COMPLEX SYSTEMS IN FOOD SCIENCE: HUMAN FACTOR ISSUES

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ABSTRACT

Building in-silico decision making systems is essential in the food domain, albeit highly difficult. This task strongly relies on multidisciplinary research and in particular on advanced techniques from artificial intelligence. The success of such systems depends on how well they cope with the complex properties of food processes, such as the large variety of interacting components including those related to human expertise; and their dynamic, non-linear, multi-scale, uncertain and non-equilibrium behaviors. Robust stochastic optimization techniques, evolutionary computation and in particular Interactive Evolutionary Computation (IEC) seem to be a fruitful framework for developing food science models. A Human-Centered approach to Interactive Evolutionary Computation is discussed in this paper as a possible pertinent way to cope with challenges related to human factors in this context.

FOOD SCIENCE AND COMPLEX SYSTEMS

Food is a major factor for health and public well-being. It is one of the most important sectors of industry and deals with chemicals, agriculture, animal feed, food processing, trade, retail and consumer sectors. Providing an adequate food supply to a growing world population is one of the grand challenges our global society has to address. Enterprises need to continuously provide safe, tasty, healthy, affordable, and sustainable food in sufficient volumes. This requires adapting to a range of factors, such as the increase in human population and health requirements, and the reduction in crops and livestock due to environmental factors and changes in the socio-political scene (van Mil et al. (2014)). Besides, there is a need for an integrated vision looking at these factors from multiple scales and perspectives:

- from emotion and pleasure generated when eating food to nano-structures of a food emulsion or food microbial ecosystems,
- from regional organization to nutritional and sociological impact,
- from health considerations to inter-crop culture and microbial complexities, within the human body and in relation to food microbial ecosystems.

In these conditions, creativity, pragmatism and optimization methods are crucial to reach breakthrough innovations and sustainable solutions. We foresee a huge opportunity for research in mathematical programming, integrative models and decision-support tools (Perrot et al. (2016)) to address the aforementioned challenges. Any proposed mathematical programming framework, however, has to deal with the following characteristic features of food systems:

- The uncertainty and variability (in process, data and available knowledge) that severely influences the dynamics and emergence of various properties,
- The heterogeneity of the data, from big volumes at the genomic scale to scarce samples at a more macroscopic level (i.e. process scales). For instance an ecosystem of 9 microorganisms can be characterized using 40,000 genes, and its dynamics with 10 aromatic compounds,
- The complexity of qualitative and quantitative information, for instance for social and environmental evaluation, at various scales in space and time,
- The variety of perspectives, types of models, research goals and data produced by conceptually disjoint scientific disciplines, ranging from physics and physiology to sociology and ethics.

Moreover, there is a need to find an appropriate description level, able to express the complexity of an ecosystem with minimum uncertainty. Building models is essential, but highly difficult; efficient modeling necessitates a rigorous iterative process combining computationally intensive methods, formal reasoning and expertise from different fields.

THE HUMAN FACTOR

The specifics of food domain bring to focus another major player, what can be called the human factor. Although not very evident, most of the computing approaches rely on human capabilities, for example, to

organize a model and generalize it. They also rely on domain experts and an appropriate methodology to handle their expertise. In fact, at every stage, human expertise and decision making are highly important for improving the understanding of food systems, and as such, they should be integrated in the computation.
There is a long tradition in artificial intelligence (AI) of involving humans in the computational loop. Expert systems, for instance, have been specifically designed for mimicking the decision-making ability of a human expert. Learning, classification, natural language processing, search and optimization are many facets of this domain, all aimed at answering fundamental questions like: How does the human mind work, and can non-humans have minds? (Kohavi and Provost (1998), Tonda et al. (2013)).
Real-world applications of AI are definitely complex, but not only. The questions asked are themselves complex. In particular, when dealing with optimization, the evaluation of a complex system state relies on multiple criteria that may be numerous, uncertain, noisy and subjective. The possible answers are dealing more with tradeoff and equilibrium stages than with the classical notion of optimum. Several, and often many, objectives have to be considered simultaneously.
The vast subject of sustainability, for instance, clearly needs multi-objective optimization tools. The United Nations have adopted the following definition on March 20, 1987: a sustainable development is a development that meets the needs of the present without compromising the ability of future generations to meet their own needs. This statement has the major advantage to emphasize management policies where economy is not the unique concern. However, it definitely requires an evaluation of a series of criteria, and an optima that represent compromises between various incompatible aims, like financial profit and nature preservation.
Evaluating sustainability in practice is extremely difficult, subjective and scale dependent. Current techniques, such as Life Cycle Analysis (LCA), consist of creating an inventory of flows from and to nature for a given system. This inventory is supposed to take into consideration every input and every output of the system. Then, some impact factors are computed according to international standards (ISO 14000 for environmental management) and available databases of typical values. Various global environmental impact factors are then computed via weightings, in which it is recognized that a high degree of subjectivity is at play. These quantities are then used for decision making.
Various critiques can be made to these types of approaches: a LCA strongly depends on available data, and databases may become obsolete as new material and manufacturing methods constantly appear. Additionally, even if LCA is a powerful tool for analyzing measurable aspects of quantifiable systems, some effects (human, social, psychological) cannot be reduced to numbers and inserted into existing models. Once again, efficient and versatile computer optimizations are desirable for improving the accuracy of existing approaches, but at the same time, it seems clear that in this context, decision making cannot be delegated to machines.

