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A Bayesian network profiler for wildfire arsonists

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Abstract. Arson-caused wildfires have a rate of clarification that is extremely low compared to other criminal activities. This fact made evident the importance of developing methodologies to assist investigators in the criminal profiling. For that we introduce Bayesian Networks (BN), which have only recently be applied to criminal profiling and never to arsonists. We learn a BN from data and expert knowledge and, after validation, we use it to predict the profile (characteristics) of the offender from the information about a particular arson-caused wildfire, including confidence levels that represent expected probabilities.

Keywords: Bayesian network, criminal profiling, expert system, wildfire arson

1 Introduction

Wildfire can be regarded as an environmental disaster which is triggered by either natural forces or anthropogenic activities, and is one of the most relevant threats to nature ecosystems and human societies according to the Food and Agriculture Organization of the United Nations (FAO) survey [10]. In this work we are interested in the latter, the arson-caused wildfire, understood as "the large and destructive fire caused by humans that spreads quickly out control over woodland or brush, calcining forest fuels located in the mount and affecting vegetation in principle was not destined to burn", which is one of major environmental problems in Spain.

As it can be seen exploring the literature on the subject, wildfires have been studied mainly from the point of view of risk assessment. Just to mention some of these studies, in Thompson et al. [24] an integrated and systematic risk assessment framework to better manage wildfires and to mitigate losses to highly valued resources and assets is presented, with application to an area in Montana, United States, while in Penman et al. [19] patterns of natural and arson ignitions were examined within a region of south-eastern Australia, to determine the extent to which management can alter the risk of ignition. Different fire risk indices have been considered in Adab et al. [1] to delineate fire risk in northeastern Iran, which is a region subjected to frequent wildfires.

Although arson is one potential cause of many fires, yet the rate of clarification of arson-caused wildfires is extremely low compared to other criminal activities. According to the interim report of the Ministry of Agriculture, Food and Environment [17], 11,928 wildfires were committed in 2015 in Spain, of which 429 offenders have been identified, representing a clarification rate of 3.6%, disregarding that not all the fires were arson-caused. This fact highlights the importance of developing methodologies that can assist investigators to hunt down the culprits by means of the implementation of the criminal profiling, consisting of inferring features (behavioral, criminological, socio-demographic and of personality) of the offender from the analysis of the evidences obtained from the place where fire started.

Focusing on the case of arson-caused wildfire, apart from some few descriptive studies (see [21]), the only statistical approach to wildifre arsonist profiling stems from the work of González, Sotoca and collaborators [22]. Their approach to this problem is through the application of different techniques of multivariate data analysis. In this paper, however, we introduce in a novel way the methodology of Bayesian Networks (from now on, BN), that has only recently been used for criminal profiling (see, for instance, Baumgartner et al. [3] and [4]) and never, as far as we know, applied for profiling of any kind of arsonist.

BN are an increasingly popular methodology for modeling uncertain and complex domains, and in the opinion of many Artificial Intelligence researchers, the most significant contribution in this area in the last years (see Korb and Nicholson [14]). BN were introduced in the 1920s as a tool that describes probabilistic understanding of cause and effect and other relations between variables, and are the soundest framework for reasoning under uncertainty. From then, this methodology has proved to be useful in assisting in many decision-making procedures in a variety of fields, and its use in risk analysis is gaining popularity and includes applications in areas as diverse as economy (Adusei-Poku [2]), public health (Spiegelhalter [23] and Cruz-Ramírez et al. [6]), environmental risk (Borsuk et al. [5] and Pollino et al. [20]), emerging diseases (Walshe and Burgman [26]), ecological disasters (Ticehurst et al. [25]) or nuclear waste accidents (Lee and Lee [15]). And with respect to criminology, for example, BN have been introduced as a novel methodology in assessing the risk of recidivism of sex offenders in Delgado and Tibau [7].

Regarding wildfire, there are some recent works as Papakosta and Straub [18], in which the authors study a wildfire building damage consequences assessment system, constructed from a BN with Hugin Expert software, and apply it to spatial datasets from the Mediterranean island of Cyprus. Dlamini develops a BN model in [8] with Netica software, from satellite and geographic information systems (GIS), with variables of biotic, abiotic and human kind, in order to determine factors that influence wildfire activity in Swaziland (see also [9]). However, up to our knowledge, there are no previous studies on the use of BN for profiling of the offender of a wildfire.

