

HI TECH MICROECONOMICS AND INFORMATION NON-INTENSIVE CALCULI

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Abstract

The article establishes link between the contributions made to the study of hi tech phenomena. It analyzes the evolution undergone by studies on the topic of the knowledge economics (HI-TECH) process carried out by different disciplines (hard and soft sciences – sociology, ecology etc.) from the point of view of the objectives they pursue. The attentions are concentrated on analysis of applicable mathematical tools used to develop realistic formal models. Information intensity is defined as the amount of information which is needed for the realistic application of a corresponding formal tool. High information intensity is desirable because it influences the model accuracy. Low information intensity is preferred when high information intensity requires more information items than are available and this is usually the case in knowledge engineering. Fuzzy models seem to be a useful extension of formal tool used in hi tech microeconomics. However, even fuzzy sets could be prohibitively information intensive. Therefore the range of available formal tools must be considerably broader. This paper introduces qualitative and semiquantitative models and rough sets. Each formal tool is briefly characterized.

Key words

Hi tech, Fuzzy, Rough, Non-intensive calculi, Microeconomics

Introduction

The process of knowledge economics (HI-TECH) embraces a wide range of activities that contributes to the generation of new technological knowledge and/or improved use of the knowledge available. It has been recognized that the HI-TECH process has had varying effects both at macro (society, economic system, and industry) and at micro level (firm).

The extent of the effects of technological development has aroused growing interest. The HI-TECH process has been studied by many disciplines having to do with a broad spectrum of socioeconomic phenomena.

Over recent years, advances have been made in bringing together contributions proceeding from differing disciplines. Furthermore, some theoretical studies have tried to integrate and find coherence among the research undertaken by variety of computer algorithms.

FORMAL TOOLS

Since the first appearance of commercially available computer hardware, it means since the seventies, numerical mathematics and statistical analysis is frequently used. Typical examples are linear programming and regression analysis. So-called hard sciences mainly engineering have developed very many different formal models. Typical examples of such models are sets of differential equations. The main reason why the hard science have been so successful in

computerisation of their objects of study is that important variables are easily measurable and it is possible to do different sorts of planned experimentation.

Soft sciences as marketing, sociology etc. are any analysis in a role of a passive observer. He/she cannot pre-plan any sequence of experiments to test his/her hypothesis. The inevitable consequence is that accuracy of models used in soft sciences is order of magnitude lower compared to hard sciences.

Nearly twenty years during seventies and eighties soft science took over algorithms and different methodologies originated in hard research [A7]. Such originally hard algorithms were used directly or were slightly modified. Therefore it was easy to predict development in computerisation trends in soft sciences by studying corresponding trends in hard sciences. Such one way knowledge transfer gradually disappeared during early nineties. During this period hard sciences were in a sort of an information crisis [A8]. Everything what was possible to analysis using numerical quantification everything what was safely measurable was analysed by the classical formal tools. However, just numbers do not quantify the real world. Many extremely important variables are so difficult to measure / observe that numbers are simply too information intensive and verbal quantification is the most accurate information we can hope for. Typical examples are long term predictions.

Briefly speaking classical formal tools such as mathematics and logic were not capable of dealing with new requirements namely analysis of very vague, sparse and heavily inconsistent information [B1]. On the other hand soft sciences cannot afford the luxury of ignoring such difficult-to-analysis knowledge and data items which have been ignored by hard sciences for a very long time simply because modest amount if numerical information items were available. The soft sciences were therefore forced to move into such areas as applied artificial intelligence sooner than hard sciences simply because of shortage of information.

The consequence was that the originally one way of knowledge transfer between hard and soft sciences was gradually transferred into a mutually beneficially exchange of ideas. An example of productivity of an originally soft idea in hard sciences is an idea of a sociological questionnaire. If prohibitively difficult problems are studied in soft sciences so the semi only way of data gathering is a questionnaire. Sociology developed a methodology how to test a level of discrimination power of different questionnaires and therefore it is possible to choose the best possible questioner [A5]. It is possible to question experts systems / computer programs using the same methodology as if human beings are questioned.

