CHAPTER 1

Generative Artificial Intelligence
Chapter 1. Generative Artificial Intelligence

1.1 Introduction

This thesis is about Generative Artificial Intelligence (GAI). At this moment GAI is in its conceptual phase. This thesis reflects this phase by explaining the ideas behind GAI and by studying contemporary AI in relation to GAI. This thesis is an analysis of contemporary AI, its shortcomings and a possible way out of the local optima it finds itself in. It is essential that modern AI is understood in new terms, before the new terms can be used to advance contemporary AI. This thesis is an investigation into a new way of thinking and reasoning about the automated creation of intelligent systems. This thesis investigates a theoretical framework for disciplines such as (cognitive) developmental robotics (Asada et al., 2001, 2009) and biological developmental neuro-sciences, where the focus is not on a stable and final system, but on a continuous developing/evolving/learning system which interacts with its environment, including humans, over long periods of time. These systems adapt their neural representations to reflect the dynamics of the system interacting with its environment (Schomaker, 2004). This is in contrast to classical AI where the focus is on a system that learns for a short period of time, if there is learning involved at all, and is subsequently executed with little or no changes to its inner workings. GAI is new in the sense that it does not see change as a means to optimize a structure (as in artificial neural networks for example), but as a means to structure the next level of adaptive processes which can structure the next level of adaptive processes ad infinitum.

At first glance GAI might seem as another interpretation of dynamical systems theory (Gibson, 1977; Kugler et al., 1980) and to some level these critics would be right. Most of the terminology used in this thesis is not from dynamical systems theory, but from post-structuralist philosophy (Deleuze et al., 1987; de Landa, 1991), which builds on top of dynamical systems theory. The post-structuralistic point of view is that everything is dynamic and forever changing. This is radically different from any approach in contemporary AI, even the ones regarded as dynamic. All algorithms in AI are used for convergence to some optimum. The theory of GAI claims that this is the wrong approach. In GAI systems do not look for an optimum of convergence, but for an optimum of the generation of possibilities which can be used by the next system to improve itself. This leads to the concept of dynamically interacting architectures. As we shall see it is important that the subcomponents have many feedback mechanisms and interactions. Actually, having the correct interaction mechanisms in place is the most important aspect. GAI claims that AI research should be focussing on the dy-
namical creation and deletion of interaction mechanisms and feedback loops instead of focusing on the creation of a fixed topology as is the case nowadays in most, if not all, contemporary AI systems.

This thesis is an analysis and a critique of contemporary AI, but it is a constructive critique. In this thesis some of the methods and interaction systems of contemporary AI are discussed. Some techniques of contemporary AI can be used in a different context for the creation of possibilities, instead of aiming for local convergence. There is a sharp contrast between GAI and most contemporary AI in that GAI promotes open and continuous systems that keep changing whereas most AI techniques have a learning and an execution phase. Thinking in that manner creates closed systems that do not keep adapting themselves to their surroundings. Some modern AI methods such as reinforcement learning (Sutton and Barto, 1998) use exploration and an exploitation as trade-offs. This is part of the solution. Instead of a training and execution phase, in reinforcement learning it is realized that there is a continuum. Depending on the situation, on the history and the internal mechanisms of the system which operates in its environment, more exploration or more exploitation is used. But even reinforcement learning is not open ended. It learns a specific set of actions for a specific task in a specific environment. Although reinforcement learning shows generalizing properties, is is not open ended in a manner such as biological evolution has turned out to be. This thesis discusses the matter of the creation of open-ended adaptive intelligence. It suggests how to change the scientific mindset in order to create such a kind of intelligence.

1.2 From Analytical Science to Generative Science

Traditionally science is about analyzing stuff. The stuff ranges from biology to inanimate matter, to thoughts, societies and even the birth of the entire universe. Science analyzes in order to understand, that is, so that humans understand. Subsequently these humans try to formalize the analysis by creating models, create text books on the subject and a new breed of scientists can try to understand the mysteries of the previous generation (Kuhn, 1962). This is, in short, the analytic phase of science that has dominated scientific thinking since the advent of science.

The formation of applicable new structures in existing matter and energy is one of the most important outcomes of science. Even mental processes concern atoms and electrons being shuffled around. Depending on the point of view one could say that
scientists are not creating anything new, but are discovering new arrangements of matter and energy that can be used for purposes that seem useful to humans. Deleuze (Deleuze et al., 1987) and De Landa (de Landa, 1991) call this the tracking of the ‘machinic phylum’, which is a lineage based on singularities, also known as bifurcations. A singularity is a place in phase space where there is uncertainty about the path to be followed, where a bifurcation might happen. Depending on both internal and external factors a path through phase space is chosen. A small change in a bifurcation parameter can cause a sudden, large and qualitative change in the behavior of the system.

This machinic phylum, the intrinsic self-organizing property that pervades the universe, is older than life on Earth. For example, evolution is part of the machinic phylum, making use of biological singularities steered by natural selection. A generative science is a science that not only tracks the machinic phylum, but also automates these tracking procedures using automated procedures to generate models. These automated procedures have to be able learn in order to generalize over observations and theories and to not repeat mistakes. The ideas from this chapter are part of a way of thinking called post-structuralism (Deleuze et al., 1987; de Landa, 1991; Varela et al., 1992) which is build on top of non-linear dynamical systems theory from quantum mechanics and the self-organizational properties of matter and energy (Prigogine, 1984).

Machines are gaining in intelligence (Kurzweil, 1999). There is no reason to believe that they cannot become smarter than humans. Even before that happens, machine intelligence can be designed to operate more effectively, that is, with less intervention of humans in the creation of the artificial intelligence. This implies that machine intelligence has to be able to create its own internal structures, its own thinking. This automated scaffolding of mental capabilities of machines is what the author calls Generative Artificial Intelligence (GAI). Without this intrinsic dynamic capability, intelligent machines will become more and more difficult to create. It is very difficult for humans to understand what intelligence constitutes to begin with. If humanity manages to create GAI, we should be able to use it for the speeding up of the development of science in general. Also we need generative science to create GAI. GAI and generative science are intertwined and the one cannot exist without the other. The term Artificial Intelligence (AI) and its derivatives are used in the broadest possible sense here. In this thesis the concepts of AI includes, but is not limited to, machine learning, pattern recognition, cognitive architectures, logical models, robot brain architectures, vision, sensor informatics and knowledge engineering. The term AI should not be regarded, as some authors do, to only deal with logical models of cognition.
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The latest metaphors for the creation of models in science contain, amongst others, the computer metaphor, the software metaphor, the neural network metaphor and lately the non-linear dynamical systems metaphor. But will these metaphors really aid us with the creation of intelligent machines? Previous metaphors were based on the latest fashion that the average scientist could understand. In the 17th century the brain was viewed as a clockwork mechanism, as was the universe. Later metaphors include the steam engine, telephone switchboard, computer, Internet and now non-linear dynamics or chaos theory, as it is known in popular science. Although using non-linearity in our analysis is an advantage to strictly linear approaches, there is no guarantee that a non-linear model, clockwork or computer model is the correct approach. Even if a non-linear model is better at describing brain states or mental trajectories (Spivey, 2004), if it is only used for analysis there is no guarantee that the same metaphor can be used to generate intelligence. To clarify this a simple example suffices: Humanity has been domesticating plants since the end of the last ice age, approximately 13000 years ago, using linear, often circular, models that were based on the rise of certain star groupings, migration of animals and other natural occurring phenomena. The growing process of plants is a highly non-linear process. Starting from a single seed, a complete plant can grow and procreate under certain circumstances, which humans were eager to provide. Thus humans have been using linear models to steer non-linear processes for a long time already. Humans were not able, though, to use the linear models for the creation of totally new types of seeds or plants.

