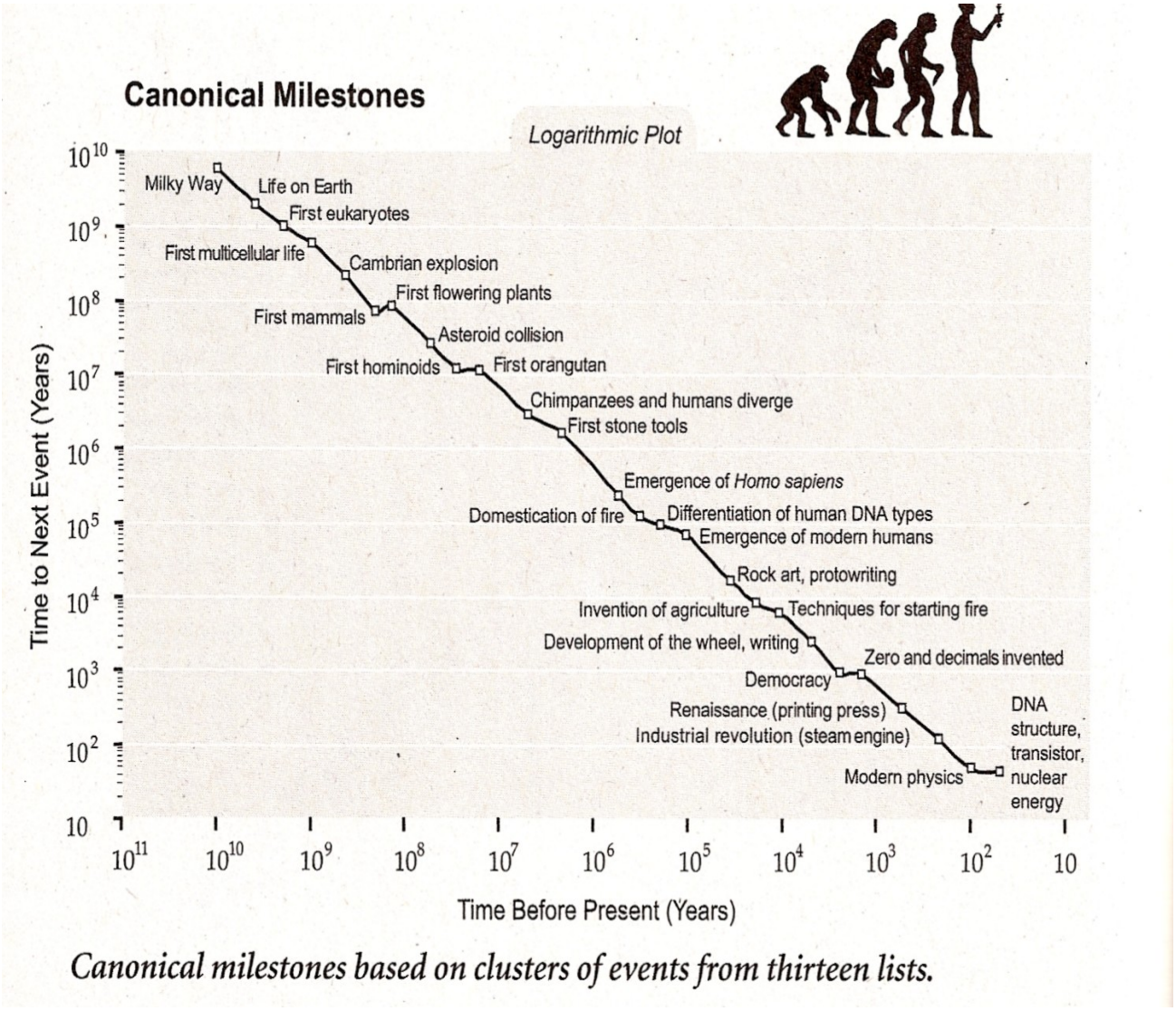
According to Ray Kurzweil the evolution of technology follows the law of accelerating returns. Each paradigm develops in three stages:

1. Slow growth (the early phase of exponential growth)
2. Rapid growth (the late, explosive phase of exponential growth) as seen in the S-curve figure below.
3. A leveling off as the particular paradigm matures

The S-curve illustration shows how an ongoing exponential trend can be composed of a cascade of S-curves.



