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Bayesian networks to explain the effect of label information on product perception

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Abstract

Interdisciplinary approaches in food research require new methods in data analysis that are able to deal with complexity and facilitate the communication among model users. Four parallel full factorial within-subject designs were performed to examine the relative contribution to consumer product evaluation of intrinsic product properties and information given on packaging. Detailed experimental designs and results obtained from analyses of variance were published [1]. The data was analyzed again with the machine learning modelling technique Bayesian networks. The objective of the current paper is to explain basic features of this technique and its advantages over the standard statistical approach regarding handling of complexity and communication of results. With analysis of variance, visualization and interpretation of main effects and interactions effects becomes difficult in complex systems. The Bayesian network model offers the possibility to formally incorporate (domain) experts knowledge. By combining empirical data with the pre-defined network structure, new relationships can be learned, thus generating an update of current knowledge. Probabilistic inference in Bayesian networks allows instant and global use of the model; its graphical representation makes it easy to visualize and communicate the results. Making use of the most of data from one single experiment, as well as combining data of independent experiments makes Bayesian networks for analysing these and similarly complex and rich data sets.

Keywords: Bayesian networks; combining data; product perception; food information.

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1. Introduction

Food product evaluation by consumers can be considered to be very complex as a result of different information processes, which are related to the processing of sensory input and cognitive information, and their interactions [1, 2]. For example, consumer preferences in food consumption are influenced not only by the intrinsic food properties but also by cultural, economical, psychological, social and environmental factors. As a consequence of this, and in a larger context, food research is moving toward an interdisciplinary approach. This trend brings together data from various related sources and experts with different backgrounds [3]. Accordingly, new methods in data analysis should be able to deal with complexity and to facilitate the communication among model end-users from different disciplines.

Bayesian network modelling is a machine learning technique that incorporates graphical elements [4]. A Bayesian network model consists of two components: structure and parameters [5]. The network structure is a graph formed by a set of variables linked to each other by a set of arrows. These arrows imply possible cause-effect relationships. The network parameters are made up by a set of conditional probability values that quantify these relationships. These two components can be inferred and estimated from the combination of (domain) expert knowledge and empirical data [6]. Despite of its popularity in many fields, such as finance, medical diagnosis, robotics and ecology [7], Bayesian networks have been rarely applied within the food domain [5, 8].

The current paper addresses the use of Bayesian networks in explaining product perception as affected by product type and label information. It is compared with a previously performed analysis of variance. Basic features of this technique as well as its advantages over this standard statistical approach in terms of communicating results and dealing with complexity are the main focus.

2. Materials & Methods

A large consumer study was performed to examine the relative contribution to consumer product evaluation of intrinsic product properties and information given on packaging. Detailed experiment designs and results obtained from analyses of variance can be found in [1]. A Bayesian network modelling technique was used on the same dataset in the present work.

2.1. Experimental design

Four groups (A, B, C, and D) each of 400 consumers participated in four parallel full factorial within-subject experimental designs. Each consumer in group A received 6 packages of fresh cods resulting from the combinations of 2 product types (denoted 'Cod type' as factor name), being 'farmed' or 'wild' (recognized as two states of 'Cod type') and 3 labels on product types ('Label'), being 'farmed', 'wild', or 'no info' (no related information available). The other three groups received 4 packages of fresh farmed cods with varying packaging information related to product freshness, quality control, farming information, and price. All fresh cod products were followed the same pre-treatment procedure before being given to consumers.

Consumers evaluated each cod product two times: before preparation (frying) and after preparation and tasting. They were asked to rate holistic attributes (*good quality, attractive, pleasant*), credence attributes (*fresh, healthy*), as well as analytical sensory attributes (*fatty, lean, dry*, *firm, juicy, tender, flabby, fishy*) on a 7-point scale (0-6, 0 = not relevant, 6 = very relevant).

2.2. Analyses of Variance

Principal component analysis (PCA) was used to reduce data and reveal broader perceptual dimensions. One single variable 'Overall appreciation' (explained 82% total variation) was created to be a weighted combination of five holistic and credence attributes, whereas three sensory variables ‘Tenderness’, ‘Firmness’ and ‘Fattiness’ were created to represent analytical sensory attributes (explained 64% of total variance). Individual scores were calculated for each of these four perceptual dimensions based on the factor scores of the original variables. Within each group, analyses of variance were then performed to examine the main effects and interactions of the independent factors on ‘Overall appreciation’, ‘Tenderness’, ‘Firmness’, and ‘Fattiness’.