What is needed to create intelligent machines, is not only a new metaphor, but a complete new way of working. The automated construction of minds needs more than keeping adding the next detail as in good old fashioned science, perhaps it even needs a change of some scientific dogmas. As Harvey puts it: It is “Philosophy of mind using a screwdriver” (Harvey, 2000). GAI would be in the business of “Philosophy of mind using a machine that operates the screwdriver and observing it work!” What is needed is to not only use the analytic stance, but also the generative stance. It is essential that the scientific knowledge about the generation of structures is applied to generate these structures automatically. It is important that the scientific community opens up to new ways for the generation of knowledge. A new method used in robotics is to set up sorting mechanisms that filter out good technologies in the form of soccer (Kitano et al., 1997) and other competitions, such as rescue robotics competitions (Kitano and Tadokoro, 2001) and domestic service robot competitions (van der Zant and Wisspeintner, 2007) with autonomous robots.
Since the dawn of the computer age it is possible to generate models automatically, although this insight took a while to develop. The robot Shakey (Fikes and Nilsson, 1971), evolutionary computations (Holland, 1975; De Jong, 2002) and especially genetic programming (Koza, 1992, 1989) are examples where models have been generated, although the automated generation and selection of appropriate models is still a relatively unknown area of the scientific endeavor. Recently disciplines outside of Artificial Intelligence (AI) are picking up some of the methods created within the AI community. Even within the AI community many are still not using (semi-)automated learning procedures for the creation and selection of models, but rely on manual labor. The automated generation and selection of models is called Generative Science, which supplements Analytic Science where humans typically do most of the modeling. In Generative Science it is important not to first create models manually and then the tools for the analysis, but to create tools to steer the generative processes in a coordinated manner and then do automated analysis on those automatically generated models. One of the few areas in science, if not the only area, where expertise on this topic is created, is AI. It is very likely, that most of Generative Science will be closely related to Generative AI, if it is not the same.

Artificial Intelligence is not yet a full-blown Generative Science, since there is a lot of manual labor involved. AI can provide the basis for GAI, but requires some reconceptualizations and more diversity of generative approaches. The “Input → Transform → Output” (ITO) systems of contemporary AI are not enough to create intelligence or intelligent behavior in machines. The use of this simple information processing concept leads to local optimization procedures which result in brittle and inflexible systems. The “transform” part is usually created by a human. But as long as the human is the generator of the “transform” part, machines will not be intelligent by themselves but merely displaying a fraction of the intelligence of their creators.

The ascent of Analytic Science does make sense. Previous to the 20th century there was no possibility to automatically generate any model at all. It is too laborious to, for example, do the Conway’s Game of Life with a pen and paper. There was no incentive to create methodologies for the automated creation of models. It was easier to be the generator of models than to be the creator of generators which create the models automatically and then have calculate the outcomes of the generators manually. With the rise of computational power and smarter algorithms, it is now time to change our points of view on the scientific process and embrace the automation of (parts of) science and the creation of Generative Science and Generative AI.
In AI, the generative part does not have a coherent overall theory on how to create models automatically, although there are many initiatives. Examples are the work in Evolutionary Computation (Fogel, 1994; De Jong, 2002) and all sorts of machine learning algorithms and pattern recognition systems (Duda and Hart, 1973; Sutton and Barto, 1998; Vapnik, 1998; Serre, T. et al., 2007) that use feedback mechanisms to update or optimize itself. The current chapter provides an analysis of the state of contemporary science, with respect to the creation of GAI. It starts with the most general generative theory, which is Dynamical Systems theory. The dynamical systems theory is inspired by models of physical processes on the quantum mechanical level that generate structures and will be treated in the light of dissipative structures far from equilibrium (Prigogine, 1977, 1984). This is in stark contrast to the way dynamical systems theory is mostly used in contemporary science, namely for the analysis of complex phenomena.

The chapter continues with a post-structuralistic discussion of the tracking of the machinic phylum, which is closely related to the autonomous scaffolding of the mind required by GAI. The post-structuralistic point of view is then applied to the development of the neural substrate in humans to demonstrate the power of this generative metaphor. Subsequently the ideas behind GAI, and the differences between Classical AI (CLAI), which is the AI where humans do the modeling, or are highly involved in the modeling, and GAI are treated within the non-linear framework of post-structuralistic philosophy. The last section treats the abstraction and formalization of the discussion so far and ends with several possible conclusions.

1.3 Dynamical systems far from equilibrium

A leap in thinking in the 20th century is the realization that systems that behave linear when they are near equilibrium, can have non-linear properties far from equilibrium. One of the first to realize this non-linearity out of seemingly linear processes was Albert Einstein when he proposed his theories of relativity. The Newtonian laws of physics form only a part of the macroscopic theory of physical systems. Physical systems near equilibrium behave linear. Einstein showed that if bodies operate near the speed of light, which is far from equilibrium, matter and energy operate in a non-linear manner. Ilya Prigogine showed (Prigogine, 2003, 1984, 1977) that the abstraction of ‘being far from equilibrium’ is more general than believed by Einstein. Prigogine uses his
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Theories to show that time is an integral and unidirectional property of our universe. This is not the main point of this dissertation, but it does elucidate the discussion.

Prigogine states that there are two different kinds of laws that govern the development of the universe. The Newtonian, and Einsteinian, view of the universe is that time can move forward and backward. The arrow of time has no influence on the laws governing matter and energy. There is a problem with this vision of the world. It is either that we are governed by fate imposed on us by physical laws (Newtonian view), or that we have some form of control which is confirmed by everyday experiences. The second law of thermodynamics, that in a closed system the entropy will be maximized, confirms that not all laws are reversible as Newton stated. In a closed system the unlikely state it will start in will move to the most likely state, near the equilibrium, which is the state where energy and matter are evenly distributed. In this process information is lost, in the form of heat for example. This information is lost forever, thus when moving the arrow of time in the opposite direction (backwards) the system will not end in its initial state. A more radical form is the infamous black hole where information is destroyed forever, thus meaning that at least some laws of physics can only move in a single direction. It is interesting is that Prigogine correlates the arrow of time, this irreversibility, to the creation of complex systems.