We learn a BN model from available data and expert knowledge and, subsequently, predict the profile of the offender from the particular characteristics of an arson-caused wildfire. The inferred arsonist characteristics include confidence levels that represent their expected probability, which enable for investigators to know what are the features of the person who sparked the blaze. Roughly speaking, we construct the most probable BN given the observed cases (learning procedure), and this model provides the optimal prediction for future cases (inference procedure), but its effectiveness for prediction purposes essentially depends on the sufficiency of the training database. We introduce different performance metrics to address this issue, and conclude that our database is actually large enough for our purposes. Having done that, we learn (*train*) both BN structure and parameters, to subsequently validate them both by split-validation and by $k-$fold cross-validation. The validation process provides information on the accuracy of the predictions.

2 Materials and Methods

The cases used in this study come from a database of policing clarified arson-caused wildfires (for which the alleged offenders have been identified), fed since 2008 throughout the entire Spanish territory, under the leadership of the Prosecution Office of Environment and Urbanism of the Spanish state. The database contains 1,423 solved cases. According to the experts, $n = 25$ variables have been chosen of the total set of 32 variables, because of their usefulness and predictive relevance. These variables are relatives to crime ($C_1, \ldots, C_{10}$) and to the arsonist ($A_1, \ldots, A_{15}$), and are described in Table 3, where their possible outcomes are also shown.

BN are graphical structures for representing the probabilistic relationships among variables, and for performing probabilistic inference with them. Given a set of random variables $V = \{X_1, \ldots, X_n\}$, a BN is a model that represents the joint probability distribution P over those variables. The graphical representation of the BN consists of a *directed acyclic graph (DAG)*, whose n nodes represent the random variables and whose directed arcs among the nodes represent conditional dependencies.

Using a BN to compute a posteriori probability is called "(Bayesian) inference": we enter an evidence and use it to update the probabilities of the network. From an evidence of the form $E = \{X_{i_1} = x_{i_1}, \ldots, X_{i_\ell} = x_{i_\ell}\}$, where $\{X_{i_1}, \ldots, X_{i_\ell}\} \subset V$ are the *evidence* variables, an inference consists in the com-

putation of probabilities of the form $P(X_{j_1} = x_{j_1}, \ldots, X_{j_s} = x_{j_s} \,/\, E)$ with $\{X_{j_1}, \ldots, X_{j_s}\} \subset V \setminus \{X_{i_1}, \ldots, X_{i_\ell}\}$ the set of *query* variables. Variables of the BN that do not appear either as query or evidence are treated as unobserved. The prediction of a query variable X given the evidence E is the instantiation of X with the largest posterior probability. That is, if $x_1, \ldots, x_r$ are the possible instantiations of X, then $x^* = arg\, max_{k=1,\ldots,r} P(X = x_k \,/\, E)$ is the prediction for X, and $P(X = x^* \,/\, E)$ is said to be the *confidence level (CL)* of the prediction.

We adopt the *score-based* structure learning method (*"Search-and-score"*), which is an algorithm that attempts to find the structure that maximizes the score function, with the BIC (**Bayesian Information Criterion**) as score function. This score function is intuitively appealing because it contains a term that shows how well the model predicts the observed data when the parameter set is equal to its MLE estimation (the log-likelihood function), and a term that punishes for model complexity. Minimum Description Length (MDL) scoring metric is equivalent to the BIC score for Bayesian networks, while the Akaike's Information Criterion (AIC) only differs from BIC on the penalty term, which is less that that of BIC, implying that AIC tends to favor more complex networks than BIC. Some works suggest that MDL/BIC consistently outperforms AIC (see [16]), reason by which we have chosen the first as score function for our work.

The *greedy search-and-score algorithm* with the BIC score function has *local scoring updating*, that it, this algorithm only needs locally recompute a few scores in each step to determine the score of the model in the next step, and performs a search through the space of possible network structures by adding, removing or reversing an arc, given a current candidate, subject to the constraint that the resultant graph does not contain a cycle, and "greedily" choosing the one that maximizes the score function, stopping when no operation increases this score.

A problem with this algorithm is that it could halt at a candidate solution that locally maximizes the score function rather than globally maximizes it. One way for dealing with this problem is what is named "iterated hill-climbing" (hc) algorithm, in which local search is done until a local maximum is obtained. Then, the current structure is randomly perturbed, and the process is repeated. Finally, the maximum over local maxima is used.

