ARTIFICIAL INTELLIGENCE IN WINE-MAKING

L'INTELLIGENCE ARTIFICIELLE EN ŒNOLOGIE

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Abstract : In this paper, some terms of Artificial Intelligence are defined. Some present and potential applications of knowledge based systems are presented in the field of wine-making. Areas of concern were: multi sensor fusion, prediction by model cooperation, and diagnosis. Artificial intelligence techniques can indeed be applied for aiding the wine-maker in his choices. They facilitate the combination between experience and recent progress in technology. When associated with statistical processing, they allow knowledge sources to be used more effectively. Beyond wine-making, the prospects of artificial intelligence are promising for research and food industry, especially for improving the robustness of measurement systems (multi-sensors, sensors interpreted or validated by models), and for process diagnosis (risk prediction, action proposal).

Résumé : Certains termes d'Intelligence Artificielle (IA) sont définis dans cette publication. Quelques applications en cours ou potentielles de systèmes fondés sur la connaissance sont présentés dans le domaine de la vinification. Les domaines d'étude sont : la fusion multi-capteurs, la prédiction par coopération de modèles, et le diagnostic. Les techniques IA peuvent aider le vinificateur dans ses choix par une symbiose entre expérience et progrès technologiques. En association avec des traitements statistiques, ces techniques permettent une utilisation plus efficace des sources de connaissances. Au-delà de la vinification, les perpectives de l'intelligence artificielle sont prometteuses en industrie alimentaire, en particulier pour améliorer la robustesse d'un système de mesure (fustion de capteurs, validation d'un capteur par un modèle) ou pour élaborer un diagnostic sur l'évolution d'un procédé (prédiction de risques, proposition d'intervention).

Key words : artificial intelligence, wine-making, sensors, fusion, model, cooperation, diagnosis

Mots clés : intelligence artificielle, vinification, capteurs, fusion, modèles, coopération, diagnostic

CONCEPTS OF ARTIFICIAL INTELLIGENCE

Artificial Intelligence (AI) is the study of how to make computers do things which, at the moment, people do better (RICH and KNIGHT 1991). AI began in the early 1960s. The first attempts were game playing (checkers), theorem proving (a few simple theorems) and general problem solving (only very simple tasks).

The best known AI technique is the Expert System (ES). It allows the representation of big sets of knowledge in specialized areas. The objective of an ES is to reach levels of performance comparable to those of the best human specialists. The ES architecture has a fact base containing data and a knowledge base compiling reasoning rules. The ES inference engine, made of procedures, manipulates the facts and the rules and provides solutions to a given problem. ES are mainly used in areas where knowledge control is essential, i.e., in medical or financial areas.

Together with ES, a large spectrum of techniques are relevant to AI: neural networks, genetic algorithms, logic programming, fuzzy logic, qualitative reasoning, etc.

ES concept was extended lately to the larger concept of Knowledge Base Systems (KBS). KBS can gather any kind of knowledge: AI models, deterministic or statistical models, data or case bases, etc.

This paper presents some applications and prospects of KBS in the field of wine-making: multi sensor fusion, prediction by model cooperation, diagnosis.

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MULTI SENSOR FUSION

“Multi sensor fusion” is an emerging technology dealing with the combination of pieces of information about a physical event, an activity, or a situation. It aims at obtaining better results than those obtained by the sensors individually (HALL 1992).

The feasibility of predicting evolution parameters in fermentation processes by means of neural network models was demonstrated by several authors, i.e., STEINMETZ *et al.* (1995, 1996), LATRILLE *et al.* (1996), TEISSIER *et al.* (1997). STEINMETZ *et al.* (1995, 1996) improved the prediction of the acidity content in Champagne wines by replacing linear models by neuronal networks. The model realized by laboratory data, obtained from micro-fermentations, was tested successfully with industrial data, demonstrating thus its robustness. LATRILLE *et al.* (1996) and TEISSIER *et al.* (1997) had good results with hybrid recurrent neural network model for yeast production monitoring and control in a wine base medium.