Closed systems form only a small part of the universe. Many systems are not closed, but open. Some examples of dynamic and open systems are: Vortices of large amounts of molecules in fast moving water, photon coherence in laser light, Earth’s biosphere by means of solar energy, animal behavior by means of sensory data and food, human societies by means food and electrical energy, and the neural substrate of animals. The examples given display properties which are impossible to derive and far from the dead universe proposed in classical physics. The systems with these interesting properties have to be open, otherwise the law of entropy ensures that such a system will die a heat death. These open systems are not reducible to their components in the traditional sense. A famous example is that life is more than the atoms it is made of, and cannot be reduced to its basic components (quantum mechanical particles). As Prigogine states:

Closed systems form, at best, only a small part of the universe. Interesting phenomena require open systems, trying to understand them in mechanistic terms is doomed to failure.

Order out of chaos, (Prigogine, 1984, p.XV)
The flow of matter and energy can be a source of order, but this dynamical order only occurs in non-equilibrium systems. These irreversible processes, irreversible through bifurcations, can be a source of order, of coherence and organization.

The second law of thermodynamics corresponds to a selection rule, to a restriction on initial conditions that is then propagated by the laws of thermodynamics.

Order out of chaos, (Prigogine, 1984, p.16)

Later he reaffirms this perspective.

. . . , the second law is a selection principle compatible with dynamics, but not deducible from it. It limits the possible initial conditions available to a dynamical system. The second law therefore marks a radical departure from the mechanistic world of classical or quantum dynamics.

Order out of chaos, (Prigogine, 1984, p.125)

A bit later in the same book he hints at how to proceed.

At the root of non-linear thermodynamics lies something quite surprising, something that first appeared to be a failure: in spite of much effort, the generalization of the theorem of minimum entropy production for systems in which the fluxes (irreversible processes) are no longer linear functions of the forces appeared impossible. Far from equilibrium, the system may still evolve to some steady state, but in general this state can no longer be characterized in terms of some suitably chosen potential (such as entropy production for near-equilibrium states).

Order out of chaos, (Prigogine, 1984, p.140)

On the next page he explains how humans might construct such systems.

In cases where instability is possible, we have to ascertain the threshold, the distance from equilibrium, at which fluctuations may lead to new behavior, different from the “normal” stable behavior characteristic of equilibrium or near-equilibrium systems.
Order out of chaos, (Prigogine, 1984, p.141)

If these principles of self-organization occur throughout the physical world, it is legitimate to ask if the neural substrate is using the same kind of principles to organize itself. It is not a far leap to think of thoughts in the neural substrate being governed by the same principles that organize vortexes in streaming water and photon coherence in laser light. The mathematics behind these physical manifestations show autopoiesis (auto (self-)creation), which is exactly the kind of properties required for the creation of intelligent machines. A possible conclusion at this point could be that the instabilities seen in optimization or learning algorithms in Classical AI (CLAI), also known as fitness landscapes, are not to be treated as a place to optimize a fitness criterion but as a place of instability which might lead to a bifurcation point and to new possibilities.

1.4 Tracking singularities

The machinic phylum is the overall set of self-organizing processes in the universe (de Landa, 1991). At first glance it seems odd that activities as different as groups of amoebas forming colonies with rudimentary organs in times of distress, $10^{24}$ water molecules forming vortices, the formation of agricultural settlements in the fertile crescent, the coordinated firing behavior of neurons and the synchronized flashing of fireflies have anything in common. At a deep level these self-assembling processes share similar mathematical structures (Prigogine, 1984; de Landa, 1991). This deeper level of the machinic phylum blurs the distinction between organic and non-organic life and processes and stresses the commonalities they share. From the point of view of a robot historian:

...humans would have served only as machines’ surrogate reproductive organs until robots acquired their own self-replication capabilities. But both human and robot bodies would ultimately belong to a common phylogenetic line: the machinic phylum.

War in the age of intelligent machines, (de Landa, 1991, p.7)

As Prigogine has shown, we have to ascertain the thresholds where fluctuations lead to autopoietic processes. The areas where these bifurcations or singularities occur show
the way to new organizing principles of matter and energy. For example, the ancient Greek had steam engines, which were toys for children. These machines could have been the ultimate technology for military conquest. They did not have a crankshaft though, and could not change the pumping behavior into a turning behavior needed for most machines such as vehicles and factories. In the language of post-structuralists (the part of philosophy which deals with the machinic phylum) the Greek had not tracked the machinic phylum far enough to create motorized vehicles. De Landa describes another example, concerning gunpowder, in (de Landa, 1991). It took several centuries of careful experimentation, i.e. tracking of the phylum, to find the optimal configuration of the ingredients of gunpowder. In this case the tracking of the machinic phylum was a very dangerous enterprise.

One of the aspects of Generative Science entails the tracking of the machinic phylum, to find new configurations of matter and energy, to find new ways of working with the physical world. The machines created using GAI will require the knowledge of the tracking that humans have done already, or at least the part that is essential for the correct operation of the machine. Specializations have to be allowed and are an essential feature of GAI, if it was only that every machine and every organism has limited resources and capabilities. GAI should provide these forms of specialization. The socio-economic environment that intelligent machines will find themselves in will steer their developments by means of bifurcations. The buildup and usage of a (mental) history ensures the possibility of specialization. The mental history can be interpreted as a path of singularities. It might be that more complex intelligence, as seen in humans, can track several singularities at the same time.

GAI differs from Generative Science in that GAI can do more than tracking the phylum: GAI should track the singularities that assists the machine intelligence in its daily functioning. From this perspective the tracking of the phylum executed by Generative Science becomes a part of GAI, while at the same time steering GAI by exploring more of the phylum. GAI should be allowed to generate a large amount of alternative options to solve a certain task. If the options do not satisfy the criterion set out by the system then it might not be solvable, or the limitations set on the generators should be loosened, which could be interpreted as ‘thinking out of the box’. The generating part of GAI (explained in the next section) constitutes one of the most important aspects of GAI. True, there are some generative procedures in CLAI, such as in evolutionary computation (De Jong, 2002), but it has not been taken to its limits, where higher order patterns found by the computations can organize themselves into new patterns ad infinitum.
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tum. A sub-field of evolutionary computation, call genetic programming (Koza, 1989),
explores the possibilities of creating new patterns. In genetic programming complete
programs are evolved which could exhibit new properties. In GAI there is no single
solution but there are many possible configurations. The goal of the machine is then
to generate sensible possibilities and track those that make sense, which means using
the feedback from the environment as a sorting mechanism to learn which possibilities
actually work.

