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A holistic approach to food safety risks: Food fraud as an example

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ABSTRACT

Production of sufficient, safe and nutritious food is a global challenge faced by the actors operating in the food production chain. The performance of food-producing systems from farm to fork is directly and indirectly influenced by major changes in, for example, climate, demographics, and the economy. Many of these major trends will also drive the development of food safety risks and thus will have an effect on human health, local societies and economies. It is advocated that a holistic or system approach taking into account the influence of multiple "drivers" on food safety is followed to predict the increased likelihood of occurrence of safety incidents so as to be better prepared to prevent, mitigate and manage associated risks. The value of using a Bayesian Network (BN) modelling approach for this purpose is demonstrated in this paper using food fraud as an example. Possible links between food fraud cases retrieved from the RASFF (EU) and EMA (USA) databases and features of these cases provided by both the records themselves and additional data obtained from other sources are demonstrated. The BN model was developed from 1393 food fraud cases and 15 different data sources. With this model applied to these collected data on food fraud cases, the product categories that thus showed the highest probabilities of being fraudulent were "fish and seafood" (20.6%), "meat" (13.4%) and "fruits and vegetables" (10.4%). Features of the country of origin appeared to be important factors in identifying the possible hazards associated with a product.

The model had a predictive accuracy of 91.5% for the fraud type and demonstrates how expert knowledge and data can be combined within a model to assist risk managers to better understand the factors and their interrelationships.

1. Introduction

Against a background of previous food safety incidents, such as BSE and dioxins, the last two decades have witnessed the establishment of increasingly sophisticated and elaborated food safety control systems, dedicated institutions, and public awareness of food safety. Despite these preventive measures, incidents do still occur. While some of the incidents were due to unintended or unforeseen consequences of practices or processes, others were linked to fraud and criminal activities, such as the adulteration of foods with non-food-grade materials such as Sudan dyes and dioxin-containing oils. Several studies have indeed mentioned fraud and criminal attacks as new threats to food safety (Spink & Moyer, 2011).

In order to prevent incidents from happening in the future, various researchers have explored the possibilities to forecast, including the timely identification of trends and events that might eventually give rise to, such food safety incidents. Generally, various international and local developments may directly or indirectly influence the performance of food-producing systems, among them climate change, economy and trade, human behaviour, and new technologies (Boland et al., 2013; GO-Science, 2011; Godfray et al., 2010; Miraglia, De Santis, Minardi, Debegnach, & Brera, 2005). The European Food Safety Authority (EFSA) defined a driver as "a driver may act as modifiers of effect on the onset of emerging risks, namely they can either amplify or attenuate the magnitude or frequency of risks arising from various sources" (EFSA, 2010). The key drivers to food safety and nutrition risks were identified recently in a scoping study on food safety and nutrition (FCEC, 2013): i) global economy and trade, ii) global cooperation and standard setting, iii) governance, iv) demography and social cohesion, v) consumer attitudes and behaviour, vi) new food chain technologies, vii) competition for key resources, viii) climate change, ix) emerging food chain risks and disasters, and x) new agri-food chain structures.

A holistic or system approach taking stock of the forces that act upon the food chain (from farm to fork) and their effect on food safety has been adopted by FAO (2003). Such an approach has also been proposed to address climate induced food safety risks (GO-Science, 2011; Marvin et al., 2009; Miraglia et al., 2005). A holistic approach includes a full host

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environment analysis of the whole food chain in which the driving forces of food safety risks are determined, including associated data sources.

Application of the holistic approach in a working system to identify known and emerging food safety risks needs a model that links all drivers and their dependencies, as well as underlying databases from various natures and origins and preferably allows scenario studies. The model should access, preferably real-time, data on the drivers, process these data, and perform calculations, such to provide predictions on (emerging) food safety risks.

To date, no modelling approach or system has been developed for the food production chain that is able to take into account underlying databases, interactions and feed-back loops of the drivers as encountered in a holistic approach. Here we advocate that a Bayesian Network (BN) approach is suitable for this purpose. BNs are a class of probabilistic models originating from the Bayesian statistics and decision theory combined with graph theory (Bonafede & Giudici, 2007; Nielsen, 2007), which are able to model dependencies between variables, manage non-linear interactions and integrate different kinds of information about the system such as expert knowledge, measurement data, feedback experience and information regarding the system behaviour (Buriticá & Tesfamariam, 2015). BNs have been applied in a number of diverse problem domains such as medical diagnosis (Wiegerinck et al., 1999), image classification (Malka & Lerner, 2004), financial fraud detection (Kirkos, Spathis, & Manolopoulos, 2007; Ngai, Hu, Wong, Chen, & Sun, 2011), nuclear waste disposal (Lee & Lee, 2006) and electrical power systems (Huo, Zhu, Zhang, & Chen, 2004).