Neural network models could be used in the future by wine-makers for wine fermentation control or wine blending optimization, thus contributing to the improvement of wines.

COOPERATION BETWEEN MODELS

I - PREDICTION OF STUCK FERMENTATION RISK

In wine-making, sluggish and stuck fermentations represent a big issue. Improvements in fermentation control have lowered the risks but the economical cost of stuck fermentations is still important. Yeast inhibition by ethanol is one of the major causes but other mechanisms are involved: nitrogen deficiency, thiamin depletion, lack of oxygen, excessive clarification of juice, inhibition of yeasts by fermentation by-products, especially octanoic and decanoic acids, by killer toxins and by pesticides… Consequently, predicting the risks of sluggish or stuck fermentations is very difficult.

Several models based on yeast physiology have been proposed to describe the kinetics of alcoholic fermentation but they cannot be applied to enological conditions which are very complex and variable. This is the reason why several ‘black box’ models have been described by BOVÉE *et al.* 1984, EL HALOUI *et al.* 1989, LOPEZ and SECANELL 1992, and SABLAYROLLES *et al.* 1993 (in anisothermal conditions). Unfortunately, none of these models applies to all enological contexts. Moreover, most of them are very imprecise at the end of fermentation, when predicting would be useful to prevent stuck fermentations.

What Artificial Intelligence allows

a) Connexionism (or neuromimetism), a way forward

The Group Data Treatment Method (GDTM) is suited to non-linear, complex or little known processes (CLÉRAN 1990). It elaborates a polynomial model, associating explained variables with explicative variables. The model is built step by step. Each step is called a layer. The first step contains all the explaining variables. A defined number of polynomes is statistically selected. The selected polynomes act as input variables for the next step (or layer) and so on. The initialization of the algorithm parameters is based more on know-how than on a theoretical approach. The database is divided into identification and validation subsets. The GDTM method is very similar to neural nets.

GDTM method and neural networks have been compared by CLÉRAN (1990) for predicting alcoholic fermentation kinetics. Neural networks provide more accurate prediction than GDTM, but the latter is more robust when applied to atypical fermentation samples.

The potential of neural networks has been evaluated by BOUYER (1991) for simulating alcoholic fermentations. Experimental values used in this work were estimated at laboratory scale fermentors with on line monitoring of kinetics (SABLAYROLLES *et al.* 1987). The characteristics of black box models made by neural networks are essentially their ability to make generalization (correct response to situations not studied during learning) and their good stability (if the network makes a mistake, it describes fairly well the shape of the response without ever diverging). The main problem is the large diversity of the fermentation kinetics to be predicted, and the fact that these data have noise. This contributes to increase the average error in a simulated curve. In the opposite, the easiness of using neural networks is certainly an advantage. By adding to the input of a net the advancement from 0 to 3 p. cent of a fermentation, recurrent networks can predict fermentation kinetics. The generalization properties of neural networks for other initial conditions (sugars, nitrogen) are satisfying, in the limit that the relative error is less than 14 p. cent. The design of specialist networks has allowed to increase significantly the generalization performances. Best results for the prediction of the end of the kinetics from the knowledge of 20 p. cent of advancement have been obtained by coupling a main component regression analysis to a multi-layer neural network approach. This technique, which consists in the decomposition of the function to be estimated with a linear component and a non-linear neural network component, has proved to be efficient in this case.

INSA *et al.* (1994) combined statistical and neural networks for predicting the risks of stuck and sluggish fermentations. They tried to compensate the lack of analytical information by precise information about the kinetics (instantaneous CO_2 production rate) and by testing a large number of musts. The objective was to predict the risk at the beginning or at the middle of the fermentation, that is to say when nutrient additions are still efficient. Fermentation kinetics were classified according to dm80 i.e., a criterion calculated from the decrease of the CO_2 production rate at the end of fermentation and proportional to the final yeast viability.

A correspondence factorial analysis was calculated from the values of the CO_2 production rate up to the half-way point of fermentation. The essential of the variance of the fermentation kinetics was described by the three first main components (F1, F2 and F3). The values of the maximum CO_2 production rate and the initial sugar concentration were also taken into account.

