

# Data-Driven Granular Cognitive Computing

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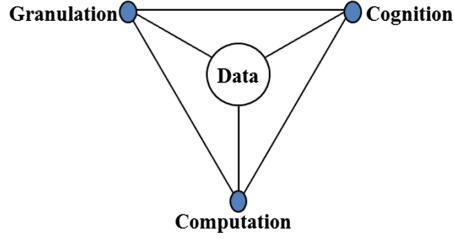
**Abstract.** Many artificial intelligence (AI) theoretical models are inspired by human/natural/social intelligence mechanisms. Three main schools of artificial intelligence have been formed, that is, symbolism, connectionism and behaviorism. Cognitive computing is one of the key fields of AI. It is a critical task for AI researchers to develop advanced cognitive computing models. Cognitive computing is the third and the most transformational phase in computing's evolution, after the Tabulating Era and Programming Era. Inspired by human's granularity thinking based problem solving mechanism and the cognition law of "global precedence", a data-driven granular cognitive computing model (DGCC) is proposed in this paper. It integrates two contradictory mechanisms, namely, human's cognition mechanism of "global precedence" which is a cognition process of "from coarser to finer" and the information processing mechanism of machine learning systems which is "from finer to coarser". According to DGCC, deep learning is taken as a combination of symbolism and connectionism, and named hierarchical structuralism in this paper.

**Keywords:** Granular cognitive computing · Cognitive computing · Granular computing · Data-driven · Hierarchical structuralism · Artificial intelligence · DGCC

## 1 Introduction

Artificial intelligence (AI) was born at a conference at Dartmouth College in 1956. Since then, many intelligent computing models with inspiration of various human/natural/social intelligence mechanisms have been developed. Three main schools of artificial intelligence (symbolism, connectionism and behaviorism) are formed.

In the middle 1950s, AI researchers began to explore the possibility that human intelligence could be reduced to symbol manipulation. It is the symbolism of AI. Newell and Simon introduced the physical symbol system hypothesis in 1976 [38]. Feigenbaum introduced expert systems [23]. The connectionism of AI was established by McClelland and Rumelhart in the 1980s [36]. It largely resulted from various dissatisfactions with the symbolism of AI. It models mental or behavioral phenomena as the emergent processes of interconnected networks



**Fig. 1.** Triangular structure of DGCC

of simple units. A lot of artificial neural network models were developed, for example, BP neural network [17], Hopfield neural network [22], Kohonen self-organizing maps [27], Boltzmann machine [1], radial basis function network [32], et al. In the behaviorism of AI, “Perception-action” model is used, which considers that intelligence depends on the perception and behavior [39]. In 1988, Brooks developed the Hexapod Walking Robot, which was composed of 150 sensors and 23 actuators [6].

In the recent 20 years, AI has more and more great achievements. Deep Blue became the first computer chess-playing system to beat Garry Kasparov, a reigning world chess champion, in 1997. Watson defeated two greatest Jeopardy champions, Brad Rutter and Ken Jennings in 2011. In 2016, AlphaGo defeated Sedol Lee, a professional Go player. The development of AI has been accompanied with the development of computer science in the past 60 years. Kelly introduced the three phases in computing’s evolution: Tabulating Era, Programming Era, and Cognitive Era [26]. AI is entering the cognitive era too.

A data-driven granular cognitive computing model (DGCC) is proposed in this paper. Its triangular structure is shown in Fig. 1. It integrates the traditional data-driven bottom-up information computing mechanism of machine learning/data mining systems, and the top-down “global precedence” law of human cognition [8, 16].

Deep learning [20, 21, 29] has great advances in machine learning and perception in recent 10 years. According to DGCC, the intelligence learning mechanism of deep learning is a new artificial intelligence mechanism called hierarchical structuralism in this paper.

## 2 Cognitive Computing

Cognitive science [33, 40] includes research on intelligence and behavior, especially focusing on how information is represented, processed, and transformed within nervous systems and machines. Cognitive computing aims to develop a coherent, unified, universal mechanism inspired by the mind’s capabilities [34]. Cognitive computing is based on the scientific disciplines of artificial intelligence and signal processing. Many intelligent computing models and machine learning models have been developed to address complex real-world problems

inspired by some specific intelligence observation of brain/mind law, biological law, natural law, and social law. Fuzzy logic enables a computer to understand natural language and reason in a similar way to human being [51]. Artificial neural networks learn experiential data by operating like the biological/human brain [1, 17, 22, 27, 32]. Evolutionary computing is based on the process of natural selection and evolution [11]. Swarm intelligence is inspired by biological systems [5]. Artificial immune systems are inspired by theoretical immunology and observed immune functions, principles and models [10]. Granular computing mimics a way of thinking that relies on the human ability to perceive the real world under various levels of granularity [47, 52]. Some researchers are trying to design a unified computational theory of the mind, and a set of mechanisms for all cognitive behaviors [34]. Cognitive-based systems could build knowledge and learn, understand natural language, and reason and interact more naturally with human beings than traditional systems [2].

