

## *Rough Set and Deep Learning: Some Concepts*

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Features of granular computing and relevance of rough sets are stated. These are followed by the characteristics of deep learning and deep architecture, and significance of deep convolutional neural networks. Finally, some sketches on granulated deep learning, and rough deep framework through evolution and learning of granules are provided.

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### **Granular Computing: Features and Rough Sets**

*Granulation* is a basic step of human cognition system. It is a process like self-organization, self-production, morphogenesis, Darwinian evolution that are extracted from natural phenomena. It may be viewed as a process of natural clustering, i.e., replacing a fine-grained universe by a coarse-grained one, more in line with human perception. Clusters or segments so formed by granulation (natural clustering) are called granules. In other words, granules evolve through information abstraction and derivation of knowledge from data in the process of granulation.

Granular computing (GrC) has evolved more than a decade back. This is an information processing paradigm that works with the process of *information granulation/ abstraction*, and where computation is performed using *information granules* and not the data points (objects). Since information granules characterize compressed information, processing based on the compressed information, rather than the individual data points, may lead to gain in computation time. This makes Granular computing (GrC) a good candidate for data mining and knowledge discovery. In other words, in processing large-scale information, GrC plays an important role that finds simple approximate solution which is cost effective and provides improved description of real world intelligent systems.

Salient features of GrC-based methodologies are: (i) GrC does not go for an excessive precision of solution which is in fact the inherent characteristic of human reasoning process, and (ii) the structural re-presentation of the problem in the work-flow of GrC makes the solution process more efficient. One may note that human reasoning-process normally follows the principle of information granulation and performs the operations on information granules. Further, modeling complex systems and data mining problems, most often, do not require high level of precisions and in fact it is often expensive and not necessary.

Rough set theory [1] that deals with the concept of a set defined over a granulated domain has proven to be effective in GrC research. Here the set is approximated in terms of granules from inside and outside (lower and upper approximations). This inexact definition of set signifies the incompleteness in knowledge about the universe, thereby resulting in uncertainty in the system. Minimization of the uncertainty (incompleteness in knowledge) played a pivoted role in image/ video processing [2], pattern recognition [3], and data mining, among others. Concept of lower/upper approximation has also been used as information granules in designing various artificial neural network (ANN) models [4] and unsupervised object tracking [5]. Before proceeding further, let us give some definitions characterizing a rough set.

Let  $U$  be a non-empty finite set of objects, and  $R$  be an equivalence relation on  $U$ , then,  $(U, R)$  is known as an approximation space. Let  $V$  be a subset of  $U$ . The lower approximation ( $R_L$ ), upper approximation ( $R_U$ ), and boundary region ( $BR$ ) of  $V$  are defined as follows:

$$R_L(V) = R(v): R(v) \subseteq V, v \in U \quad (1a)$$

$$R_U(V) = R(v): R(v) \cap V \neq \emptyset, v \in U \quad (1b)$$

$$BR(V) = R_U(V) - R_L(V) \quad (1c)$$

Here,  $R(v)$  denotes the equivalence class (called, granules) constituted by the relation  $R$ . Lower ( $R_L$ ) and upper ( $R_U$ ) approximations signify, respectively, the inner and outer approximations of the set  $V$  in terms of  $R(v)$ . They represent, respectively, all those  $R(v)$ s that definitely belong to  $V$ , and definitely as well as possibly belong to  $V$ . If,  $R_U(V) \neq R_L(V)$ , i.e.,  $BR(V) \neq \emptyset$ , then the set  $V$  is said to be rough with respect to  $R$ . This inexact (vague) definition of  $V$  in  $U$ , in terms of upper and lower approximations, signifies the incompleteness of knowledge about  $U$  with respect to the relation  $R$ . Otherwise, if  $R_U(V) = R_L(V)$ , then  $BR(V) = \emptyset$  and the set  $V$  is said to be exact with no roughness with respect to relation  $R$ . It may be noted that though the name of the set  $V$  is given by Pawlak [1] as rough set, this is nothing but a crisp set with rough representation.

The roughness of the set  $V$  with respect to  $R$  can be characterized numerically as [1]

$$\text{Rough}(V) = 1 - (|R_L(V)| / |R_U(V)|). \quad (2)$$

This means, if  $\text{Rough}(V) = 0$  then  $V$  is crisp (exact) with respect to  $R$ , and if  $\text{Rough}(V) > 0$  then  $V$  is rough (i.e.,  $V$  is vague with respect to  $R$ ).

