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Knowledge transfer in system modeling and its realization through an optimal allocation of information granularity

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ABSTRACT

In this study, we introduce and discuss a concept of knowledge transfer in system modeling. In a nutshell, knowledge transfer is about forming ways on how a source of knowledge (namely, an existing model) can be used in presence of new, very limited experimental evidence. In virtue of the nature of the problem at hand (a situation encountered quite commonly, e.g. in project cost estimation), new data could be very limited and this scarcity of data makes it insufficient to construct a new model. At the same time, the new data originate from a similar (but not the same) phenomenon (process) for which the original model has been constructed so the existing model, even though it could applied, has to be treated with a certain level of reservation. Such situations can be encountered, e.g. in software engineering where in spite existing similarities, each project, process, or product exhibits its own unique characteristics. Taking this into consideration, the existing model is generalized (abstracted) by forming its *granular* counterpart – granular model where its parameters are regarded as information granules rather than numeric entities, viz. their non-numeric (granular) version is formed based on the values of the numeric parameters present in the original model. The results produced by the granular model are also granular and in this manner they become reflective of the differences existing between the current phenomenon and the process for which the previous model has been formed.

In the study on knowledge transfer and reusability, information granularity is viewed as an important design asset and as such it is subject to optimization. We formulate an optimal information granularity allocation problem: assuming a certain level of granularity, distribute it optimally among the parameters of the model (making them granular) so that a certain data coverage criterion is maximized. While the underlying concept is general and applicable to a variety of models, in this study, we discuss its use to fuzzy neural networks with intent to clearly visualize the advantages of the approach and emphasize various ways of forming granular versions of the weights (parameters) of the connections of the network. Several granularity allocation protocols (ranging from a uniform distribution of granularity, symmetric and asymmetric schemes of allocation) are discussed and the effectiveness of each of them is quantified. The use of Particle Swarm Optimization (PSO) as the underlying optimization tool to realize optimal granularity allocation is discussed.

1. Introductory comments: a concept of knowledge transfer

In modeling systems, processes and phenomena, we can regard a resulting model as a source of knowledge. Once being constructed on a basis of some usually quite large experimental data **D**, this source of knowledge can be used afterwards for a variety of prediction, control and description tasks thus contributing to the better understanding of the system. The quality of the model and usefulness depends upon the nature of the new scenarios in which the model is used. In particular, prior to its use it becomes essential to assess how these new situations are different from those manifesting by the data used to construct the model. In many complex problems of planning, cost estimation of software projects, each scenario is quite different. The sources of knowledge (models) formed so far could be useful but must be treated with caution when being applied to new situations. They might be useful but the results require some interpretation.

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Let us consider that for a current problem at hand we are provided with a very limited data set–some experimental evidence **D**′. Given this small data, two possible scenarios could be envisioned:

(a) we can attempt to construct a model based on the data **D**′. As the current data set is very limited, designing a new model does not look quite feasible: it is very likely that the model cannot be constructed at all, or even if formed, the resulting construct could be of low quality.
(b) we would like to rely on the existing model (which although deals with not the same situation but has been formed on a large and quite representative body of experimental evidence. We may take advantage of the experience accumulated so far and augment it in a certain sense so that it becomes adjusted to the current quite limited albeit current data. In doing this, we fully acknowledge that the existing source of knowledge has to be taken with a big grain of salt and the outcomes of the model have to be reflective of partial relevance of the model in the current situation. We quantify this effect by making the parameters of the model granular (viz. more abstract and general) so that one can build the model around the conceptual skeleton provided so far. In this case, viewing the model obtained so far as a sound source of knowledge, we are concerned with a concept of an effective knowledge transfer. The knowledge transfer (which, in essence, is represented by some model denoted here by N) manifests in the formation of a more abstract version of the original model – a so called granular model, G(N) where the granular nature of the model associates with the augmentation (abstraction) of the original model N being realized in presence of new data.

The process of knowledge transfer is intuitively appealing and becomes visible in many endeavors. As a compelling example, let us consider models of quantitative software engineering [1,2,10,13,14,16,22]. We build models of processes and qualities of software. In software cost estimation, project planning, quality assessment, to name the main phases of the overall development process, we come up with some models whose construction heavily relies on collected experimental data. In several cases, fuzzy sets are used as a vehicle to capture a lack of detailed numeric data when dealing with software cost estimation as discussed in [1,2,14]. In some others we resort to forming more advanced regression models as being presented, e.g. [10,13], visualization techniques [16] or an incorporation of advanced techniques of genetic optimization in the design of the cost estimation models, see e.g. [22].