### 3 Granular Computing

Granular computing has emerged as a quick growing intelligent computing paradigm in the domain of cognitive intelligence and artificial intelligence [47]. It is often regarded as an umbrella term to cover theories, methodologies, techniques, and tools that make use of granules in complex problem solving [48]. Bargiela and Pedrycz consider granular computing as a conceptual and algorithmic platform for analyzing and designing human-centric intelligent systems [3]. Zadeh considers granular computing as a basis for computing with words [51]. Skowron uses rough approximations to model syntax, semantics, and operations of information granules [25]. Multilevel granulation structures could be induced by hierarchies of the universe and neighborhood systems. Zhang proposes a quotient space theory for problem solving inspired by the human thinking ability of perceiving the real world under various levels of granularity in order to abstract and consider only those things that serve a specific interest and switching among different granularities [52]. Formal concept analysis could be adopted to automatically derive ontology from a set of objects [45]. The granular structure of concept lattices in formal concept analysis is useful for knowledge reduction [9, 47]. Yao views granular computing as a complementary and dependent triangle shown in Fig. 2, which integrates three important perspectives [49, 50]. Wang proposes a bidirectional cognitive computing model (BCC) based on a qualitative and quantitative mapping model for expressing and processing of uncertain concepts [31]. It uses 3 parameters (expected value, entropy, hyper entropy) to describe the intension of a concept, while a set of samples to describe its extension. A multiple granularity concept generation model was developed for generating hierarchical concept trees as shown in Fig. 3 [31]. Xu and Wang develop an adaptive hierarchical clustering approach to generate a hierarchical tree as shown in Fig. 4 [46].

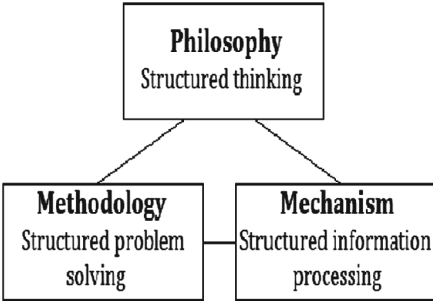


Fig. 2. GrC triangle

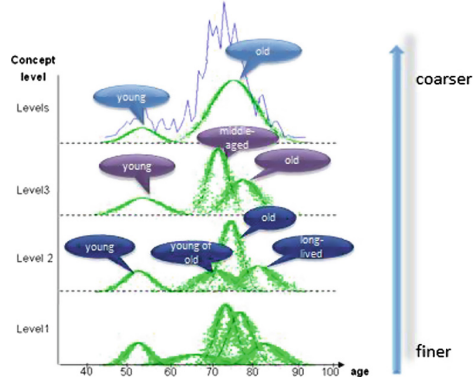


Fig. 3. Hierarchical concept tree

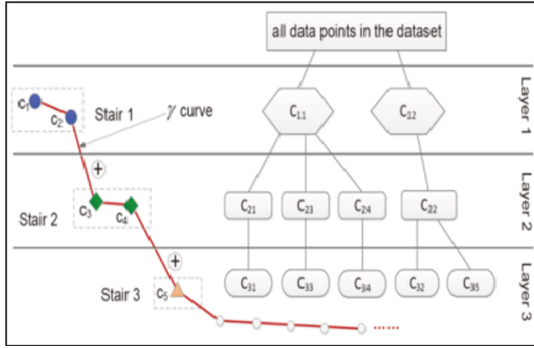


Fig. 4. Hierarchical clustering

## 4 Data-driven Granular Cognitive Computing

In classical intelligent information systems, original data is collected from environment at first, useful information is extracted through analyzing the input data then, and it is used to solve problems at last. In traditional machine learning, data mining and knowledge discovery models, knowledge is always transformed (extracted) from data. It is a unidirectional transformation from finer granularity to coarser granularity as shown in Fig. 5.