1.5 Sorting machines, meshworks and generators in cyclic flux

De Landa, in his book on non-linear history (De Landa, 2000), describes an abstract
machine of non-linear dynamics. He applies this machine as a metaphor to the rise
of cities in (Western) Europe. His account is worth repeating here briefly. His dis-
course starts with the flow of matter (goods) and energy that forms the basis of human
development. Due to this flow of matter and energy, which is a state far away from
equilibrium, organizational structures can be created. Often these structures are in a
crystalline, liquid or gaseous form, metaphorically speaking. Although the language
used to describe these structures are mere metaphors, they are useful metaphors since
they relate directly to human experience. These structures can exhibit phase transitions
and our vocabulary should be adapted to reflect this. Using the metaphors of gas, fluid
and crystalline structures might provide a better understanding of the underlying pro-
cesses than, for example, talking about the mathematical properties of strange attractors
in chaos theory. The process of accretion, for example, can be used for the formation of
mineralized/crystalline structures. Some structures, such as crystalline city buildings,
sustain the flow of matter, such as goods and food, by gaseous interaction, such as the
people coming to the market to sell or buy the matter.

It is important that these generated structures posses the same kind of function, which
is that they are similar parts of an abstract search engine. This search engine consists
of many different configurations of the same class or type of instances. For example,
many towns had the possibility to become a large city, but only a few did. Becoming a
city is akin to the movement toward a singularity. The towns all had different configu-
rations. Every town was different! The best configurations, in the struggle to become
a city, won. The sorting mechanism was the co-evolutionary environment of other towns, cities and states. Cities and towns formed interacting structures, called meshworks. The different configurations of meshworks form an abstract search mechanism. The city states had to compete with each other for the limited resources available at the time. The configurations best adapted to their fluctuating environment became the most powerful. Please notice that there is not a single ‘best’ configuration, but that the cities and their interactions are dynamical and adapt themselves continuously to changing circumstances. One could say that humanity went from a gaseous state (pre-agricultural) to a liquid state (family groupings of farmers who had to move every few decades when the soil was depleted of nutrients) to a crystalline state (slowly growing cities and towns made of solid materials such as stone, with walls around them for protection). What De Landa does not mention explicitly is the cyclic flux of many of the generators, such as daily, seasonal and generational patterns. Although the structure of a settlement changes slowly, when the cyclic flux of the generative processes come to a halt, any structure depending on the cyclic flux usually deteriorates quickly. The seeming stability of a structure does not imply that there is little internal activity! The feedback loops created by some of the generators can have (adjustable) control parameters that could be used to steer the generated structures into desired directions. Sorting machines can be interpreted as selection mechanisms searching for preferable values of the control parameters of generators in flux.

Another example of the abstract searching machinery is evolution and natural selection. Genes fluctuate randomly. The fluctuations are usually referred to as mutations. They create new possibilities and function as generators. Some of the new possibilities, in this case new body plans which are already a meshwork of interacting structures (cells) interacting with other bodies (animals, plants), get through the sorting mechanism, called natural selection. The different configurations of bodies are also a case of an abstract searching mechanism. The same patterns occurs here, namely that there are generators, a sorting machine and an abstract searching mechanism. In this last example the scaffolding mechanism is open on both ends: on the lower levels the interacting genes already form an abstract searching mechanism which took hundreds of millions of years to create complex single cell organisms (another layer of generators in flux) from amino acids (generators) also by means of natural selection (sorting machine). On higher levels groups of bodies (amoebas, plants, animals) can form groupings (generatorive meshworks) and even collaborations with other bodies (meshworks, abstract searching mechanism), with its own level of competition (sorting machine).
Figure 1.1: *The generative search machine (a scaffolding mechanism):* At the bottom are generators that produce (dynamical) structures (top). Some structures survive the sorting mechanism, which is represented by the siphon in the center. These structures are dynamically stable but (often) also possess dynamical internal mechanisms. The structures can form meshworks of interactions, represented in the lower half of the figure. These meshworks, in all their configurations, are a searching mechanism because they explore the problem space. Some solutions can form the next layer of generative processes (the upward arrows) generating dynamical structures, ad infinitum. The entire process is recursive. Feedback loops are an integral part of the machinery. Generators are often in a cyclic flux, thus looping back to themselves, with the aid of a sorting machines to steer the looping behavior toward the next singularity. During the search process the sorting machine can change too, in order to overcome local optima.
The generators are often processes possessing cyclic feedback mechanisms. The control parameters of these loopy processes fluctuate and generate similar, but often not the same, kind of structures. These generators in flux are actively sampling the solution space using feedback from the selection mechanism. Generators use this feedback to improve on their creation of structures. The improvement is either by means of the adjustment of the control parameter(s) of the same generators or by means of the generation of similar generators with an adjustment in their control parameter(s). Generators can be replaced in this process by new generators which are generated from another level of sorting machines and generators. The abstract machine is recursive, but an implementation should exhibit levels or strata. It is more likely that the abstract machine exhibits similar procedures on the different levels than that for every level different procedures are in place. This is a matter of chance. If a working recursive procedure exists then it can develop faster than methods which behave very differently on every level. So even if a non-recursive abstract machine exists, it is out competed by a recursive one.

Many different types of artificial neural networks exist, but none has the complexity in found in biological machines. Although this is not an argument in itself, the lack of complexity and flexibility is likely to be a limiting factor in the level of intelligence that classical AI can reach using artificial neural networks. The topology of artificial neural networks is usually fixed. These networks can only be used for local optimization, not for the generation of new possibilities. The knowledge of the neural substrate in biological organisms is also lacking an overall theory of how to construct the mind from matter.

Generalizing over the previous section one could state that that generators exist which generate structures. Some structures survive the sorting machine and form (semi-)stable meshwork-like pattern. These structures and their meshworks are often dynamic and flexible, just as in the dynamical structures of Prigogine. The structures can be crystalline (as in the case of cities), liquid (as in the case of body plans and of large, pre 20th century, armies) or gaseous (such as human society before the discovery of agriculture). These meshworks can undergo phase shifts. The meshworks with their dynamical components can form a generator for the next sorting machine. Generators are internally flexible and able to adapt to different circumstances. From an evolutionary point of view this makes sense: Systems which are able to adapt themselves to their surroundings are more likely to survive than non-adaptive structures. These meshworks are dynamical, as can be expected, since stable structures far from equilib-
rium are stable and dynamical by their very nature. This mechanism is schematically represented in figure 1.1. The implementation of this mechanism can be called: The generative search machine. The next section describes a post-structuralistic perspective on the development of the biological neural substrate, applying the terminology set out in this chapter.

1.6 A neo-cybernetic view on the biological neural substrate

1.6.1 The hominid neural substrate

In the development of the neural substrate of humans two kinds of processes can be distinguished: Progressive and regressive (Elman, J. et al., 1996; Low and Cheng, 2006). Progressive processes are about creation, regressive processes are about destruction. The most important progressive events are the following:

Neurogenesis The formation of neurons, the displacement or movements of neurons, most of which occurs before birth. An abundances of neurons are created, more than half will not survive into adolescence.

Axon formation Axons grow over large distances until early childhood. Axons are output mechanisms for the soma or cell body of the neuron. Often multiple axons are projected over long distances before all but one projection is pruned. On the end of the axon, the axon terminal, there is usually a little axonal sprouting over a short range. This axonal sprouting typically occurs after the axon pruning and functions as a fine-tuning procedure.