2.3. Bayesian network modelling

In Bayesian network modelling, consumer ratings of fish products before preparation were included. They were considered consumer expectations of the products given the observation of the fresh product and the information on packaging. Following the same procedure described before, these data were also reduced to the expectation dimensions: ‘Expected appreciation’, ‘Expected tenderness’, ‘Expected firmness’, and ‘Expected fattiness’.

The network structures were defined by expert knowledge. The parameters were estimated from data. Parameter learning and inference were supported by Hugin Bayesian networks software (Hugin researcher, version 7.4, http://www.hugin.com). Starting from a conceptual model, a Bayesian network model was refined based on data of group A, here named LABEL model. In this model, continuous data of ‘Expected appreciation’ and ‘Overall appreciation’ were discretized into four states or categories, being 0-4; 4-5; 5-6; and 6-7, before feeding to the pre-defined network structure.

3. Results & Discussion

3.1. Analyses of variance

For each experimental group, the effects of the independent variables on ‘Overall appreciation’, ‘Tenderness’, ‘Firmness’, and ‘Fattiness’ were presented by means (SD), effect size, and p-values in tables [1]. In addition, some significant main effects and interactions were visualized by plots. For example, Fig. 1a shows main effect of ‘Cod type’ and ‘Label’ on ‘Overall appreciation’; Fig. 1b shows interaction effect of ‘Price’ and ‘Farming information’ on ‘Overall appreciation’.

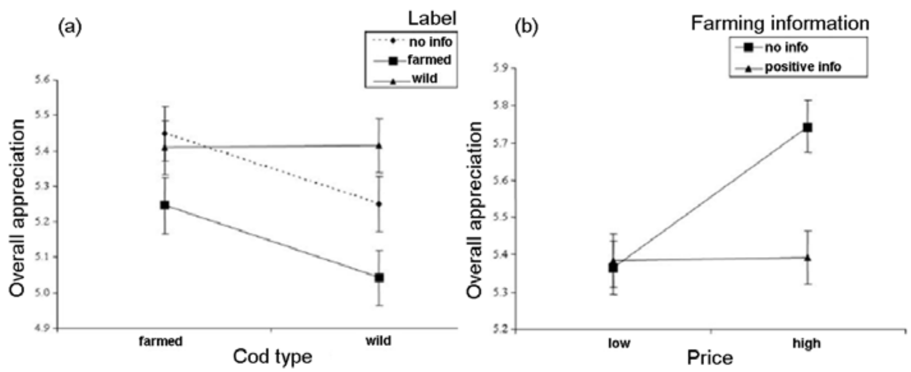

Fig.1. Examples of visualizing main effects and interaction effect, (a) & (b) (Adapted from Kole et al., 2009 [1])

This type of visualizing results from these statistical procedures becomes inefficient when dealing with complex systems. Visualisation of all interacting effects would require a considerable number of plots. Interpretation of the information becomes difficult in this way. A causal representation of the effects of (combinations of) input variables on output variables, that enables inference on these variables, would make the results from statistical modelling more efficient to exploit the information structured by it.

3.2. Bayesian network modelling

The present study was in a favourable position for Bayesian network modelling, because the experiment was already designed with some ‘Product evaluation’ conceptual model (Fig. 2) in mind. This model was built based on expert knowledge. In this conceptual model, we assumed that the consumers’ expectation about a certain product before consumption (‘Expectation’) is influenced by the product itself (‘Product type’) as well as by the information given with the product (‘Product information’). In turn, the expectation would impact the final evaluation on the product after consumption (‘Product evaluation’). While the influence of ‘Product information’ on ‘Product evaluation’ was assumed to only go through ‘Expectation’, the influence of ‘Product type’ was added as a direct pathway. On the graph of the conceptual model, the rectangles indicate concepts, and arrows imply possible cause-effect relationships.