UCERTANTIES

Complex systems cannot be analysis on the deterministic level because there are always simplifications and many variables are therefore not considered. Therefore such models cannot perfectly reflect behaviour of real systems. Uncertainty problems have been studied for centuries on philosophical level, see e. g. [R1] and consequently formalised using available mathematical tools, see e g. [R2]. The availability of computers which can perform complicated numerical algorithms generated certain optimism, see e g. [R3 – 4]

However, a short period of optimism swiftly disappeared in confrontation with reality. The current pessimism can be briefly characterised as follows:

Exceptionally high level of variability of objects studied as knowledge economics research, their dimensionality, uniqueness is extremely difficult if not impossible to follow strictly according the requirements of statistical analysis because it would mean that the requirements concerning the total number of available observations would be prohibitively high

Similar or quasi-identical situation appeared in all branches of science and engineering. Therefore attempts were made to formalise a simplification of problems [R5] Even engineering in spite of the relative abundance of data reached such level of its development when it was unacceptably expensive to increase accuracy of its models. Pressure of industry generated new formal tools capable of dealing with different types of uncertainties, for example

- Interval algebra [T1]
- Order of magnitude modeling [T2]
- Semiquantitative analysis [T3]

It is impossible to study all these calculi in details. It is clear that some of them will be used in research soon. Their applicability is mainly question of attracting attention of experts and their ability to learn how to use them.

The new formal tools mentioned above cannot solve all problems linked to the data shortages. They are still too information intensive. Human brain solves problems without numerical quantification. This fact triggered the development of artificial intelligence, which represents an unbelievable broad spectrum of different algorithms and philosophies. A useful introduction and definitions of basic concepts is given in [T6] [T7].

Practical applications of artificial intelligence have been done so far by expert systems. Expert systems are computer programs. Such programs can be relatively simple or extremely sophisticated algorithms and their prices can vary from several dollars to hundreds of thousands dollars. Suitable classical introductions can be found in [T8], [T9].

Expert systems mimic the human way of solving problems. There are very many different approaches e.g. fuzzy logic and qualitative reasoning. The complexity of underpinning theory usually eliminates self-made expert systems. Therefore an average user is forced to use commercially available expert systems. Users are in a very similar situation as far as the statistical packages are concerned [A4].

Users are forced to concentrate their attention on vague information items [A2]. To collect such items is not easy without modifying them. However, any modification means a potential loss of information. Therefore knowledge engineering was developed to facilitate the data collection.

INFORMATION NON-INTENSIVE CALCULI

The following are considered as promising formal tools [A3, B2,B3, B4]:

- qualitative modeling

- fuzzy sets
- semiquantitative modeling
- rough sets

The most frequently used information non-intensive calculus is fuzzy mathematics. . However, under certain conditions even fuzzy descriptions can be too information intensive and therefore require a quality of information which is simply not available [V1]. Therefore less information intensive calculi are needed.

Roughly speaking human like way of thinking is based on non-mathematical approach to a solution of two basis problems namely [A3]:

- quantification of uncertainties and risks linked to these uncertainties
- non numerical solutions

see e g [W1]

The first problem was discussed above. Non numerical problem solution is based on experience gathered during lives of all human beings. Such type of experience is not accessible for any computer. Even a small baby intuitively understands that he can pull his toy if the toy is on a rope but such toy cannot be pushed.

Let us try to answer the following question using traditional mathematics:

Can a toy on a rope be pushed?

The traditional way of answering would require many quantitative data and application of sophisticated algorithms of strength analysis. However, the common sense application eliminates all such complex data sets and methods.

Problems of diagnosis of complex engineering systems, e.g. nuclear submarines originated research of methods, which, to certain level, mimic human common sense reasoning, see e.g. [W2] using naive physics, see e.g. [W3]

Concepts of naivety looks simple, however to formalise it is a tricky task. Simple qualitative information items, which are typical information inputs to naive algorithms, are

- *increased investments into hi tech development generate increased sales*
- *costs of local advertisements is lower compared to federal advertisements*

Qualitative modeling is a promising approach to naïve reasoning. Therefore it can be used even in an information intensive environment (e.g. diagnosis of electronic circuits). It is not the goal of this paper to specify an algorithm for qualitative modeling. There is already an extensive literature covering this subject. From this point of view of uncertainty, however, it is clear that one major reason for using qualitative modeling is our ignorance of the numerical values of the constants in the equations (conventional model) describing complex hi tech microeconomics systems [A1].