Synaptogenesis Synaptogenesis is the formation of synapses, which are the connections between the axons and the dendrites. Dendrites are the input mechanisms for the neuron. Synaptogenesis is an additive mechanism. Synaptic sprouting has been demonstrated in response to changes in environmental conditions. Usually a neuron has many dendrites and only one axon in adults.

Retention of exuberant connections Usually in case of abnormal development. Exuberant connections can be used for a different functionality if the insult occurs early in the development of the neural substrate.
Reprogramming of existing connections  The functionality of a group of neurons can be adapted using Hebbian learning mechanisms. This can occur if an injury occurred.

There are also important regressive events:

Apoptosis  Apoptosis means programmed cell death. It is uncertain what causes the cell death. It could be regulated by the genes but another theory is that cells which cannot make successful connections kill themselves. Programmed cell death has been observed in most parts of the developing nervous system. Apoptosis attributes to the removal of more than 50% of the excess projections of neurons and dendrites seen in early development. There is a temporal correlation between apoptosis and synaptogenesis in the early development of humans and mammals in general.

Axon pruning  In the first few years of the human infant many neurons form several long range projections of axons. During these years those axons which cannot form useful connections are pruned or eliminated. The remaining axon starts to sprout over a short distance for fine-tuning.

Dendrite pruning  Dendrites with few or no successful connections are pruned. This pruning occurs in several waves. The early visual cortex reaches its peak in humans after four months, while the neo-cortex reaches its peak around the age of two years. Experience steers the formation of the connections. A more accurate description would be that inactive connections are disassembled, which means that a lack of experience steers synaptic disassembly. The elimination process is competitive. Only a small subpopulation of synapses are removed during synapse disassembly. It is an alternative and less disruptive strategy than apoptosis.

The information about the progressive and regressive processes in neural wetware in humans as describe above are well established facts (Elman, J. et al., 1996; Low and Cheng, 2006). The human brain contains the same types of neurons and the same types of neural mechanisms as other primate species. The topology, the structure of the brain, is the most important difference between humans and primates (Deacon, 1998). The timetable of the progressive and regressive processes is different in different mammal species, resulting in different brain topologies. Most of the sensitive periods of the
homo sapiens last longer than in primates. The sensitivity is essential for a human in order to adjust itself to the complex world it finds itself in.

A coarse-grained schedule of the neural development of a hominid would be the following. During the fetal period there is little sensory information. Most neurons are formed before birth. Apoptosis selects those neurons that do not form connections with enough activity in the synapses. From birth to the age of 2-3 years the axon pruning is one of the most important aspects of the selection mechanism. The axons lay the basic infrastructure of the brain and have to deal mainly with sensory information processing. It is in this age that the infant learns that it has a body. The child gains some control over its limbs and also the basic configurations of the neural sensory processing systems are formed. The infant adapts itself to the sounds of the local language and to the shapes and colors of its environment. Although synaptogenesis occurs throughout the entire life of a human, most of the synapses have formed by this age. In the period from 4-5 years until puberty the main process is synapse strengthening and synapse disassembly. There is an increased metabolic rate in the brain compared to the adult, which has peaked around the age of four. The increased metabolic rate is an example of of generators in cyclic flux. It consumes more energy to actively sample the solution spaces than that it costs for the execution. This period of increased metabolic rate is a refinement period where the subtleties of the local language are acquired and the control over the body is improved. During puberty, due to the influence of hormones, there is an increase in synapse disassembly. By the time the human reaches adulthood the disassembly slows down again and the metabolic rate stabilizes. During puberty the human selects its life path out of all the possible path candidates. The education and treatment of children to which the western society is tuned follow the development of the neuronal structures. During the pruning of the axons (0-4 years) little is expected of the infant. From the age of 5 till the advent of puberty the child has to fine-tune itself to the local environment. It follows primary education and learns the basic principles of social structures in society. During puberty the adolescent has to find a specialization which it is supposed to perform during its adult life.

1.6.2 A neo-cybernetic perspective on neural development in hominids

In the development of the neural substrate are many iterative processes similar to the processes described in section 1.5. What follows is a list of the different stages in the
developing brain. Several processes have a temporal overlap, which means that the brain is able to track more than one singularity at a time.

- During neurogenesis an abundance of cells are generated. The programmed cell death functions as a selection mechanism for the networks/meshworks which do not form successful connections. The successful structures function as a generator for the next level of processing. Neurogenesis (Changeux et al., 1973; Changeux and Danchin, 1976) is a biological implementation of the abstract search engine looking for fit solutions for the developing brain. Pruning the solution space (Michod, 1989) causes the brain to adapts itself to the body it finds itself in.

- The axon formation and axon death. The generation and subsequently sorting out of the unsuccessful connections of the axons is a mechanism where first many axons are generated. The axons which cannot form successful connections, which are essentially networks or meshworks of neurons, are eliminated (sorted out) using axon pruning. The brain is searching for fit solutions to the information processing problems it faces.

- Synaptogenesis is a generator of possible connections. The unsuccessful connections, or more precisely stated, the unsuccessful networks/meshworks of connections, are disassembled to give the successful connections the opportunity to form/search for better configurations. The neural implementation of the abstract search engine is generating a next level of thinking.

- The retention of exuberant connections is a useful byproduct of the dynamical systems discussed in section 1.5. If there is a change in the underlying processes this propagates throughout the system. Higher levels of organization have to adapt, to be dynamic, to find new stable patterns in their topologies. The only other option is degeneration, which can occur if the change is too radical or if the higher levels of organization are too mineralized already.

- Waves of synapse formation and disassembly throughout the brain, from lower level pattern recognition systems to higher level reasoning, follow the same pattern over and over again. A level mineralizes when stable patterns in the phase space have been encountered. The search for these stable, dynamical patterns
is a process of generating many possibilities of neural configurations. The unsuccessful networks/meshworks of neurons are sorted out and the successful networks serve as a generator for the next level of neural processing.

A prediction of the theory of GAI is the following: The layered structures in the brain often have more connections going against the data stream than with the flow of the data. From the theory of GAI, these backwards going connections function as sorting mechanisms of the topologies of the previous layer(s). Topologies are sorted out by the Hebbian types of learning rules of the sorting mechanisms. In the beginning of development all the layers further in the data stream (the higher levels) function as a selection mechanism. This implies that first a higher level in the neural substrate is a sorting machine. The topology if these layers slowly mineralize. A mineralized layer can still be flexible, but often the basic information processing capabilities do not change too much and the flexibility is restricted. This implies that layers that first function as a sorting machines later operate as a generator. The 'knowledge' acquired by the sorting mechanism is reused in the form of a generator. The fine tuned sorting machines generate useful information for higher levels of thinking. Network configurations which generate stable patterns are reinforced. These layers become mineralized, they undergo a phase transition. The layers the closest to the sensory data have to be mineralized first, making use of all the above lying layers to select topologies. Temporal procedures ensure that there is a mineralization procedure where first the lower level layers undergo a phase shift and become rigid before the higher level layers. The rigid layers function as the dynamical but stable underground of generators on which the higher layers can search for successful configurations. The mineralized layers remain dynamic and flexible by means of synapse (dis-)assembly. In short: The development of the brains of mammals consists mainly of the sorting out of connections which are rarely used. This iterative sorting process generates networks of connections which functions as the basis to form higher level thinking. Neural subsystems first function as a selection mechanism that is being fine tuned. A fine tuned selection mechanism can function as a generator for higher levels of cognition.