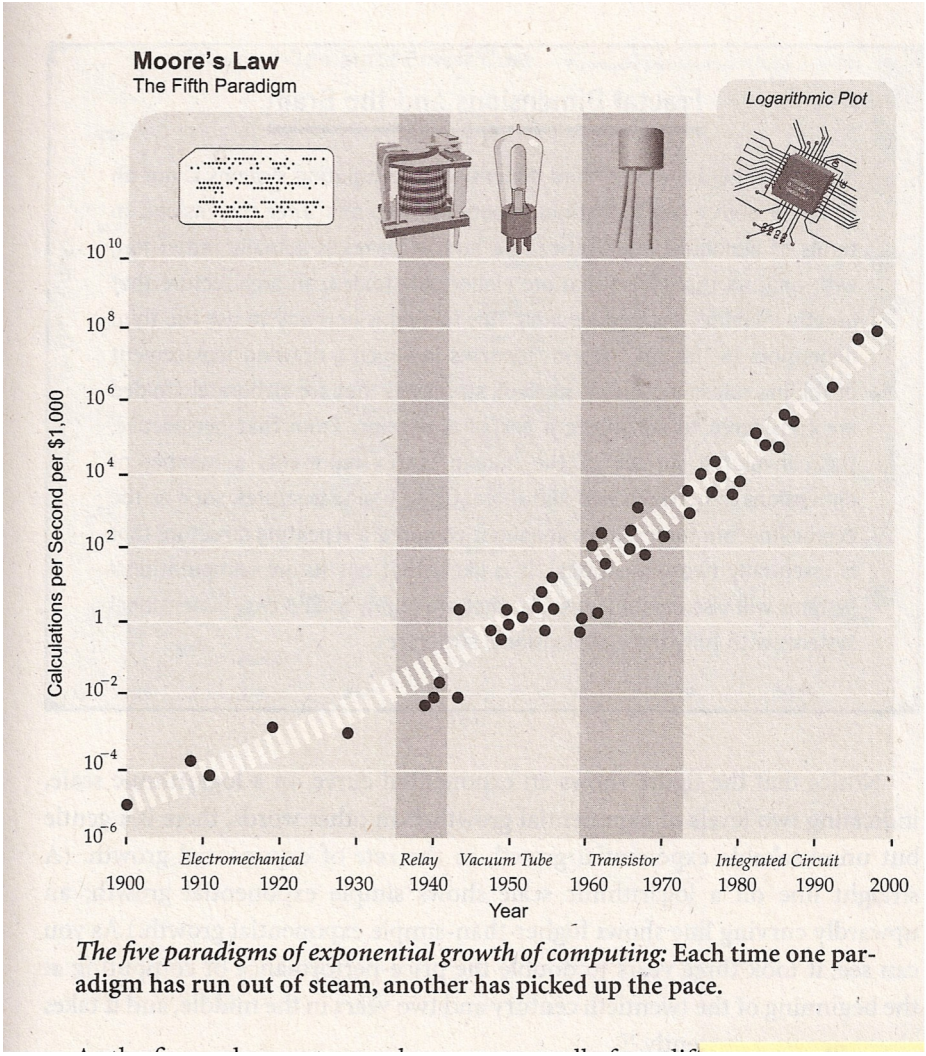
This exponential growth is illustrated by the graph on milestones of evolution from the origin of life to todays technology.
The data are compiled from thirteen different sources and clearly show the exponential acceleration of the emergence of innovation during the process of evolution. This yields a straight line in log-log coordinates.



Canonical milestones based on clusters of events from thirteen lists.