For this study, fraud was chosen as a case particularly given its role in a number of landmark food safety incidents, such as the illegal use of Sudan dyes, admixture of PCB/dioxin containing industrial oils with edible oils, and addition of melamine to milk used for infant formula (Unnevehr et al., 2010), (Guan et al., 2009; Jia & Jukes, 2013). Food fraud is a collective term that is driven by economic gain and encompasses the deliberate substitution, addition, tampering, or misrepresentation of food, food ingredients or food packaging, or false or misleading statements made about a product (Spink & Moyer, 2011). Food fraud may thus cause food safety risks and is driven by different factors from within and outside the food supply chain (NSF International, 2014). Examples of factors contributing to food fraud opportunities were presented in the NSF international report (NSF International, 2014): (i) increase of the complexity of supply chain networks, (ii) the rapid development of technology (internet, printing, mobile phone etc.) provides powerful tools to fraudsters, (iii) the rapid growth of warehouse systems and refrigerated transport enabling the long term storage and transfer of large quantities of perishable food. The aim of this research was to demonstrate the usefulness of BNs in connecting different drivers, data sources and their interactions in a holistic approach in order to determine the main factors influencing food fraud.

2. Methods

The approach applied consisted of four steps: (i) collection of reported food fraud cases, (ii) identification of the main drivers that can affect food fraud and collect data from different data sources such as: literature (Everstine, Spink, & Kennedy, 2013; NSF International, 2014), food fraud databases, (EMA, 2014; RASFF, 2015) and food fraud expert knowledge; (iii) building the BN including nodes, arrows, states, and the parameters for each node in the form of Conditional Probability Tables (CPTs); (iv) and validating the model. Fig. 1 shows the steps followed.

2.1. Collecting reported food fraud cases

Two publicly available databases that publish (detected) food fraud cases in the EU (Rapid Alert for Food and Feed (RASFF)) (RASFF, 2015)

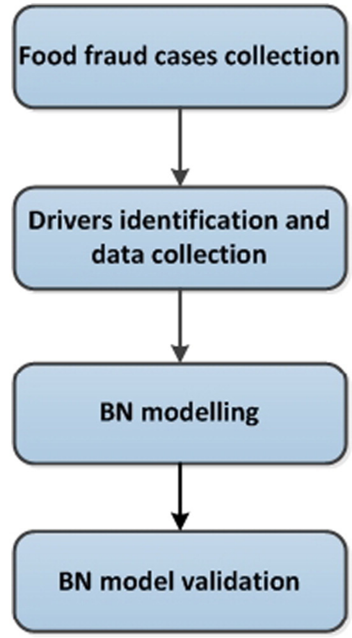

Fig. 1. Steps in the development of the BN model for food fraud.

and in the US (Economically Motivated Adulteration incidents database (EMA)) (EMA, 2014) were used as references to real detected cases. All notifications reported in the RASFF database under the hazard category "adulteration/fraud" were extracted from the period 01/01/2000 to 31/12/2015 (in total 1035 records). Each RASFF record contains the following information: month, year, country notifying, notification type, product, product category, hazard and origin country. All food fraud incidents reported in the EMA database were extracted from the period 01/01/2000 to 31/12/2015. The database contains 651 distinct food fraud incidents grouped into 20 food product categories. The food fraud incidents reported in RASFF and EMA (i.e. in total 1686 records) were divided into seven categories based on the description provided in these databases. The categories are defined in Table 1. For each food fraud report in RASFF and EMA, data on the identified drivers (see next section) from the time (i.e. month and year) of the particular food fraud incident were collected and stored in an underlying database. In this way, information recorded in RASFF and EMA (e.g. fraud type, product, country of origin, detecting country and date of detection) was expanded with available information retrieved from other data sources, as related to drivers (i.e. in total 15 different data sources) that are directly or indirectly linked to the occurrence of the food fraud incident.

Table 1
Food fraud types in RASFF and EMA.

Fraud type	Description
HC	Improper, fraudulent, missing or absent Health Certificate (HC)
Illegal importation	Illegal or unauthorized import, trade or transit
Tampering	Adulteration, fraud or tampering, substitution, counterfeit, artificial enhancement, transhipment, intentional distribution of contaminated product, dilution.
CED	Improper, expired, fraudulent or missing common entry document (CED), import declaration, or analytical report
Expiration date	Expiration date
Origin labelling	Mislabelling, origin labelling
Theft and Resale	Theft and resale

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