There is a human cognition law called “global precedence” [7, 8, 16]. In Fig. 6(a) [16, 35], there are 4 large characters (the global level) made out of 2 small characters (the local level). People always recognize the large characters in the global level at first and then the small characters in the local level. It is easy to draw and recognize a people, as shown in Fig. 6(b), through his/her caricature, which has just a few lines, without analyzing detailed pixels. It shows the cognition law of the information processing in human visual perception. It is a process from coarser to finer.

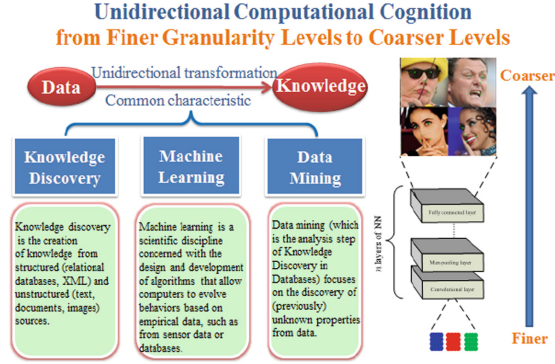


Fig. 5. Unidirectional transformation from finer to coarser

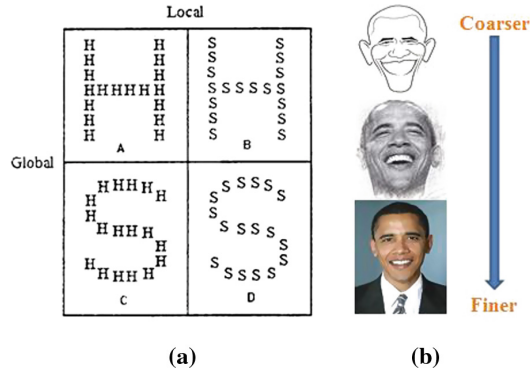
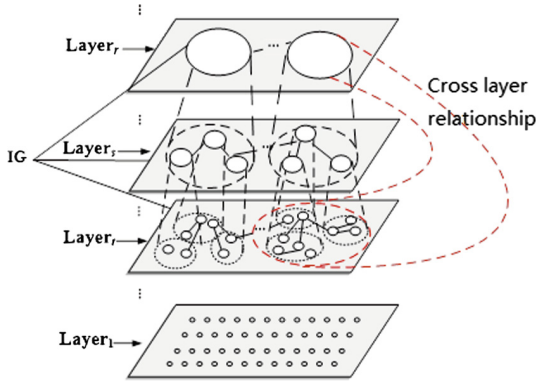


Fig. 6. Human cognition: from coarser to finer

There is a contradiction between the unidirectional transformation mechanism “from finer granularity to coarser granularity” of traditional intelligent information systems with the global precedence law of human cognition. A data-driven granular cognitive computing model (DGCC) is proposed to integrate them. Its triangular structure is shown in Fig. 1. Computation emphasizes the data science which includes all efficient computing models and methods for processing big data; cognition emphasizes the smart understanding of big data and the intelligent interaction between users and information systems; granulation emphasizes the multiple granularity thinking and modeling for dealing with big data. Computation, cognition and granulation are all implemented in a data-driven manner. Wang developed a general multiple granularity structure for DGCC as shown in Fig. 7 [44]. DGCC has the following key features.

- In DGCC, data is considered to be knowledge in the lowest granularity level, and knowledge is considered to be the abstraction of data in different granularity layers.

- There could be relationship both between nodes (concepts) in a same granularity layer, and between nodes (concepts) in different layers.
- Nodes in different granularity layers could take action jointly and simultaneously in a parallel way, while not just sequentially.



**Fig. 7.** A general multiple granularity structure for DGCC

There are many theoretical issues to be studied for implementing a DGCC model.

(1) Multiple granularity representation of data, information and knowledge.

As shown in Fig. 7, data is in the bottom layer, information in the middle layers, while knowledge in the high layers. In DGCC, data is considered to be the knowledge represented in the lowest granularity layer. In other words, data is viewed as the extension of concepts (knowledge in a higher granularity layer), while a concept is viewed as the intension (abstraction) of some data. The idea of taking data as a format for encoding knowledge was introduced in our early work about domain-oriented data-driven data mining (3DM) [43]. Data, information and knowledge are encoded in a hierarchical multiple granularity space together. A general multiple granularity structure needs to be set up for expressing data, information and knowledge.

(2) Integration of the human cognition of “from coarser to finer” and the information processing of “from finer to coarser”.