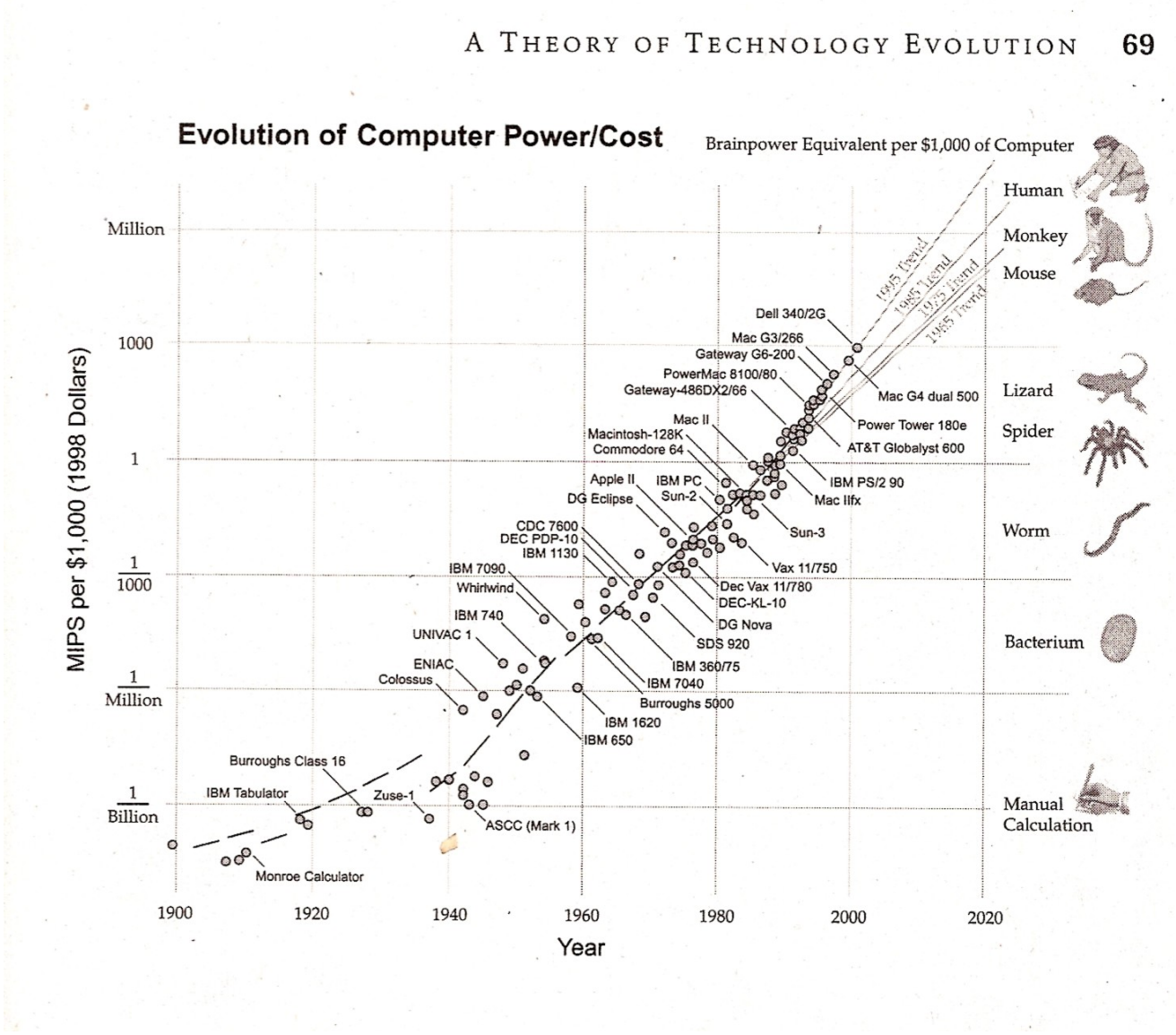
Note that several milestones of the Kurzweil graph coincide with levels of our evolutionary Hierarchy in chapter one. This is not surprising, since our order criterion for the hierarchy was the first observation of the emergence of a new level. According to our hierarchy the next evolutionary level should emerge within the Internet and we named it the Web Agent level. Independent software modules communicate within the web directly with each other without human Intervention. This is already the case in many applications of Amazon and Google.
According to the operator hierarchy these modules aggregate to form finally self-replicating units and for science fiction writers the sexual reproduction of Web Agent modules is near.