Each software project is unique so the model designed on a basis of the previous data might not be completely relevant however at the same time could not be neglected at all. Building a model for this specific process or software quality could not be feasible – simply one might have a very limited data set, especially in case of an initial phase of the project or when there have not been substantial efforts to systematically collect data. In light of these, we encounter knowledge transfer – here the available model is viewed only as an initial construct that requires more revising/adjustments.

In general, the essence of the process of knowledge transfer is illustrated in Fig. 1. The original model, call it N, built on basis of **D** is now *abstracted* through its granulation, yielding its granular version G(N), and this occurs when dealing with a new data **D**′. The granular model becomes more in rapport with the environment currently encountered. Furthermore the level of granularity is regarded here to be an important design asset whose efficient or optimal allocation helps in an effective usage of knowledge already acquired on a basis of **D**. The allocation itself is regarded as an optimization vehicle to make the model more in rapport with the reality.

The generalization of the effect of knowledge transfer can be discussed in case of "p" different sources of knowledge – models built on a basis of $\mathbf{D}_1, \mathbf{D}_2, \ldots, \mathbf{D}_p$, say $N_1, N_2, \ldots, N_p$. We are interested in determining such N_{i0}, which is can be abstracted (granulated) in the most efficient way. In other words, N_{i0} is the one for which $G(N_{i0})$ leads to the best representation (quantified by means of some objective function) among all models available. Denoting this objective function of interest to us by Q, the problem is formulated as an optimization task of the form:

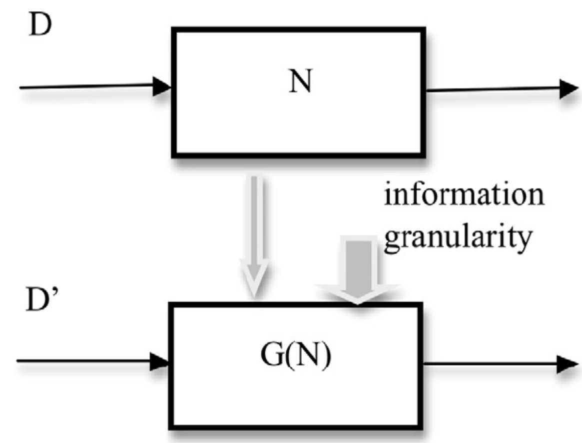

Fig. 1. From model (N) to its granular counterpart (G(N)) being a result of the realization of knowledge transfer.

$$i_0 = \arg\min_{i=1,2,\ldots,p} Q(G(N_i)) \quad (1)$$

Again as before, a certain level of information granularity becomes available to form a granular version of the original model; refer to Fig. 2 highlighting the very concept of knowledge transfer.

The main conceptual and algorithmic developments presented in this study could be of direct interest in the design of neural networks, cf. [9,11,12,15]. The study links to the ideas of building metamodels [7], which in the context of our investigations could be cast in a different perspective.

The paper is organized in the following way. We start with an introduction to fuzzy neural networks that are studied here as a transparent, logically-driven modeling environment (Sections 2–4) followed by a concept of optimal allocation of information granularity being regarded as an essential design asset, Section 5. We discuss a way of quantifying the quality of the allocation process. Various protocols of allocation of granularity levels are presented along with an evaluation of the flexibility levels offered by them. Numerical experiments are covered in Section 6. Conclusions and future directions are given in Section 7.

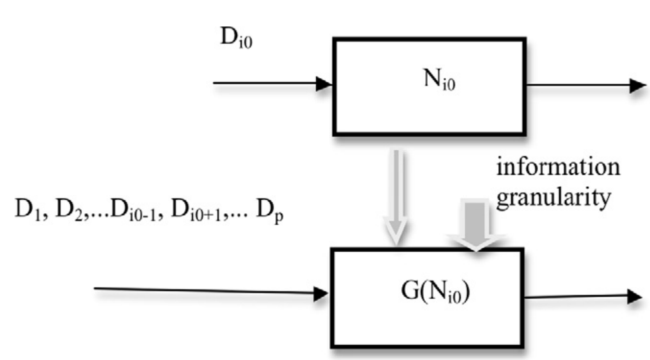

Fig. 2. Formation of the best granular model among a family of locally constructed models N1, N2,. . .,Np.