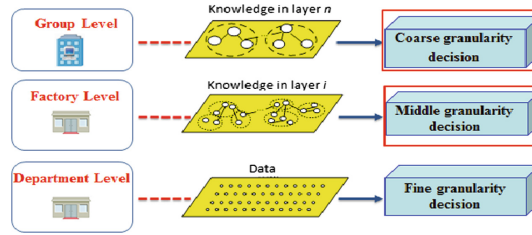
In DGCC, there are two kinds of transformation operators, namely, upward operators and downward operators. An upward operator transforms the data/information/knowledge in a low granularity layer to a high granularity layer, while a downward operator transforms the data/information/knowledge in a high granularity layer to a low granularity layer. Downward operators mimic the human cognition of “from coarser to finer”, while upward operators mimic the information processing of “from finer to coarser”.

(3) Transformation of the uncertainty of big data in a multiple granularity space.

Generally speaking, concepts (information and knowledge) in a higher granularity layer would be more uncertain than the ones in a lower granularity layer. A concept in a higher granularity layer is the abstraction of some objects (data or concepts in a lower granularity layer). Exceptionally, some concepts in a lower granularity layer could also be more certain than the ones in a higher granularity layer, since there is more detailed information in a lower layer.

(4) Multiple granularity joint computing model and problem solving mechanism.

Data, information and knowledge are encoded in a multiple granularity space together. They could be used in problem solving simultaneously in a parallel way. As shown in Fig. 8, decisions in a manufacturing industry group are being made at several different layers simultaneously every day. Decisions in different layers might be either dependent or independent. Mechanisms for joint computing and decision making in a multiple granularity space is required.



**Fig. 8.** Joint decision making in a multiple granularity space

(5) Dynamical evolution mechanism in a multiple granularity knowledge space.

Most real life systems are dynamical. The data, information and knowledge of an intelligent information system would also be dynamical, while not static. Dynamic evolution mechanisms need to be developed to deal with the dynamic data, information and knowledge in a multiple granularity knowledge space.

(6) Affective progressive variable granularity computing method.

Usually, coarser answers could be generated in a higher granularity layer with less time cost, while finer answers in a lower granularity layer with more time cost. Affective progressive variable granularity computing method should be developed. Some kinds of coarser answers are generated in a higher granularity layer at first, and more exact answers will be available in lower granularity layers later.

(7) Calculation goes ahead of some perception.

In some real life applications, not all input information (data) is available simultaneously in the beginning. It would be better to make a draft decision according to some partial inputs available at first, while not wait for all inputs. In some problem solving tasks, we do not need all inputs. In such cases, in order to take efficient actions, an answer (decision) in a lower granularity layer

could be generated based on partial inputs at first, and then an improved answer (decision) could be generated in a higher granularity layer after more inputs are available. A decision (answer) will be generated according to partial inputs in a lower granularity layer if it is impossible to have all inputs.

(8) Distributed multiple granularity machine learning method.

Since data, information and knowledge are encoded in a multiple granularity space together, a parallel and distributed learning process would be possible. It is not needed to learn layer by layer.

(9) Multiple granularity mechanism of associative memory with forgetting.

The information storage mechanism of computers is a mechanical one. Information (data, knowledge) could be either stored in a memory system or not. It will be unavailable after being removed. However, there is an association mechanism in human brain. The bidirectional cognitive computing model in [34] might be used to implement such an association mechanism of human brain. Upward operators could simulate a forgetting process through transforming information in a lower granularity layer to some abstracted information in a higher granularity layer, while downward operators could simulate an associating (recalling) process through transforming information in a higher granularity layer to some detailed information in a lower granularity layer.

## 5 Hierarchical Structuralism: A New Mechanism for Artificial Intelligence

Various deep learning architectures like deep neural networks [4, 37], convolutional deep neural networks [30], deep belief networks [20] and recurrent neural networks [14] have been applied in many fields such as image recognition [28], speech recognition [12], et al., successfully. Deep Learning architecture built from artificial neural networks (ANN) could date back to the Neocognitron in 1980 [13]. The challenge of ANN study is to train a network with multiple layers. In 1989, LeCun applied the standard BP algorithm to a deep neural network with the purpose of recognizing handwritten ZIP codes [30]. In 1995, Hinton trained a network containing six fully connected layers and several hundred hidden units using the wake-sleep algorithm [19]. However, the time cost was too high, making it impractical for general applications.