1.6.3 A neo-cybernetic perspective on development in robots

The biological neural substrate has the advantage of being an open ended system. There are limitations on the use of the brain, such as the amount of energy it requires to oper-
ate, disposing the heat and the space it occupies. The brain does seem to be a general purpose machine for the creation of intelligence. The brain is shaped by evolution. Different implementations of artificial brains could have radically different forms of intelligence. Looking at pathologies in humans a wide range of mental phenomena can be demonstrated and there is no reason to believe that the limits posed on the brain are due to something else than evolutionary forces.

A question that arises in cognitive developmental robotics (Asada et al., 2001, 2009) is how to create open ended developing systems. Looking at the processes in evolution it can be argued that a level below the learning mechanisms is required to create flexible and open ended learning systems. Focusing directly on the learning mechanisms themselves means that it will be humans who are creating the learning mechanisms and not the machines. This limits the learning capabilities of robots and is less of an automated procedure than that what one would like to see in artificial creatures creating their own intelligence.

Taking a step back from the learning mechanisms implies that science should put a focus on mechanisms which create learning mechanisms. This is a loopy kind of structure which can fold back upon itself. By creating better learning mechanisms it might be able to use these mechanisms to create even better ones. This loopy kind of machine learning is one of the core messages of this thesis. It is very difficult to create these kind of mechanisms. It might be easier to create environments where these mechanisms can evolve in an open ended manner. This requires the setting up of generative mechanisms to create open ended structures and the use of sorting machines to select the fit solutions which can create learning mechanisms for autonomous systems. This could happen in the same manner, but with perhaps with different implementations, as in biological organisms. A candidate for the creation of the layer below learning mechanisms could be evolutionary or genetic programming (De Jong, 2002; Koza, 1989; Fogel, 1994).

If the science behind the neurogenesis of the human brain is correct, then focusing on the automated creation of networks/meshworks using AI could improve the performance of artificial systems drastically. This probably means that it will be hard, if not impossible, for humans to understand exactly what goes on in the AI, but using the correct tools it should be possible to steer the development. An example could be a robot who is shown some locations in a building and then starts to wander around. It only needs to store a few way points now and then and can use, for example, a nearest
neighbor (Dasarathy, 1990) algorithms to check where it should go from any position to any position (research in progress by author). In such a manner the robot does not create a map (not even a topological one) but it creates the required network of way points on the fly. Using clustering algorithms on the way points ensures generalization and also allows for open ended continuous learning.

1.7 Generative Artificial Intelligence

It is not easy to give a definition of a science which does not exist (yet), but a description of what Generative Artificial Intelligence (GAI) could constitute is possible. GAI can be described as a science of the automated engineering of models, of the autonomous construction of ideas, of the scaffolding of the mind, of generating subjectiveness in machines. It requires a different set of tools and concepts than Classical Artificial Intelligence (CLAI), which is almost all AI so far. GAI is also different from Analytical Science in general. This does not mean that there is no analysis in GAI. The set of concepts and tools in GAI builds on top (or perhaps underneath is a better metaphor) of the set already available to scientists.

GAI is about processes and becoming, instead of objects and being (Prigogine, 1981). GAI is about the process of automating model construction and testing. GAI is therefore well suited as the basis for the creation of robotic brains, if the robot is to show continuous learning capabilities. GAI can also be seen as the next step toward a post-human science (the previous step being CLAI), i.e., a science which does not rely (mainly/solely) on human endeavor for its development.

The simple solutions to the often simple and artificial problems of CLAI do not extrapolate easily to complex real world problems. Even many roboticists, who claim to be working with intelligent machines in the real world solving real world problems, mostly belong to CLAI. The created robots are not able to learn new behaviors in order to deal with new environments, but can only optimize behaviors for a particular situation they were programmed to find solutions for. The mental machinery of these robots is literally stuck.

There is a phletora of techniques available in CLAI. Also there are many theories and implementations of 'cognitive' architectures. Sadly, there is no system today which can construct cognitive structures in a general manner. Instead of finding specialized
solutions to partial problems, as shown schematically in figure 1.2, machine intelligence should possess general methods or strategies to find solutions to many types of problems. The reason for this is simple: Complex real world problems often require complex solutions! If the goal is to have machines operating in our societies then new paradigms have to be experimented with. Creating machine intelligence requires a change in the way scientists operate. We should not expect to understand truly intelligent machines completely, but we should have tools to work with them and to steer their development.

Figure 1.2: Classical AI and Generative AI:
In Classical AI (left figure) there is often an optimization toward some end-state and (preferably) the outcome is predictable. In both the training and the execution phase this system can be classified as: Input $\rightarrow$ Transform $\rightarrow$ Output. The ‘transform’ part is an implemented model (handcrafted or learned). The left figure is in a stable equilibrium. In Generative AI the path followed through the phase space depends on the internal dynamics of the system and the interactions with the environment. The models are created and tested automatically. The creation process can be steered, but the outcome is unpredictable to some extent. The entire process is moving toward lower resistance (down on the Y-axis). There is no difference between a training phase and an execution phase. The system learns while executing.

The linear increments of the complexity of the methods used in CLAI do not show general applicability, general intelligence, or intelligent behavior (called ‘intelligence’ in the rest of this thesis). The intelligent systems created by humans are not intelligent,
but perform a smart trick. The methods of AI are good at optimization of a solution to a specific problem, but there is no bifurcation principle that allows the AI to grow (see figure 1.2). What are required are phase transitions which do not arise from the linear, near equilibrium, accumulative processes seen in CLAI. If the AI cannot bifurcate, i.e. find or track the singularities that give them the power to scaffold subjectiveness and intelligence, if there is little or no history in this creative process, if data cannot be transformed into information, then these systems are doomed to remain dumb and ignorant of the world they participate in. The simple “Input → Transform → Output” (ITO) systems of Classical AI cannot be the answer to the question of ‘how to create intelligence?’