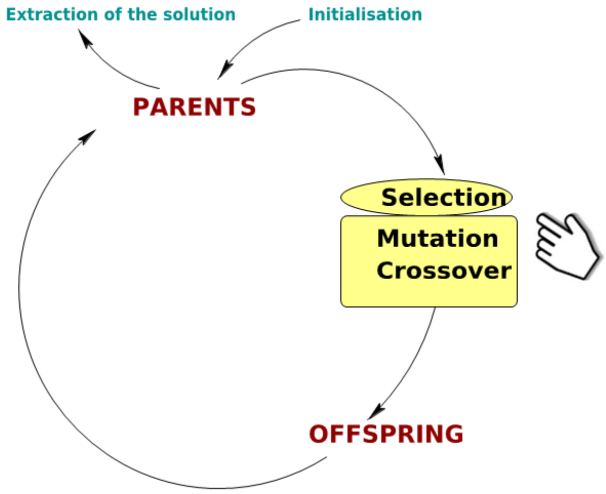

Figure 1: The evolutionary loop. User interactions can occur at any stage including selection/evaluation of individuals and the genetic operators.

THE HUMANIZED COMPUTATION PERSPECTIVE

The idea of a humanized computational intelligence consists of directly embedding the capability of a human in a computational system, instead of using a representative model as more classical AI approaches. In other terms, it aims at dealing with complex problems by combining human capabilities with autonomous computations, leveraging the strengths of both sides (Takagi (1998)).

Interactive Evolution

One of the most advanced techniques in this direction are interactive evolutionary computation (IEC) approaches, based on evolutionary algorithms. Evolutionary Algorithms (EAs) are stochastic optimization heuristics that copy, in a very abstract manner, the principles of natural evolution that let a population of individuals be adapted to its environment (Goldberg (1989)). An EA considers populations of potential solutions exactly like a natural population of individuals that live, fight, and reproduce, but the natural environment pressure is replaced by an optimization pressure. Reproduction (see Fig. 1) consists of generating new solutions via variation schemes (the genetic operators), that, by analogy with nature, are called mutation if they involve one individual, or crossover if they involve two

parent solutions. A fitness function, computed for each individual, is used to drive the selection process, and is thus optimized by the EA. More specifically, Interactive Evolutionary Computation (IEC) is focused on the optimization of subjective quantities captured via a user interface.
Whereas current IEC research has focused on improving the robustness of the underlying algorithms, much work is still needed to tackle human-factors in systems where adaptation between users and systems is likely to occur (Mackay (2000)). Applications of IEC range from artistic to scientific projects (Takagi (1998), Lutton (2006), Tonda et al. (2013)). For scientific and engineering applications, IEC is interesting when the exact form of a more generalized fitness function is not known or is difficult to compute, say for producing a visual pattern that would interest a particular user. Here, the human visual system, together with the emotional and psychological responses of the user in question are far superior than any pattern detection or learning algorithm.

The Visible & Hidden Roles of Humans in IEC

The role of humans in IEC can be characterized by the evolutionary component at which they operate (Fig. 1), namely: initialization, evolution, selection, genetic operators, constraints, local optimization, genome structure variation and parameters tuning, which may or may not be desirable from a usability perspective especially for non-technical users.
The general approach when humans are involved, especially for parameter tuning, is mostly by trial-and-error and reducing the number of parameters. Such tasks are often visible, in that they are facilitated by a user interface. However, there exists a hidden role of humans in IEC that has often been neglected. Algorithm and system designers play a central role in deciding the details of the fitness function to be optimized and in setting the default values of system parameters (contributing to the "black box" effect of IEC systems). Such tasks are influenced by the previous experience of the designers and end-user task requirements. Besides this hidden role in the design stage, there is a major impact of the human in the loop on the IEC itself. This problem is known as the "user bottleneck" (Poli and Cagnoni (1997)), i.e. a human fatigue due to the fact that the user and machine do not live and react at the same speed. Various solutions have been considered in order to avoid systematic and repetitive or tedious interactions, such as: (i) reducing the size of the population and the number of generations; (ii) choosing specific models to constrain the exploration in a-priori interesting areas of the search space; and (iii) performing an automatic learning (based on a limited number of characteristic quantities) in order to assist the user and only present interesting individuals of the population, with respect to previous votes or feedback from the user. These solutions require considerable computational effort.