In the field of computing technology this regularity of exponential increase in calculations per seconds is shown in the following graph and commonly known as Moor's Law.
Note the trend is followed despite the drastic change in technology from simple Hollerith punched cards over electromagnetic relays, vacuum tubes, transistors up to integrated circuits.
The graph also shows a decrease in doubling time (higher than simple exponential or superexponential growth).

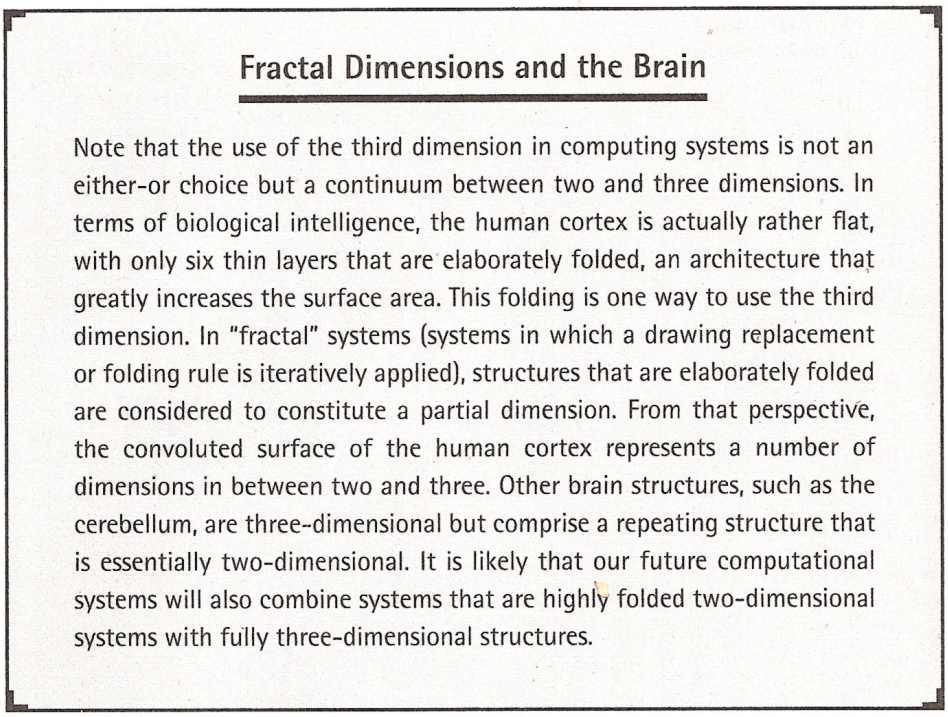


The five paradigms of exponential growth of computing: Each time one paradigm has run out of steam, another has picked up the pace.

The following graph shows this acceleration of exponential growth in terms of computing cost (MIPS per $1.000) over time. The more we advance in time the steeper the slope of the extrapolated line and eventually this process should lead to a singularity of near infinite growth in time.
The brain power of a single human should be reached in the near future at least by 2020 and the time where total artificial computing power will exceed the total brain power of mankind is not far.



Concerning the future emerging technologies which make the exponential growth possible we add another citation of Ray Kurzweil.



Fractal Dimensions and the Brain

Note that the use of the third dimension in computing systems is not an either-or choice but a continuum between two and three dimensions. In terms of biological intelligence, the human cortex is actually rather flat, with only six thin layers that are elaborately folded, an architecture that greatly increases the surface area. This folding is one way to use the third dimension. In "fractal" systems (systems in which a drawing replacement or folding rule is iteratively applied), structures that are elaborately folded are considered to constitute a partial dimension. From that perspective, the convoluted surface of the human cortex represents a number of dimensions in between two and three. Other brain structures, such as the cerebellum, are three-dimensional but comprise a repeating structure that is essentially two-dimensional. It is likely that our future computational systems will also combine systems that are highly folded two-dimensional systems with fully three-dimensional structures.