The ITO procedure is not outdated, though. There are many examples in the world that, on a local scale, use ITO mechanisms. Figure 1.3 shows that there are difficult fitness landscapes, both in ITO and GAI problems. There is a big difference in the treatment of these fitness landscapes. In CLAI it is important to find the “global optimum”, which is a minimalization problem in figures 1.2 and 1.3. Many algorithms are designed to not get stuck in a “local optimum”, but to find the “global optimum”. Finding a global optimum in the solution space for a certain problem does not imply that the system is capable of scaffolding internal mechanisms in order to grow beyond its starting capabilities. In GAI there still is a fitness landscape, and forms of ITO operate upon the landscape. The goal in GAI is not to find a “global optimum”, but to find methods that will lead to the next bifurcation point. The goal of this process is to reduce the internal resistance of the processing of energy, or, in the case of mental structures, to reduce the resistance of the processing of data. Lower resistance will lead to a system which can process more energy using approximately the same amount of matter, or in the case of mental structures, the system can process more information using approximately the same amount of computational resources. It costs an extra amount of energy to get beyond a bifurcation point, but the extra costs are being spend with a reason: More energy/information can be processed with the same amount of resources, because the topology of the system adapted itself. Local processes operate on the fitness landscape, but not with the goal of finding the “ultimate” solution to an answer. There is no such answer. In the real world there is no optimum. This is in stark contrast to the toy problems of contemporary or classical AI. Although in contemporary AI there are systems that operate in the “real world”, they are not free to roam around. The systems created in CLAI are confined to a small subset of the real world. These systems are created with ITO in the back of the mind of their creators.
This hinders the progress of machine intelligence on a level that is so profound that many scientists do not realize it at all. The ITO systems should be designed not for optimization, but for the generation of probable good/fit solutions. The ITOs should not stop according to a halting criterion, but slow down and focus on certain regions of the search space to generate more good solutions. If the higher levels depending on the solutions of a lower level start to perform less well, then it is time to speed up again and to broaden the search parameters. This broadening might keep the structures that are scaffolded on top of it (partially) intact and the higher levels can adapt. A system that operates on these principles is adaptive and flexible on all levels.

Figure 1.3: Classical AI and Generative AI with local optimizations:
On a local scale there are local optimizations which are essential. In Classical AI the local optimizations lead to a local optimum which is usually the end of the process. Even the “global optimum” from Classical AI (the vertical arrow in the left figure) might not be the desired solution. Often the possible solutions in CLAI are not complex and flexible enough to solve the problem. From the perspective of Generative AI, there is no global optimum, but there are processes that generate possibilities. Some possibilities might lead to the next bifurcation, although most will not. The fitness landscapes from CLAI should not be treated as “a problem to be solved” but as “a place where new possibilities might arise from”. Again the system moves toward lower resistance (down on the Y-axis). Usually it costs energy to reach a state with lower resistance. CLAI and GAI both have in common that many solutions do not lead to desired outcomes, but GAI at least has the possibility to lead to new outcomes.

Important questions in GAI are: How to adapt the methods already available in CLAI to GAI. How to find new methods that follow the GAI paradigm? The answers are not clear, but there are several reasons to not use the CLAI way of working. For example, it could be that the fitness landscape is ill-defined, or worse (from a CLAI perspective)
that the fitness landscape of solutions to a problem is continuously changing and the solutions must therefore also fluctuate (within certain limits). In case of a fluctuating fitness landscape an ITO system will not work the way the designers intended the ITO mechanism to function. This is also the case with the evolution of biological species through natural selection. There are no “global optima” in the biological world. Sometimes, during stable climatic periods, species become more and more specialized in a certain niche of the environment. During periods of climate change there are fluctuations before settling into a new dynamical equilibrium. It is during large environmental changes that the less specialized species thrive and bifurcate to fill the new niches of the new environment. One of the most prominent examples is the rise of mammals after the disappearance of dinosaurs. Mammals had been around for tens of millions of years during the era when dinosaurs roamed. Only when the sorting machine (the evolutionary environment) changed, new configurations of a new type of animal (mammals) were able to generate new species. These mammals were less specialized than the much older reptilian species and had more opportunities to bifurcate, using a new type of body plan, resulting in better adaptability. The new body plan of mammals, compared to their reptilian ancestors, is a clear example of a phase transition in types of animal lifeforms. Due to this phase transition it took less energy to adapt. The less specialized solutions often possess more general searching mechanisms to find new structures that function better in a new environment.

The same kind of processes can be seen in high-level thinking creatures such as many mammals. In the infant and adolescent stage in hominids, for example, there are several unstable periods that lead to the building up of bifurcation points. First there is the battle of the axons in early childhood that leads to the adaptation of the mind to the particular situation the infant is in. The brain gets tuned to the local language, sounds, colors, objects, … of the local environment. Then during a relatively stable period, where the infant learns about local social structures and basic survival skills (such as the creation of stone tools or the use of the Internet) another unstable periods arrives, called puberty. In this period the brain is actively searching for new singularities and deleting poorly functioning generative procedures. The paths in the phase space that the brain is following form a defining period for the hominid involved. This prepares the adolescent for its adult life, where the possible singularities that exist are limited by the history of the cognitive system. From this perspective, the (hominid) brain is an assemblage of singularities by means of the tracking of the phylum. The unstable periods where transitions in the phase space occur are similar to what is seen in processes in quantum
mechanics (Prigogine, 1977) and social structures (de Landa, 1991).

It is essential to create intelligent machines with internal mechanisms which are far from an equilibrium state. Only systems in flux, far from the equilibrium, are able to track the singularities needed for higher order systems (Prigogine, 1984). These internal mechanisms have to operate on top of a continuous flow of energy. In the case of intelligence, this ’energy’ is data acquired by senses/sensors. The continuous flow of data pushes the intelligent machines out of its equilibrium state, and the intelligent machines can bifurcate. ITO is not enough, worse even, the relative success of ITO systems has been leading the AI community astray for more than half a century!

The processes operating on large data streams can transform data into (useful) information required for the continuous scaffolding of the intelligent system. If these constructive processes are steered well enough (by humans and the real word, for example), then the scaffolding can generate structured information and intelligence comprehensible by humans. It is comprehensible the same way that the behavior of an animal makes sense, through meaningful interactions with the surrounding world. The creation of information or intelligence is then defined as “finding stable, but dynamical, patterns floating on top of the data streams and on top of previously developed dynamical internal mechanisms”. The scaffolding causes an increase in the complexity and amount of information that the total system can process.