In a first step, a multi-linear regression was tested with these 5 parameters: only 35 p. cent of the sluggish fermentations were correctly predicted. Using a discriminant factorial analysis, the prediction was better i.e, 58 p. cent. Linear models were then replaced by 3-layer neural networks with 5 input variables, one output variable (dm80), and 3 neurons in the hidden layer. The precision of the prediction was the same than the one obtained by discriminant factorial analysis.

Other kinds of networks have proved to be interesting for processing data about fermentation breakdowns. I. ALVAREZ (1995) has used the software NeuroAgent (IntelliSphère) which permits to visualize with the same formalism knowledge extracted by learning and knowledge extracted from the expert.

A discretisation of the variable inputs was made. For a classification into 5 equidistant classes, the results of prediction for all classes mixed were not very good, in the order of 60 p. cent. Reversely, concerning the prediction of two sensitive classes (non-finishing risks), scores were 64.7 p. cent and 70 p. cent for the learning class, and 70 p. cent in average for the test base. When the number of input variables increases, results are better: 76 p. cent for classes sensitive to the learning base, and 70.5 p. cent for the test base (the prediction of sensitive classes is unchanged for the test base). The use of a simple probabilistic network gives good results for the identification of risky musts.

b) Model based on expertise

GRENIER *et al.* (1988) have suggested to formalize by production rules the available know-how, concerning the piloting of alcoholic fermentations in enology. They have faced the lack of available expertise, and the necessity of constituting reliable databases for extracting additional knowledge.

With the objective of collecting observations according to a standard format, AGABRA *et al.* (1997a) have realized an inquiry about sluggish fermentations. The first results, added to the interview of scientists, have permitted to propose a system of organization and implementation of contextual knowledge in a knowledge base system (AGABRA *et al.* 1997b). This system describes the links of causality between parameters such as: kind of vineyard, grape variety, soil, yield, enherbment, pesticides, harvesting technique, rain falls, stemming, pellicular maceration, must turbidity, additions of bentonite or caseine, vat, yeast strain, yeast inoculum, chaptalisation, oxygenation, thermal regulation…

The causality graph designed by AGABRA *et al.* (1997b) reminds as much expert systems as qualitative reasoning. It permits to formalize a system when the functioning is known, but where the statement of mathematical expressions is not always possible (STEYER 1991, GUERRIN *et al.* 1993).

c) Cooperation between models

In the case of complex systems or processes, it might be difficult to use one single type of model. For instance, deterministic models might carry too much imprecision for proper use. This is the case when biochemical mechanisms are little known or too much complex for an exhaustive description. The deterministic model is then uncomplete. The model applies to some data and under certain hypotheses (steady state phenomenon, uniform mixing…). Accordingly, a model based on expertise can be too rough for leading to a conclusion, as expert knowledge is often qualitative. As far as models built by learning are concerned, they work as black boxes and their ability to explain is low. In addition, it is difficult to control over time their ability to make generalization.

The limits of each type of model have encouraged researchers to combine them. For instance, the expert system can give clues that can be used as inputs of neural networks (ROLI *et al.* 1995). One system is used for permitting an adaptation or an optimization of the other. A neural network can be used for modifying uncertainty coefficients of rules inside of an expert system, or for adding rules (NOTTOLA *et al.* 1991). Reciprocally, fuzzy sets can be used as activation functions in a neural network (KRISHNNAPURAM and LEE 1992).

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AGABRA and ALVAREZ (1997) suggest, for the prediction of sluggish fermentation, a cooperation between models which includes the final user, whatever expert or not (ALVAREZ 1992). The cooperation deals with the consistency between models (RIVIERE 1994) in order to bring into relief the weakness of each model (default of generalization in a model built by learning, default of knowledge in a model built by expertise, weakness of hypotheses in a deterministic model, etc) and to permit also, with the help of the expert, the improvement of the results of the global system. Other cooperation possibilities can be studied, based on the characteristics of each model as a function of the context (AGABRA 1998a, 1998b).