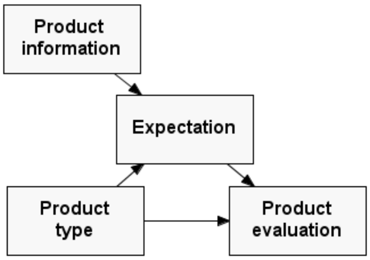

Fig. 2. ‘Product evaluation’ conceptual model

Based on the conceptual model, the structure of LABEL model network relating ‘Overall appreciation’ to ‘Expected appreciation’, ‘Label’, and ‘Cod type’ was defined (Fig. 3a). In this model, the variables, i.e., being measurable quantities and indicated by circles, replaced the corresponding concepts in the conceptual model. All arrows from the conceptual model were kept, except for ‘Product type’ → ‘Expectation’. Because the experimenters assumed that consumers do not perceive any difference in appearance of the two cod types, ‘wild’ vs. ‘farmed’.

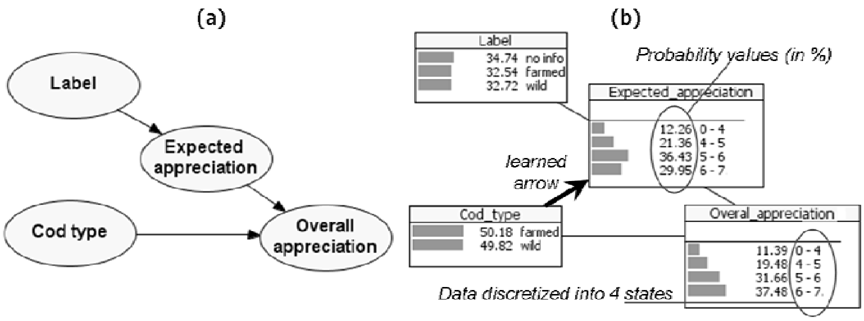

Fig. 3. Structure (a) and Initial probability distribution (b) of the LABEL network model

When feeding data to the structure on Fig. 3a, the arrow 'Cod type' → 'Expected appreciation' was proposed by the algorithm as shown together with the initial probability distribution (Fig. 3b) of LABEL model network. This "learned" arrow suggests that the variation observed in 'Expected appreciation' cannot be explained only by the difference in information provided. Therefore the assumption that consumers did not notice any difference between the two cod types (wild, farmed), so that this factor did not affect their expectations, should be questioned. This outcome demonstrates that build-in features of machine learning techniques can also help in modifying hypotheses, therefore generating an update of current knowledge.

The initial probability distribution of LABEL model represents the probability distribution of all variables alone, without being given any information on the others. These distributions were calculated based on the model parameters estimated from the data in the learning process (details about this are beyond the scope of the current paper, see e.g. [6]). Having obtained the initial probability distribution of a model, it can be used for inferences, i.e. to compute probabilities for a variable of interest given information on the value of other variables of the Bayesian network. Fig. 4 shows examples when evidence was set on either 'Label' (Fig. 4a), i.e., given that the cod product is labelled as wild or farmed, or 'Cod type' (Fig. 4b), i.e., given the cod product being farmed or wild.

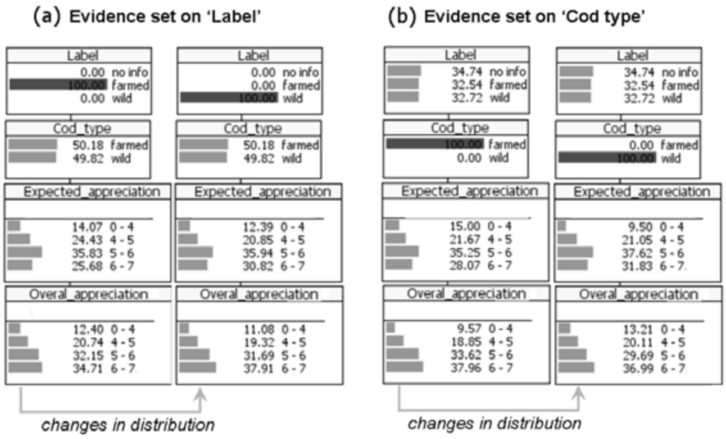

Fig. 4. Inference on LABEL network model. Probability distribution of the network is automatically updated when evidence set on 'Label' (a), being P('Label' = 'farmed') = 100% or P('Label' = 'wild') = 100%, and on 'Cod type' (b), being P('Cod type' = 'farmed') = 100% or P ('Cod type' = 'wild') = 100%