In GAI the data, the internal mechanisms and the environment steer the construction of informative, but dynamical, states and processes. The combination of steering by data, internal processes and the environment embeds the machine and its intelligence in the environment. Context thus becomes an integral part of the development of intelligent machines, avoiding the contextual problems of CLAI. A system developed using GAI principles should be able to adapt itself, to grow (mentally) and also to optimize itself for tasks. The capacities of such an intelligent machine depends on the initial state and the history of the system. Small fluctuations in the initial conditions can propagate through the system resulting in different perspectives (as in the same artificial neural network topology applied to the same problem with different (random) initializations of the weights of the connections), and different histories can also results in different perspectives (as in two identical twins who are never identical mentally). One of the tasks of GAI is to find the initial conditions of mental processes with the highest probability to develop into the matured machine intelligence which is desired by the designers (or users) of the intelligent machines.
1.8 **Formalization**

The formalization of the principles discussed earlier in the chapter has to be recurrent. The lexicon is the following:

\[ A = \text{The (implementation of the) Abstract Search Mechanism to find bifurcation points in phase space} \]

\[ S = \text{Sorting Machine} \]

\[ G = \text{Generator(s), mechanisms far from equilibrium generating possibilities (structures)} \]

\[ St = \text{Structure(s)} \]

\[ Q^{pos} \rightarrow R = Q \text{ can generate R} \]

\[ x^* = \text{configurations of } x \]

\[ \tilde{x} = \text{a meshwork of } x \]

\[ G \rightarrow St^{*} \quad (1.1) \]

Equation (1.1) states that a generator creates (different configurations of) structures. The internal mechanisms of the structures can be static or dynamic. Generated structures can be similar or even the same.

\[ \tilde{S}t \rightarrow A \quad (1.2) \]

Equation (1.2) states that a meshwork of structures and their interactions can form an implementation of the abstract searching mechanism. The interactions of the structures are local. This implies that because a structure can only have a limited amount of interactions, there will be many different meshworks with similar components searching the phase space of possible configurations. This implies massive amounts of parallelism. Both the structures and the interactions vary within a certain boundary which restricts the search space. The structures do not have to be of the same type. Out of the interactions between the structures new properties can emerge by means of self-organization,
auto-catalytic loops and perhaps other means. A question for GAI would be whether it is possible to predict these interactions and steer the development of the system in a predictable manner. It is uncertain before running the implementation how much of the state space the system will search. Too much and too little exploration leads to poor performance.

\[ S(A) \rightarrow G \]  

(1.3)

The last equation (1.3) states that a sorting machine applied to an implementation of the abstract searching mechanism has the possibility to form a generator. Generators form the beginning of the chain of events, closing the loop.

\[
G_1 \rightarrow \text{St}^* \rightarrow \tilde{\text{St}} \rightarrow A \rightarrow S(A) \rightarrow G_1^{\text{pos}} \rightarrow G_2
\]  

(1.4)

Equation 1.4 explains the entire cycle. A (group of) generator(s) \((G_1)\) forms structures. The structures which do not assist in the formation of (a) new generator(s) are selected against and will not be part of the next level of generators. Some of the structure can form interactions. Often several layers of interacting systems can be discovered before the next level of generative processes is functioning well enough to form its own structures. The interacting structures form the Abstract Search Mechanism, creating many possible solutions for the selection mechanism to operate on. The recursion means that since the generators of \(G_1\) are flexible structures themselves, the structures it generates can also change. These structures influence the \(G_1\) generators by means of the selection mechanisms. Sometimes this process generates a new level of generators \((G_2)\) which can assist either \(G_1\) in the creation of new generators, or form a system that behaves differently and cannot interact with \(G_1\) anymore but depends on it for its maintenance. In the last case a phase shift occurred, a higher level is created. The creation of a phase shift does not depend on new mechanisms, but can be explained using the same interactive and iterative processes that generate all the levels. Phase transitions are naturally occurring processes arising from naturally occurring events. No new machinery is required.
1.9 Possible conclusions

There are many conclusions that can be drawn from this chapter. Let’s start with the least optimistic, the one that leads nowhere, and gradually build up the possibilities to see where it leads to.

Conclusion I

The ideas of this chapter can be diminished as making no sense at all, but that would not help the research in AI out of the conundrum that it finds itself in at this particular moment in time. Machines do not seem to be intelligent but are at most capable of showing of some kind of neat tricks, which often tells more about the designers than the capabilities of the machines involved. This conclusion leads to nowhere and it is not a likely candidate to get AI research anywhere else than creating more of the contemporary "Input → Transform → Output" systems.

Conclusion II

Another conclusion is: The analysis that machines need more than what is happening in contemporary AI research is correct. It could be, though, that the way out is not to move to a new paradigm but to do more of the research that is already being done. Gradually the AI becomes more intelligent. A counter argument against this conclusion is that for more than half a century science has followed this approach, and still there are no machines with a form of general intelligence. Nobody can predict the future, but doing more of the same thing is unlikely to generate the transition(s) in methodologies that are needed for the creation of intelligent machines.

Conclusion III

It can be concluded that the analysis is correct in the sense that ‘something else’ is needed. On the other hand, in contemporary AI research already a phletora of frameworks exist on many levels and these levels only have to be integrated into a complete system. The robotics (embodied) community has already learned that only a complete and integrated approach works well (Pfeifer and Scheier, 2001). If the abstractions from a certain module do not follow (or flow) out of other modules, then this certain module lacks grounding and most likely any form of understanding the world. But if a modules can “grow” out of previous (lower) modules, then it is grounded. Which leads to the fourth conclusion.

Conclusion IV
1.9. Possible conclusions

The analysis is correct, as is the part which states that the intelligent machines must be capable of building up a history. But, this building up of a history and the scaffolding of the mind can only be executed by the neural substrate found in biological creatures or an implementation of this neural substrate in a computer. Although this conclusion might be correct, it is a limiting one because it diminishes the possibilities of the AI research programmes. Part of the beauty of AI is that it is not tied to the biological substrate for the creation of intelligence. This conclusion is not post-human and it reeks of bio-chauvinism. This conclusion might not be optimal if one is changing the intelligence part from the biological substrate to an artificial one. This leads us to the fifth conclusion.

**Conclusion V**

The analysis is correct, but it is uncertain and unlikely that the solution of generators, meshworks and sorting machines is also correct. In this case scientists have to find alternatives to the line of reasoning promoted in this chapter.

**Conclusion VI**

The analysis set out in this chapter is correct, and now it is time to determine whether the mechanisms proposed are already available in contemporary AI research, or if some have still to be developed. If all components of the abstract machinery are available, then researchers should start to experiment with the new paradigm of GAI. Only when the to become intelligent machines actually possess the mechanisms of GAI we can ascertain whether the paradigm is sufficient. Since this is not deductible from the premises without running a GAI system, it is essential to build machines with GAI principles and analyze the resulting intelligence of the machines. An important goal of GAI would be to describe the abstract machinery in more details and to research whether all aspects of the abstract machinery have been described already. It could be that the processes as described in this chapter do not describe the complete machinery needed for the scaffolding of the (artificial) mind.

Conclusion VI is the point of view that will be used in the rest of this thesis. The rest of this thesis consists of peer-reviewed articles, which all show different aspects of AI. The paragraphs with the same background color as this chapter are comments on the AI research from the perspective of Generative Artificial Intelligence. None of the articles shows a complete GAI system yet. The major problem seems to stimulate a phase shift in the meaning of the information which is being transfered through the system. Humans have little difficulty with such a transition, but it remains a mystery.
how to create this inside the machines in use nowadays. The chapters do show that all the basic components are available in contemporary AI. It not a question whether science is ready for the next paradigm (generative science). The question is how to use the new ideas (of GAI) to speed up the scientific process and to create truly intelligent machines.