Example: Guided Search for Agronomy

EvoGraphDice (Boukhelifa et al. (2013)), was designed to aid the exploration of multidimensional datasets where 2D projections of combined dimensions are of interest to agronomists. Starting from dimensions whose values are automatically calculated by a Principal Component Analysis (PCA), an IEC progressively builds non-trivial viewpoints in the form of linear and non-linear dimension combinations, to help users discover new interesting views and relationships in their data. The criteria for evolving new dimensions is not known a-priori and is partially specified by the user via an interactive interface. Pertinence of views is modelled using a fitness function that plays the role of a predictor: (i) users select views with meaningful or interesting visual patterns and provide a satisfaction score; (ii) the system calibrates the fitness function optimized by the evolutionary algorithm to incorporate user's input, and then calculates new views. A learning algorithm was implemented to provide pertinent projections to the user based on their past interactions. The evaluation of EvoGraphDice (Boukhelifa et al. (2015a;b)), followed a mixed approach where, on the one hand we observed the utility and effectiveness of the system for the end-user (user-centered approach); and on the other hand we analysed the computational behaviour of the system (algorithm-centered approach). Based on these evaluations, it appears that the interactive evolutionary algorithm, with the help of user feedback, was able to converge quickly to an interesting view when a clear task was specified (Boukhelifa et al. (2015a)). In the other direction, the IEC allowed users to laterally explore different possibilities (Landrin-Schweitzer et al. (2006)),better formulate their research questions and build new hypotheses for further investigation (Boukhelifa et al. (2015b)).

CONCLUSION: RESEARCH OPPORTUNITIES FOR IEC IN FOOD SCIENCE

Decision making in food science requires methods able to efficiently cope with experts knowledge. IEC represents an attractive framework for embedding expertise and human factors in computational systems. However, user-driven optimization processes rely on systems that adapt their behavior based on user feedback, while users themselves adapt their goals and strategies based on the solutions proposed by the system. This two way communication and adaptation presents prospects to conduct future research. We discuss these below as research opportunities aiming to facilitate and support the different roles humans play in IEC, i.e. in the design, interaction and evaluation of IEC systems.

- *Human-Centered Design:* during the design, development and evaluation of many of our tools (see Tonda et al. (2013)), we worked with domain experts at different levels. For EvoGraphDice, for instance, we largely benefited from having a domain expert as part of the design and evaluation team. However, this was carried out in an informal way. Involving end-users in the design team is a long-time tradition in the field of Human-Computer interactions (HCI) as part of the user-centered design methodology. Participatory design, for instance, could be conducted with IEC end-users to incorporate their expertise in food domain at the design level of the algorithm.
- *Interaction and Visualization:* often the solutions proposed by the IEC are puzzling to the end-user. This is because the inner workings of the evolutionary algorithm and user exploration strategies that led to the solution are often not available to the user. This black box effect is challenging to address as there is a fine balance to find between the richness of a transparent interface and the simplicity of a more obscure one. Finding the tipping point requires an understanding of evolving user expertise in manipulating the system, and the task requirements. Whereas user-centered design can help elicit these requirements and tailor tools to user needs over time, visualization techniques can make the provenance of views and the system status more accessible: there exists rich and varied interaction techniques to facilitate user feedback in parallel to developing robust user models that try to learn from the provided input.
- *Multifaceted Evaluation:* the evaluation of an IEC system remains a difficult task as the system adapts to user preferences but also the user interprets and adapts to system feedback. Getting a clear understanding of the subtle mechanisms of this co-adaptation (Mackay (2000)) is challenging and requires to consider evaluation criteria other than speed of algorithm convergence and the usability of the interface. In the context of data exploration, desirable features can be characterized by lateral thinking, surprising findings, and the way users learn how to operate the interactive system and construct their own way to use it. Our observation is that the tunable balance between randomness and user-guided search provided by IEC seems to be very efficient for this purpose.

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