A fractal hierarchy of computer structure, a fractal hierarchy of the human brain, a fractal hierarchy of Artificial Neural Networks all seem to point into the same direction in a convergent way.

From a theoretical point of view recent progress in multi / infinite dimensional coding theory, complex valued and multidimensional Neural Networks [Murthy, 2008] point the direction of future research.

Conclusions

Self-similar structure and processes of self-organized systems

1 . All observable evolutionary systems can be described as hierarchical Energy&Information transformation webs .
2. The graph of the web is directed. On each level, energy transformation processors feed upgraded energy into higher levels and feed downgraded energy back to lower levels . This holds for natural evolutionary systems (astrophysical, geochemical, ecosystems ...) but also for artificial or man-made evolutionary systems (city systems,economic systems ...).
3. Energy transformation processors in all observable evolutionary systems show birth and death processes . We presented a simple model for an energy transformation processor, which is general enough to be applicable to any type of energy transformation. A Birth and Death processor is characterized by a limited transformation capacity in which dissipation energy is irreversibly internally accumulated until a threshold capacity is reached .
4. Birth and Death processors can formally be described from two points of view - from an energy-transformation point of view, a Birth and Death processor continuously transforms and accumulates energy up to a threshold (breakdown at death or replication at birth).
- from an information-transformation point of view however, as observed by the metasystem of the processor, a Birth and Death processor is equivalent to a binary threshold automaton or formal neuron with the two possible states : e.g. in the energy processing hierarchy the two states are 0-state (operation or silence) or 1-state (firing at death) .
5. Birth and Death processors organized in an hierarchical transformation system (trophic web) are as a consequence formally equivalent to a neural network of the feed forward type. Lower level processors feed into higher level processors. Hence all the features of neural networks, like memory, adaptation/learning and optimization can be looked at in an analog way in trophic webs of energy/information transformation processors.
6. The error-distribution of a single neuron trained with back-propagation according to gradient descent follows a Pareto-Zipf distribution .
7. Pareto-Zipf distributions are stable under addition, hence we should observe error-distributions of this type also for massively parallel processor networks (like trophic webs) trained with back-propagation.
8. Long tailed distributions or power laws of the Pareto-Zipf-Mandelbrot type, called generalized life-symptoms, are empirically observed for symptoms of virtually all known types of Energy / Information transformation systems .

Self-organized systems have memory (network topology and weights of links)

If we consider that self-organized systems are complex modular scalefree networks of interaction units of the Small World type , they can be mapped on multilayer Perceptrons. Artificial Neural Networks of this type, called multilayer feed forward networks with back-propagatio of errors reveal memory.

The memory lies in the specific **topology** of the network (individual neurons) and in the weights of each **interaction link**. Thus the complex network topology viewed within the ANN paradigm can explain the enigma of how information is stored in the system over many processing cycles.

It's the global field generated by all processors that "drives" the process of evolution based on energy optimization (maximum entropy production) specific to the level of evolution.
GUT, gravitation, strong nuclear, weak nuclear, electo-magnetic, chemical, geothermal, wind, water, fire, genetic code, words, written codes, computer codes ...

Self-organized systems are learning (Hebb's rule, engrams)

Learning (adaptation) of the network takes place in the form of back-propagation . The downgraded energy of each processor is re-cycled influencing the processor parameters in the next processing cycle. Training of the web functions according to gradient descent through positive (or negative) feed-back from higher level processors to lower level processors in both senses of the word (energetic feed-back and cybernetic feedback) .