3 Constructing the BN profiler

In this section we construct our expert system, which is a BN profiler. This construction is based on a data set of solved cases, from which the BN will be learned. The BN allows characterizing the wildfire arson in terms of the relationships between different variables and their strengths. These (in)dependence relationships are expressed in a very simple way in the BN, through the absence/presence of arcs in its DAG (see Figure 1). One of the most interesting features of BNs is their ability to compute posterior probabilities, that is, probabilities of some query variables given evidences. Once learned, the BN profiler will be used in the following way: given an evidence in terms of the crime variables for a given

wildfire, we will predict the value of the query (arsonist) variables, which form the predicted profile of the arsonist.

With a view to "split-validation", the initial data set $\mathcal{D}$ with 1,423 cases is randomly partitioned into a training set $\mathcal{T}$ and a validation set $\mathcal{V}$ such that they are disjoint. Thus, none of the validation cases are used for training and can be considered to be new to the BN model. We use the common "80/20 % rule" in order to do that, although there is an extensive literature on how to carry out this partition. Therefore, the training set $\mathcal{T}$ has $M = 1{,}138$ cases and the validation set $\mathcal{V}$ has $N = 285$ cases. The sufficiency of the set $\mathcal{T}$ in order to learn the BN is studied in Section 3.1. We use exclusively discrete (categorical) random variables, by discretizing the (few) continuous variables in the original database. By expert knowledge we choose a total number of 25 variables from the initial set of 32. The choice is the result of a balance between the benefits of having a high number of variables (more realistic model with higher accuracy) and the drawbacks arising from the corresponding increasing complexity (need for more data to estimate the probability distributions properly). We deal with missing values transforming them into blank values. After training from $\mathcal{T}$, we will apply an inference engine with the BN to the cases from $\mathcal{V}$ in order to estimate accuracy of predictions of the arsonist variables, given an evidence based on the crime variables, to predict new cases. We follow up "split validation" with "$k-$fold cross validation", allowing us to obtain a measure of the errors in estimating accuracy.

From the training data set $\mathcal{T}$, we use the bnlearn package of R to learn the structure of the BN (DAG), shown in Figure 1, as well as the parameters. Package bnlearn has implemented sampling methods for inference and does not include any exact inference algorithm, while exact inference with gRain package is possible. This procedure relies on transforming the BN into a specially crafted tree to speed up the computation of conditional probabilities. Such a tree is called *junction tree*. Once the junction tree has been built and its conditional probability distributions have been computed, we can input the evidence into the junction tree. The local distributions of the nodes to which the evidence refers (evidence variables) are then updated, and the changes are propagated through the junction tree. If $x_1, \ldots, x_r$ are the possible instantiations for a variable X, with $x_1 =$blank, then we introduce $x^{**} = arg\,max_{k=2,\ldots,r} P(X = x_k \,/\, E)$ as the (corrected) prediction for X, and $P(X = x^{**} \,/\, E)/\big(1 - P(X = x_1 \,/\, E)\big)$ as the (corrected) *confidence level (CL)* of the prediction.

3.1 Performance metrics

The performance of the BN learning algorithms (both for structure and parameters learning) always depends on the sufficiency of the training database, which is determined by the number of nodes, the size of their domain (set of possible instantiations), and the underlying probability distributions. While the nodes and their domain are known from the problem formulation, the underlying probability distributions are typically unknown a priori.

To determine whether the training database $\mathcal{T}$ with $M = 1{,}138$ cases is sufficient to estimate a BN model of criminal behavior of wildfire arsonists,

Crime variables	Author variables
C_1 = season	A_1 = age
C_2 = risk level	A_2 = way of living
C_3 = start time	A_3 = kind of job
C_4 = starting point	A_4 = employment status
C_5 = main use of surface	A_5 = educational level
C_6 = number of seats	A_6 = income level
C_7 = related offense	A_7 = sociability
C_8 = pattern	A_8 = prior criminal record
C_9 = traces	A_9 = history of substance abuse
C_{10} = who denounces	A_{10} = history of psychological problems
	A_{11} = stays in the scene
	A_{12} = distance from home to the scene
	A_{13} = displacement mean
	A_{14} = residence type
	A_{15} = wildfire motive