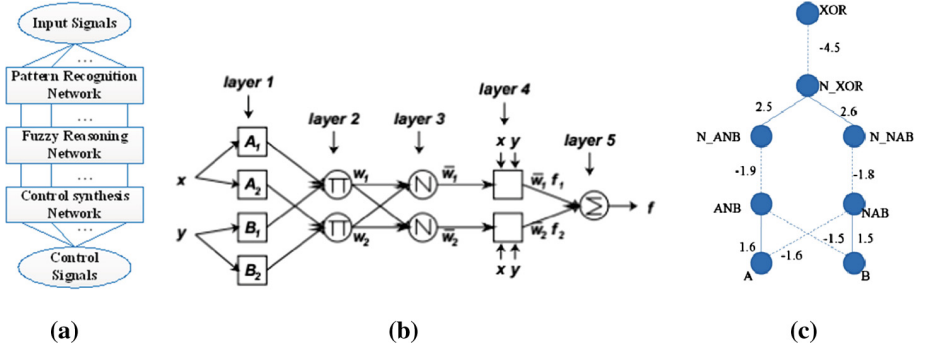
It is always very difficult and time consuming to train a traditional ANN with multiple layers. The inner structure of a traditional ANN is always considered as a black box. Thus, there is no observable, understandable structure or feature in a trained network. The more hidden layers an ANN has, the more difficult and time cost to train it. This is the reason that almost all ANN researchers usually used networks with only 3 layers before deep learning was developed.

In 2006, Hinton effectively pre-trained a many-layered feed forward neural network one layer at a time, treated each layer in turn as an unsupervised restricted Boltzmann machine, and then fine-tuned it using supervised back propagation [18]. It has become part of many state-of-the-art systems in various disciplines in recent years. Deep learning is a branch of machine learning



based on a set of algorithms attempting to model high-level abstractions in data by using a deep graph with multiple processing layers of linear or non-linear transformations [15].

In fact, there were some ANN researchers who had also implemented such ideas in their many-layered neural networks in 1990s. Wang developed a neuro-fuzzy network (FCN) for bucket motion control with 9 layers in 1992 [41]. As shown in Fig. 9(a), it is composed of 3 structured sub networks. Jang developed an adaptive-network-based fuzzy inference system (ANFIS) in 1993 [24], which is a neural network with 5 layers as shown in Fig. 9(b). Wang developed a triple-valued or multiple-valued logic neural network (TMLNN) in 1996 [42]. As shown in Fig. 9(c), each neuron of TMLNN is a triple-valued or multiple-valued logic neuron. A TMLNN with 5 layers could implement any logic function like XOR (Exclusive OR).



**Fig. 9.** Many-layered neural networks. (a) FCN; (b) ANFIS; (c) TMLNN for XOR

It is easy to train an FCN, ANFIS and TMLNN with a low time cost since they have clear logical structures. Unfortunately, both computation power and data were very limited in 1990s. It was impossible to use them to solve large scale complex real life problems at that time.

From the above discussion, it could be found that FCN, ANFIS and TMLNN have the same idea of deep learning. A concept in a higher layer is learned from the ones in a lower layer. It is a kind of multi-granularity representation structure discussed in Sect. 4. The inner structure of these multi-level ANN models is not a black box. Neurons in each layer have distinct logic meaning. The links between neurons correspond to their logic relationship. This kind of ANNs could be considered as a kind of logic reasoning networks of symbolism systems. It is a special case of DGCC, and called hierarchical structuralism. It has the following  $HD^3$  characteristics.

- **Hierarchical.** The knowledge and information are encoded in a hierarchical system. The inner structure of a hierarchical system is understandable.

- Distributed. The knowledge and information are encoded in a distributed manner.
- Data-driven and training based. It is set up based on training in a data-driven manner.
- Dynamical. The inner structure of a hierarchical system could be dynamically adjusted in an adaptive and evolutionary way.

## 6 Conclusion

Inspired by human's granularity thinking based problem solving mechanism and the cognition law of "global precedence", a data-driven granular cognitive computing model (DGCC) is proposed. It integrates two contradictory mechanisms, human's cognition mechanism of "global precedence" which is a cognition process of "from coarser to finer" and the "from finer to coarser" machine learning mechanism. It is a multiple granularity representation of data, information and knowledge. It could implement multiple granularity joint computing and problem solving, simulate the dynamical knowledge evolution. Both computing mechanisms of progressive variable granularity computation and calculation going ahead of some perception could be realized. Multiple granularity mechanism of associative memory with forgetting could also be implemented in DGCC. A hierarchical structuralism for artificial intelligence is proposed based on DGCC, which is a combination of symbolism and connectionism.

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