## Deep Learning and Architecture: Concepts and Issues

Machine learning (ML), a branch of artificial intelligence (AI), basically means learning patterns from examples or sample data. Here the machine is given access to the data and is asked to learn from it. The data (or examples) could be labeled, unlabeled, or their combination. Accordingly, the learning could be supervised, unsupervised or semi-supervised. Artificial neural networks (ANNs) that have the ability to learn the relation between input and output from examples are good candidates for ML. ANNs enjoy the characteristics like adaptivity, speed, robustness/ ruggedness, and optimality. In the early 2000s, certain breakthroughs in multi-layered neural networks (MLP) facilitated the advent of deep learning. Deep learning (DL) means learning in depth in different stages [6]. DL is thus a specialized form of ML which takes the latter to the next level in an advanced form. This is characterized by learning the data representations, in contrary to task-specific algorithms.

Deep Learning algorithms/ networks are inspired by the structure and function of the human nervous system, where a complex network of interconnected computation units (nodes) works in a coordinated fashion to process complex information. In order to extract the complex representation from rich sensory inputs, human information processing mechanisms suggest the need of deep (learning) architectures [7]. Convolutional neural network (CNN, or ConvNet) [8] represents one such deep architecture which is most popular for learning with images and video.

Deep learning (DL) has dramatically improved the state of the art in object recognition [7], among other applications. However, since DL relies on sample data (or previous experience), the learning performance depends on the number of such samples. Larger the number is, more accuracy is the performance. Today, we have abundant data; so DL has become a meaningful choice. DL often requires hundreds or thousands of images for the best results unlike the conventional (Shallow) learning. Therefore, DL is computationally intensive and difficult to engineer. It requires a high-performance GPU (Graphical Processing Unit).

## Granulated Deep Learning and Rough Deep Framework: Concepts and Sketches

While deep learning is a computationally intensive process and the aforesaid granular computing paradigm, on the other hand, leads to gain in computation time, **it may be appropriate and logical to consider their integration judiciously so as to make the deep learning**

### **framework efficient in terms of computation time requiring only CPU.**

Recently, an attempt has been made in this line where rough set theoretic spatio-colour granulation in convolution layer enables CNN based deep learning framework speedy motion detection and moving object recognition [9]. Here instead of scanning the entire image pixel by pixel in the convolution layer of DL, one jumps over the granules only. For a 32x32 image with N granules, sliding the filter is done only N times instead of over 32x32 pixels, where  $N \ll 32 \times 32$ . Hence a *significant speed up* is observed, compromising some accuracy. Granulated RCNN [10] is another such recent example of deep architecture demonstrating the merits of GrC in extracting exact regions of interest for multi-object detection and tracking in terms of *accuracy and speed*.

One may further note that, DL is basically an abstract concept. Although significant research is going on for formulation of DL algorithms in neural network paradigm, one may consider the design of DL architecture in rough set theoretic framework. For example, the learning mechanism in Rough set theoretic DL framework may have several steps or layers to learn granules (that are evolved through information abstraction and derivation of knowledge from data), and their representations in terms of rough lower and upper approximations. Learning the size and shape of lower/upper regions and/or information granules, thus evolved in different layers, would enable better structural representation of the data, the patterns therein, and hence the derivation of knowledge. In this way, uncertainty arising from granularity in data, as well as the computation time in decision-making would also get reduced.

The use of granular flow graph [5] for knowledge representation and updating, and rough filter [11] in successive layers may be considered to enrich the said framework. Granular flow graph maps the decision-making paths in terms of granular information. Its updating may result in in-depth learning of the input patterns.

## **Conclusions**

Rough set and Granular computing (GrC) are proven technologies for knowledge mining and discovery in large data sets. They have characteristics like dimensionality reduction, uncertainty analysis, and gain in computation time. Deep learning (DL) and Big data analytics (BDA) has recently drawn the attention of researchers and practitioners because of its promising role in several fields, including commerce and business, biology, medicine, public administration, manufacturing, banking, and education. DL has dramatically improved the state of the art in object recognition, among many other applications. However, DL requires hundreds or thousands of images (samples) for the best results unlike the conventional (*Shallow*) learning, so it is computationally intensive and sometimes difficult to engineer. Some thoughts to

overcome these are outlined here. These include the concepts of:

- Granulated deep learning by incorporating granulation in the convolution layer of rough DL network.
- Rough DL framework consisting of different layers, instead of using neural net paradigm, where granules of various sizes and shapes evolve in different stages and are learnt; thereby providing a better structural representation of the data. Use of rough filter and granular flow graph may be explored to enrich the knowledge extraction and learning the data representation in terms of lower/upper approximations.
- Evolution of adaptive granules at different layers.
- Parameters of the variable granules may be used later on for transfer learning models.

One may refer to recent investigations [12] and [13] for further enrichment in this line.

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