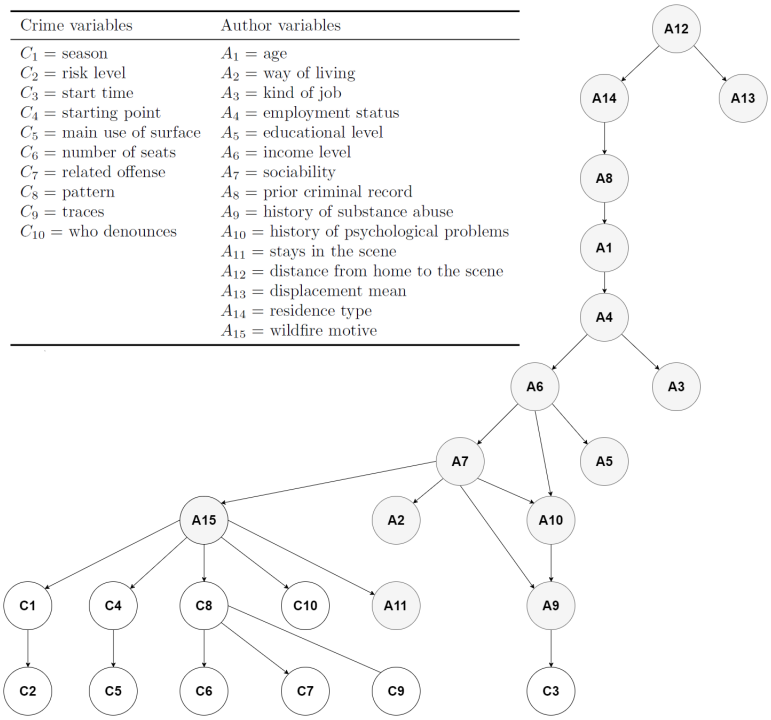

Fig. 1: Learned structure (DAG)

subset samples from $\mathcal{T}$ of size ranging from 25 to 1,138 in increments of 5 cases, have been randomly generated. For every sample, we learn a BN model and the BIC score function is computed and plotted on a learning curve, as a function of the number of training cases, as Figure 2 shows. We see that a saturation point is reached before attaining $M = 1{,}138$ (approximately at 900), from which the score does not improve even if we increase the number of training cases. Therefore, it does seem to have enough training data in $\mathcal{T}$ to learn the network. In addition, first graph in Figure 2 shows clearly that if we impose no restriction at all (in black color and continuous line), the BIC score function takes higher values practically in all the range of the number of training cases than if we inhibited arcs connecting crime variables among them (in red color and dashed line). Moreover, inhibiting arcs from any crime variable to any arsonist variable gives the same model structure than with no restriction, reason by which we finally decide no consider restrictions on the learning structure procedure and obtain the DAG in Figure 1. Second graph in Figure 2 shows the smoother learning curve corresponding to the mean of the BIC values for 10 different random partitions (in black color and continuos line).

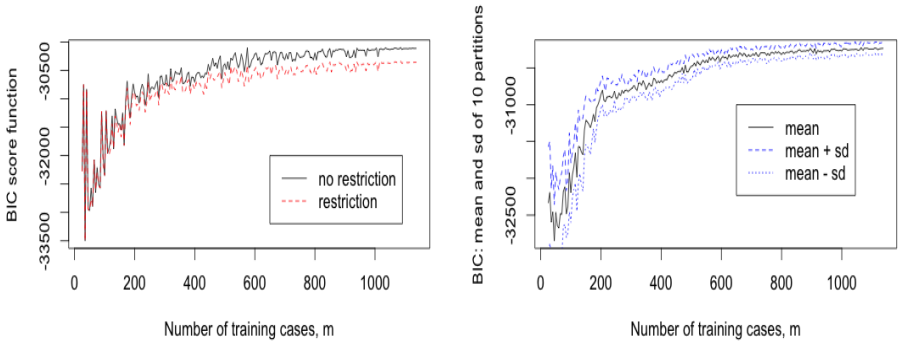

Fig. 2: BIC learning curve as function of m: with partition $\mathcal{T}-\mathcal{V}$, and with 10 partitions (mean and mean$\pm$ standard deviation). Increment $\Delta m = 5$