1. ***ritualization*** **(repetitive use of pathways, Hebb's rule), hardwires the networks information flow, like timetables hardwire a railroad, or air transportation network.**

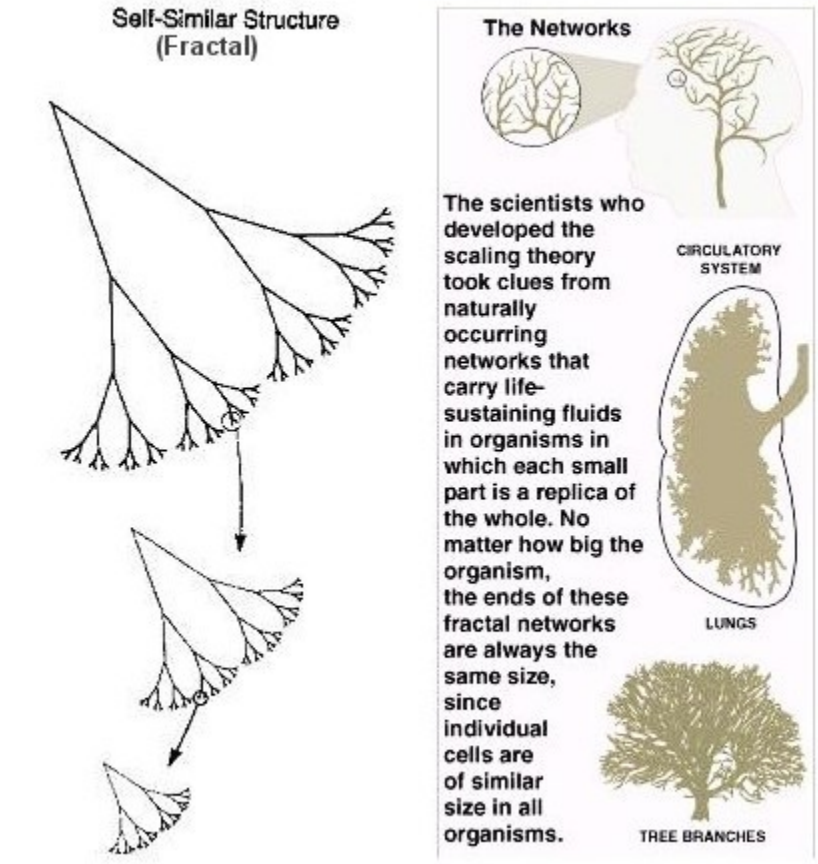
Figure. Hebb's rule "*cells that fire together, wire together*"

Hebbian theory has been the primary basis for the conventional view that when analyzed from a holistic level, **engrams are neuronal nets or** neural networks.

Gordon Allport

"If the inputs to a system cause the same pattern of activity to occur repeatedly, the set of active elements constituting that pattern will become increasingly strongly interassociated. That is, each element will tend to turn on every other element and (with negative weights) to turn off the elements that do not form part of the pattern. To put it another way, the pattern as a whole will become 'auto-associated'. We may call a learned (auto-associated) pattern an ***engram***."

Image dans son **contexte original**, sur la page universe-review.ca/R10-35-metabolic.htm.



Self-organized systems are intelligent (maximum or minimum objective function)

Most theoretical attempts to explain the evolution of specific network topologies are based on extremum principles, which means that the self-organized network strives to achieve a maximum or minimum of a function which characterizes the global system. The principle of maximum entropy production could be a good candidate to apply in most cases of real networks.

The above approach may be the basis for a general theory explaining self-organization, self-learning and evolution in nature.