II - ESTIMATION OF POLLUTION CHARGE

1) Context

Designing a waste treatment unit requires precise knowledge of pollution fluxes at peak time and in average along the grape-picking period. Experience shows an important variability of estimated pollution charges. Thus a thorough validation of measurements is required.

GRENIER *et al.* (1998) have suggested a methodology for estimating a winery pollution charge based on the cooperation between two sources of knowledge: a reference database in one hand, measurements and their interpretation in the other hand. The method requires the knowledge of the annual ratio of consumed water to produced wine and the duration d of the grape-picking period. It works with only 3 parameters: Volume of wastes (V), Oxygen Chemical Demand (OCD), and Suspended Solids (SS). These parameters are enough to characterize roughly winery wastes.

A database was built for winery wastes, including: enological practice, water consumption, volume and characteristics of wastes, and specific pollution charges for some unit operations. Trends were presented by unit operation and by geographical area. The regional context permits to classify quite well the winemaking practice.

2) Cooperation between database and measurements

Measurements, made during a minimum of 3 days at about 3 days after the peak of maximum grape daily input into the winery, permit to estimate the average values of the parameters V_{peak}, OCD_{peak}, and SS_{peak}. Then, the cumulated values of these parameters over the grape-picking period are estimated as functions of the duration of the grape picking period (d), of the peak parameters (V_{peak}, OCD_{peak} and SS_{peak}), and of coefficients A, B or C evaluated by experience.

V_{total} = function of (d, A, V_{peak})

OCD_{total} = function of (d, B, OCD_{peak})

MES_{total} = function of (d, C, MES_{peak})

The database provides a ratio between annual wine production and consumed water, and average OCD and SS concentrations in wastes. The database thus permits to estimate reference values for V_{total}, OCD_{total}, and SS_{total}.

The question is: can the values of V_{total}, OCD_{total}, and SS_{total} estimated by measurements be accepted as good values according to the database reference, or should the measurements be made again?

This is where the model cooperation takes place. The term model is taken here in the broad meaning of a piece of knowledge formalizing facts. The prediction of V_{total} from measurements is considered as a model. And so is the database reference estimation.

The method follows the reasoning that an expert would have, while taking benefit from applied mathematics rigor. Uncertainty of measurements and of reference values are combined and yield fuzzy numbers representing levels of acceptability between 0 and 1 as a function of possible values. The measurements are accepted as being good when the level of acceptability is above 0.5.

Of course, there are some particular cases. When a case is special, when it remains special after repeating the measurements, when a fuzzy comparison between repetitions yields an acceptability level above 0.5, and when there is an expert explanation to its particularity, then the average of the two measurements is considered as a good estimation.

DIAGNOSIS

In ROGER (1995), the term “diagnosis” is defined as follows: based on observations made on a system, a diagnosis consists in characterizing the state of the system, i.e., the whole set of parameters able to influence it. Practically, diagnosis is based on a reasoning upon facts with causality or expert knowledge. It consists in hypothesis generation thanks to knowledge sources such as models, followed by a deduction phase.

An effective method for generating hypotheses in a diagnosis approach is to consider case base reasoning whenever a significant amount of experience is available. Case base reasoning systems work with an indexed base. When a new case is met, the system makes an investigation for suggesting the closest case to the study case. A solution adapted to the study case is elaborated from the selected past case.

Interesting applications of the diagnosis paradigm can be expected in risk assessment of jeopardizing quality during wine processing.

CONCLUSION

Some present and potential applications of knowledge based systems in wine-making were presented in this paper. Areas of concern were: multi sensor fusion, prediction by model cooperation, and diagnosis. They illustrated how artificial intelligence techniques in enology can aid the wine-maker in his choices. They facilitate the combination between experience and recent progress in technology. When associated with statistical processing, they allow knowledge sources to be used more effectively.

Beyond wine-making, the prospects of artificial intelligence are promising for research and food industry, especially for improving the robustness of measurement systems (multi-sensors, sensors interpreted or validated by models), and for process diagnosis (risk prediction).

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