Changes in probability distribution of 'Expected appreciation' and 'Overall appreciation' of the network show that consumers appreciate it more if the cod product is labelled 'wild' both before and after consumption ('wild' labelling produces higher probabilities for 6-7 ratings and lower probability for 0-4 and 4-5 ratings). However, across different labellings (no value set for 'Label'), farmed cods is more appreciated after consumption, even though the expectation is slightly lower. These observations are in line with the results from analyses of variance. Inference in Bayesian networks can be performed not only for single-effects, i.e., evidence set on one single variable, but also for combined-effects, in which information for two or more variables provided at once within the networks. For example, one can predict the consumers' appreciation given that they would consume farmed cods and labelled as wild (inference not shown). With this feature, the interaction among variables can be examined if the data for that are available. In short, the probabilistic inference in Bayesian networks allows instant and global use of the model; the graphical representation makes it easy to communicate the results among model users.

Furthermore, the LABEL model can also be extended by including analytical sensory variables, i.e., 'Fattiness', 'Tenderness', 'Firmness', and their expectation counterparts. While developing the structure for the extended model (Fig. 5) from LABEL, experts can draw an arrow from each of these analytical variables to 'Overall appreciation' or 'Expected appreciation', as well as from the expected analytical variables to their counterpart. Based on this structure, new arrows can always be learned if the data support as shown for the case of 'Cod type'→ 'Expected appreciation' for the LABEL model.

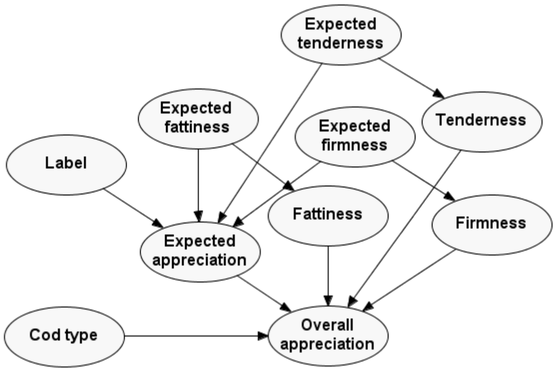

Fig. 5. Structure defined by experts for the extended LABEL network model

The application of Bayesian networks does not limit itself in modelling data obtained from one single experiment. Bayesian networks offer also a possibility to combine data from related studies. For example, more types of 'Product information' related to product freshness, quality control, farming information, and price could be included into the extended LABEL network. Such an overall model network would make use of all four datasets of this consumer study at once. This perspective is subject to our future investigation.

4. Conclusions

Bayesian networks provide features to formally make use of the expert knowledge in modelling. By combining empirical data with the pre-defined network structure, new relationships can be learned, thus new knowledge. Thanks to its probabilistic and graphical nature, this technique is able to deal with complexity and facilitate communication among model end-users. This feature is especially valuable for visualising the results of inference that can effectively be used for hypothesis generation and decision making.

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References

[1] Kole APW, Altintzoglou T, Schelvis-Smit RAAM & Luten JB. The effects of different types of product information on the consumer product evaluation for fresh cod in real life settings. *Food Quality and Preference* 2009; **20**: 187-197.

[2] Garber Jr LL, Hyatt EM & Starr Jr RG. Measuring consumer response to food products. *Food Quality and Preference* 2003; **14**: 3-15.

[3] Grunert KG. Purchase and consumption: the interdisciplinary nature of analysing food choice. *Food Quality and Preference* 2003; **14**: 39 - 40.

[4] Heckerman D. 1995. A tutorial on learning with Bayesian networks. In: Technical report MSR-TR-95-06. Microsoft Research.

[5] Phan VA, Dekker M, Garczarek U & van Boekel MAJS. Bayesian networks for food science: theoretical background and potential applications. In: Jaeger S.R. & MacFie H, editors. *Consumer-driven innovation in food and personal care products*, Cambrige: Woodhead Publishing Limited; 2010, p. 488 - 513.

[6] Heckerman D, Geiger D & Chickering DM. Learning Bayesian networks: The combination of knowledge and statistical data. *Machine Learning*, 1995; **20**: 197-243.

[7] Pourret O, Naïm P & Marcot B. *Bayesian Networks: A Practical Guide to Applications*. Wiley; 2008.

[8] van Boekel MAJS. Bayesian solutions for food-science problems?. In: van Boekel MAJS, Stein A & van Bruggen AHC, editors. *Bayesian Statistics and Quality Modelling in the Agro-Food Production Chain*. Dordrecht: Kluwer Academic Publishers; 2004, p. 17-27.

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