A semiquantitative model is a model which is somewhere between a conventional quantitative model and a qualitative model. The driving reason behind an attempt to develop such a hybrid model is to achieve a compromise between the accuracy of a quantitative model and the ease with which it is possible to develop a qualitative model. A semiquantitative model to a certain extent keeps the advantages of both models and eliminates their disadvantages.

Semiquantitative modeling is very similar to both qualitative reasoning and order of magnitude reasoning. The main advantage that semiquantitative reasoning has over these two techniques is that it is more general than either. Its main disadvantage is that it can be very time consuming.

It is easy to show that qualitative reasoning is a special case of semiquantitative reasoning, by considering a set of semiquantitative values with $k = 1$. Thus, it is possible to use semiquantitative algorithms for the solution of qualitative problems. The set of intervals are the only quantifiers in semiquantitative reasoning systems, and so not only the values of variables but also the values of their derivatives must be expressed using three intervals.

Rough sets solve the problem of non-exactness using a new formalism. The basic idea is surprisingly simple [D1, D2].

Conclusion

In practice a hi tech microeconomics makes semi optimal decisions using its past experience which is not formalized at all. Usually no severe mistakes are made provided more or less routine problems are solved. However, fairly often non-traditional decisions must be made. If a knowledge base is to be used in a realistic complex task, it must be heterogeneous. This will inevitably require the integration of many different kinds of knowledge. Therefore a flexible structure of interrelated

This is the background image for sub models of different nature (fuzzy, qualitative, semiquantitative, rough, conventional) is needed. This paper has investigated the properties of semiquantitative modeling largely by comparison with qualitative modeling. Semiquantitative modeling is in some sense a generalization of qualitative modeling, and allows one to reason with more precise information. This property may be useful in situations in which qualitative algebra are prone to over-abstract, giving many identical solutions. Semiquantitative or order of magnitude modeling can overcome these problems.

To a certain degree rough models are degraded semiquantitative models [D1]. The degradation means that an interval is substituted by a verbal quantifier. Therefore there is a close link between rough and semiquantitative models. There are, however, some things that qualitative modeling can achieve that semiquantitative systems cannot [D3]. Qualitative modeling can be used on very sparse knowledge, producing reasonable results. Simply knowing that the time derivative of a quantity is positive allows us to determine that it will grow in magnitude. Such results are not achievable with methods that have a greater reliance on numbers. Thus none of the techniques are superior in every respect, and the hi tech microeconomics is likely to need them all.

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Summary

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HI TECH MICROECONOMICS AND INFORMATION NON-INTENSIVE CALCULI

Hi tech effects on microeconomics are prohibitively vague and thus difficult to formalize. The failure to formalize these connections will, however, make the issues very difficult to study. Results of some parts of applied artificial intelligence are used to describe difficult-to-model multidimensional and interdisciplinary problems. These include calculi such as, e.g., qualitative modelling, fuzzy logic and rough sets. These calculi are not able to fully replace the hitherto indescribable algorithms employed by human brain for the resolution of complicated or even seemingly simple problems. The answer to the question whether a toy on the string can be pushed in front of you or pulled behind you can be arrived at by means of a system of partial differential equations and complicated measurements of the string properties. Or it is possible to do what for instance a two-year old child would do, i.e. to use common sense.

In this article, partial formalization of common sense in hi tech issues and thus also in some areas of knowledge economy is discussed. The article does not deal with these issues mathematically. Rather, it explains to those who are not experts in the field of applied artificial intelligence that there exist algorithms that can be used to formally describe extremely vague systems. It is well-known that formalization is a prerequisite for the use of computer technology with further positive effects for the enhancement of objectivity of the study through the methods for the identification of possible discrepancies in input information.

Without the employment of new calculi, it is not possible to replace classical statistical methods in cases where, because of a complete lack of input information, classical values like, e.g., the mean, cannot be quantified. The study of hi tech aspects of microeconomics is one of areas characterized by such a lack of information. It very often is a description of something that has yet to come into existence and therefore there is no measurable information about it. All or an overwhelming majority of input data are based on estimates and analogies.

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