

Granular Computing

Georg Peters

Munich University of Applied Sciences, Germany

INTRODUCTION

It is well accepted that in many real life situations information is not certain and precise but rather uncertain or imprecise. To describe uncertainty probability theory emerged in the 17th and 18th century. Bernoulli, Laplace and Pascal are considered to be the fathers of probability theory. Today probability can still be considered as the prevalent theory to describe uncertainty.

However, in the year 1965 Zadeh seemed to have challenged probability theory by introducing fuzzy sets as a theory dealing with uncertainty (Zadeh, 1965). Since then it has been discussed whether probability and fuzzy set theory are complementary or rather competitive (Zadeh, 1995). Sometimes fuzzy sets theory is even considered as a subset of probability theory and therefore dispensable. Although the discussion on the relationship of probability and fuzziness seems to have lost the intensity of its early years it is still continuing today. However, fuzzy set theory has established itself as a central approach to tackle uncertainty. For a discussion on the relationship of probability and fuzziness the reader is referred to e.g. Dubois, Prade (1993), Ross et al. (2002) or Zadeh (1995).

In the meantime further ideas how to deal with uncertainty have been suggested. For example, Pawlak introduced rough sets in the beginning of the eighties of the last century (Pawlak, 1982), a theory that has risen increasing attentions in the last years. For a comparison of probability, fuzzy sets and rough sets the reader is referred to Lin (2002).

Presently research is conducted to develop a Generalized Theory of Uncertainty (GTU) as a framework for any kind of uncertainty whether it is based on probability, fuzziness besides others (Zadeh, 2005). Cornerstones in this theory are the concepts of information granularity (Zadeh, 1979) and generalized constraints (Zadeh, 1986).

In this context the term Granular Computing was first suggested by Lin (1998a, 1998b), however it still lacks of a unique and well accepted definition. So, for example, Zadeh (2006a) colorfully calls granular

computing “ballpark computing” or more precisely “a mode of computation in which the objects of computation are generalized constraints”.

BACKGROUND

Humans often speak and think in words rather than in numbers. For example, in summer we say that it is *hot* outside rather than that it is 35.32° Celsius. This means that we often define our information as an imprecise *perception-based linguistic variable* rather than as a precise *measure-based number*. The impreciseness in our formulation basically has four reasons (Zadeh, 2005):

1. *Bounded ability of human sensors and computational limits of the brain.* (1) Our human sensors do not have the abilities of a laser based speed controller. So we cannot quantify the speed of a racing car as 252.18 km/h in Albert Park, Melbourne. However on the linguistic level we can define the car as *fast*. (2) Most people cannot numerically calculate the exact race distance given by $5,303 \text{ km} * 53 \text{ turns} = 307.574 \text{ km}$ due to computational limits of their brains. However they probably estimate that it will be *around 300 km*.
2. *Lack of numerical information.* Melbourne is considered as a shopping paradise in Australia since there are *countless* shops. Maybe only local government knows the exact number of shops.
3. *Qualitative, non quantifiable information.* Much information is provided rather qualitative than quantitative. If one describes the quality of a pizza in an Italian restaurant in Lygon Street in Melbourne's suburb Carlton only a qualitative, linguistic judgment like *excellent* or *very good* is possible. The judgment is hardly to be quantifiable (beside a technical counting of the olives or the weight of the salami etc.).

4. *Tolerance for imprecision.* Recall the example, Melbourne as a shopping paradise, given above. To define Melbourne as shopping paradise its exact number of shops is not needed. It is sufficient to know that there are many shops. This tolerance for impression often makes a statement more robust and efficient in comparison to exact numerical values.

So obviously humans often prefer not to deal with precise but favor vague information that is immanent in natural language.

Humans would rarely formulate a sentence like:

With a probability of 97.34% I will see Ken, who has a height of 1.97m, at 12:05pm.

Instead most humans would prefer to say:

Around noon I will almost certainly meet tall Ken.

While the first formulation is computer compatible since it contains numbers (singletons) the second formulation seems too be to imprecise to be used as input for computers.

A central objective of the concept of granular computing is to bridge this gap and compute with words (Zadeh, 1996). This leads to the ideas of information granularity or granular computing which was introduced by Zadeh (1986, 1979).

The concept of information granularity has its roots in fuzzy set theory (Zadeh, 1965, 1997). Zadeh (1986) advanced and generalized this idea so that granular computing subsumes any kind of uncertainty and imprecision like “set theory and interval analysis, fuzzy sets, rough sets, shadowed sets, probabilistic sets and probability [...], high level granular constructs” (Bargiela, Pedrycz, 2002, p. 5). The term granular computing was first suggested by Lin (1998a, 1998b).

FUNDAMENTALS OF GRANULAR COMPUTING

Singular and Granular Values

To more formally describe the difference between natural language and precise information let us recall the example sentences given in Section 2. The infor-

Figure 1. Mapping of Singletons and granular values

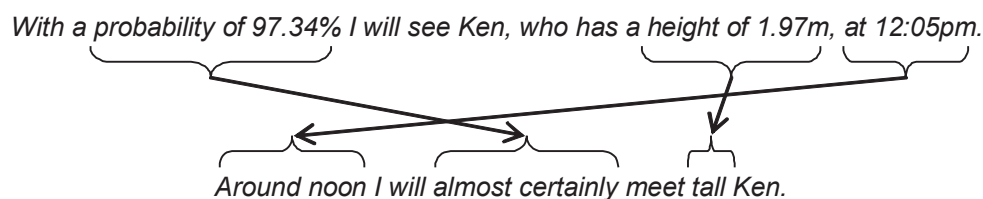


Table 1. Singular and granular values

Variable	Singular Values	Granular Values
Probability	97.34%	almost certainly
Height	1.97m	tall
Time	12:05pm	around noon

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