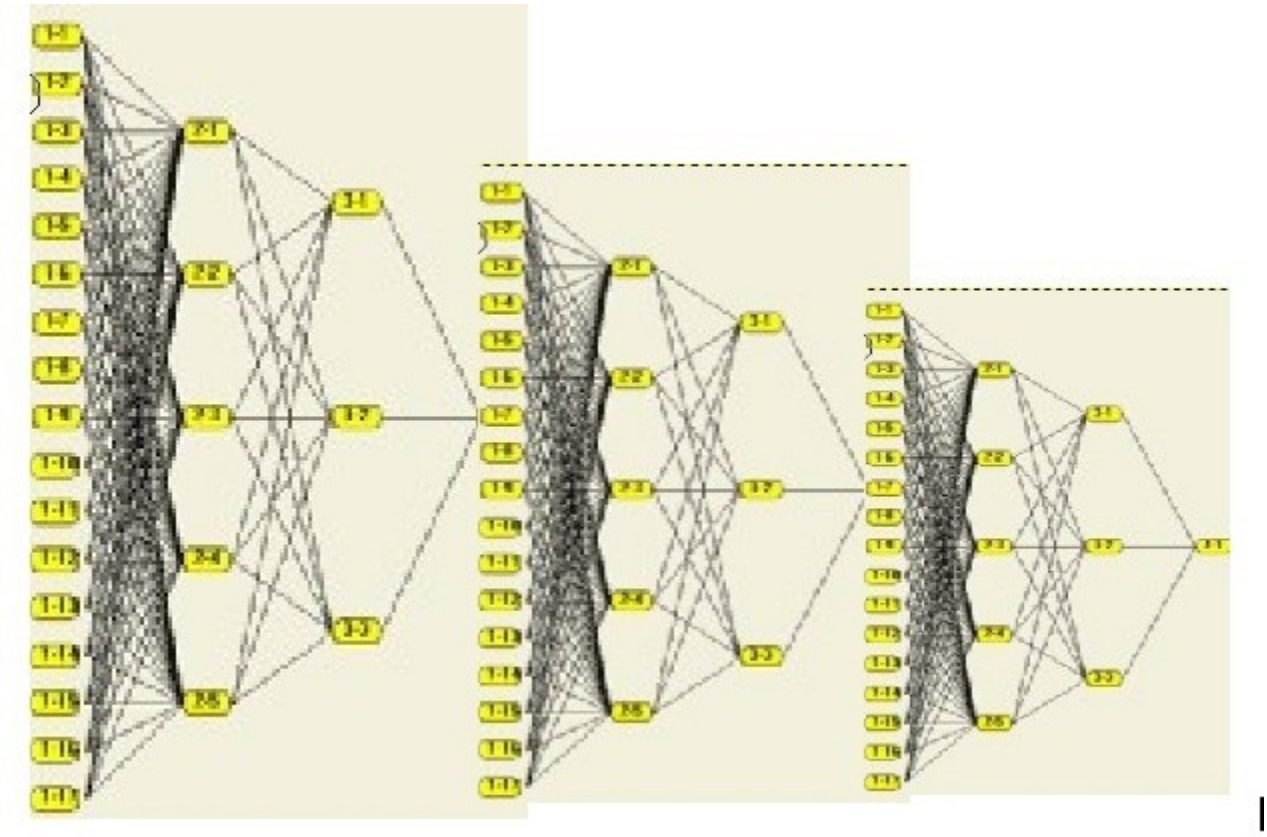


Figure. The universe: a self-similar hierarchy of multilayer Perceptrons, from stars to the World Wide Web.

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About the author, from Wikipedia, the free encyclopedia

Peter Winiwarter (born October 4, 1945) is an Austrian-born French resident scientist. Since more than 25 years he is Director of the Bordalier Institute in France.

He introduced in 1983 the *first law of genesis* stating that the complexity of self-organized systems can only increase and the *second law of genesis* stating that unit-size distributions of self-organized systems follow a Pareto-Zipf-Mandelbrot PZM law. He introduced in 1992 the equivalence concept of trophic webs and artificial neural networks. At hand of numerous examples he shows the widespread empirical evidence of PZM regularities in natural, technological and social systems, from stars to the World Wide Web.

Contents

Birth and education

Winiwarter was born to an Austrian father and a German mother in the community of St.Valentin in Lower Austria close to the city of Linz. His father, Friedrich, was a surgeon and director of the local hospital, while his mother, Ida, assisted his father as aid. He attended high school at the 'humanistic gymnasium' in Linz, specializing in humanities and classical languages (8 years of Latin and 6 years of ancient Greek). At the age of 17 he graduated and won an American Field Service Scholarship to the United States where he spent one year in Southern California. Between 1964 and 1970, he studied physics , mathematics and philosophy at the University of Vienna; during that time, he began doing research in general systems theory.

In 1970 he earned a Ph.D. In Nuclear Physics under the direction of P.Hille in the field of Spin Distribution of Nuclear Level Density.

In 1974 he received an M.B.A. from INSEAD, Fontainebleau, France, the European Institute for Business Administration, one of the highest rated business schools of the world, which has now a second campus in Singapour.

Academic career

In 1970 Winiwarter received a fellowship by the Austrian Ministry of Research and Education at the Nuclear Data compilation Center of the OECD NEA nuclear data bank at Saclay France, where he worked on the first worldwide Nuclear Data Base in the field of IT.

In 1971 he received a fellowship of the United Nations to work under the direction of Nobel prize winner Y.M. Franck as a Senior scientist at the, Joint Institute for Nuclear Research. at Dubna USSR, where he lived as the only western scientist during one year.

Subsequently he worked as a consultant for the International Atomic Energy Agency. in Vienna, Austria.

In 1974 he received an M.B.A. from one of the world's top businesses schools INSEAD in Fontainebleau, France leaving his Nuclear physics career behind and concentrating on the management of complex computer systems in the field of business.

In subsequent years he worked for an American Think tank Arthur D. Little (ADL), Cambridge, Massachusetts with assignments in North-Africa and the most important countries in Europe.

Since 1983 Winiwarter joins his primary interest in Systems Theory and Hierarchy Theory at the Bordalier Institute with part-time assignments as consultant to earn the necessary funds to do transdisciplinary research, not financed by the academic institutions.

It is this financial independence which allowed him to do unconventional research in transdisciplinary systems theory.

As of 2001, Winiwarter is a French citizen, and a permanent resident of France.

Research and achievements

Winiwarter has been a major contributor to the development of complex systems theory, together with several other scientists from physics, mathematics, and computer science (Ilya Prigogine, Manfred Eigen). His biggest role has been the introduction of the *periodic system of systems concept* . Among the topics in systems theory Winiwarter has studied the Behaviour of Open Systems with Limited Energy Dissipation Capacity and the mapping of trophic webs to Artificial Neural Networks.

Awards

American Field Service (AFS) International Scholarship

Austrian Ministry for Research and Education fellowship

United Nations Research fellowship

Selected publications see list above

Acknowledgments

First of all I would like to thank Professor Czeslaw Cempel from the Poznan Institute of Technology in Poland for the more than 20 years of intense collaboration. We have published many papers together and the discussions with him were always full of helpful advise.

I thank also the contributors to more technical sections of this book. Stan Salthey, from Bingham University, the 'pope' of hierarchy theory contributed with a special section on the difference between compositional and subsumptional hierarchy, not easy to grasp at first sight and often confused in the literature.

Thanks to Gerard Jagers, whom I got to know at the first conference on evolution and development of the universe. [www.evodevouniverse.com]. Gerard contributed with a section on operator hierarchy.

The early works of my research have been largely influenced by my colleagues of the International Society for Systems Science, Pierre Auger – now French academician – and Bertrand Roehner from the Laboratory of Theoretical Physics of the university Paris VII, where I held a position of visiting professor for one year.

Finally I thank Nobel prize winner Manfred Eigen (the father of the hypercycle) for heaving read several of my manuscripts and who has encouraged me to pursue the difficult task of transdisciplinary researcher.

Back cover *Neural Network Nature*

"What I like about the book is the employment of the idea of network evolution as a pattern that permeates all orders of magnitude, implying the universe is networked. I also find the ideas of network and ecology to be the dominant images and metaphors of our time which seem to converge and synthesize in this ***unified theory of networks****."*

Richard Thomas, Beal Institute

Recursionism

In the philosophy of Subhash Kak **recursionism** refers to the idea that replicated forms and self-similar forms are common in the physical world, and that this has some mystical significance. Kak describes recursionism as follows:

> *Patterns repeat across space, time, scale and fields. Recursion is an expression of the fundamental laws of nature, and it is to be seen both at the physical and the abstract levels as also across relational entities. Recursionism provides a way of knowing since it helps us to find meaning by a shift in perspective and by abstraction.*

The idea of recursionism also occurs in Hindu Vedanta philosophy, where it is seen most prominently in the Upanishads. There are recursionist strands in the works of Fichte, Schopenhauer,Nietzsche.