3.2 Internal consistency

Before proceeding to consider validation of the constructed BN, we study if the training data set is internally consistent. To this end, we compute some measures (metrics) of discordance between the BN learned at each of the previous steps, that is, learned from each training subsample of $\mathcal{T}$ of size $m = 25, \ldots, M = 1{,}138$, that we denote by BN_m, with respect to the final BN, which is that learned from the whole training database, denoted by BN_M. We also consider two measures of concordance. For that, we compare the binary matrix indicating directed arcs of network BN_m with that of the final network BN_M. We use notations: $a =$ number of matches 1 in the two matrices, $b =$ number of 1 in the matrix of BN_m being 0 in the matrix of BN_M, $c =$ number of 0 in the matrix of BN_m being 1 in the matrix of BN_M, $d =$number of matches 0 in the two matrices. The measures of concordance we consider are the *sensitivity*, which is $a/(a+c)$, that is, the proportion of arcs of BN_M that are already in BN_m, and the *accuracy*, which is $a/(a+b)$, that is, the proportion of arcs in BN_m that are in BN_M. Both increase to 1 as $m \to M$ as can be seen in Figure 3.

The first measure of discordance we consider is the *Structural Hamming Distance (SHD)* (see [13]) that describes the number of changes that have to be made to BN_m for it to turn into BN_M (lower is better), is $b+c+e$ being e the number of directed arcs in BN_m that are incorrectly oriented comparing with BN_M. We see in Figure 3 that, indeed, SDH tends to zero as $m \to M$. The second one is the *Jaccard dissimilarity* [12], defined by $1 - a/(a+b+c)$, and finally, we can also compute the dissimilarity index of Sokal-Michener (see [11]), which is $1-(a+d)/(a+b+c+d)$. Note that both Jaccard and Sokal-Michener dissimilarity measures take values in [0, 1], the first one taking into account the concordances only in the sense of present arcs in the networks, and the second one, also considering matches in absences, whilst SHD index takes values in $\mathbb{Z}^+$

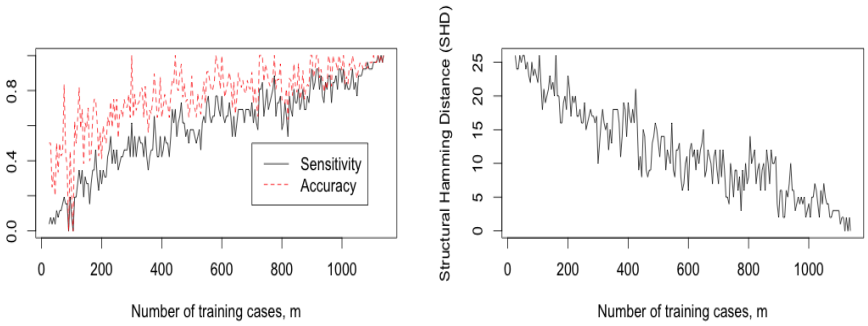

Fig. 3: Sensitivity and Accuracy, and Structural Hamming Distance metrics, as functions of number of of training cases. Increment $\Delta m = 5$

and does not takes into account concordances. In Figure 4 it can be seen the evolution of these two dissimilarity measures and how they converge to zero.

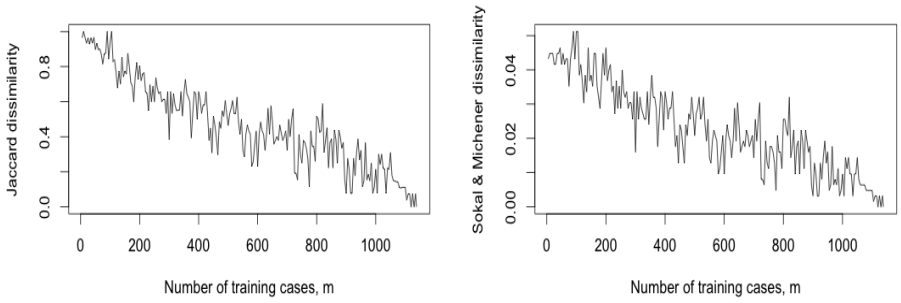

Fig. 4: Jaccard and Sokal-Michener metrics. Increment $\Delta m = 5$

Graphs in figures 3 and 4 show the internal consistency of the dataset. Indeed, concordance measures increase to 1 while discordance metrics go to 0, as the subset of the training set increases to the whole set, at the same time that variability in the measures decreases.

4 Validation and assessment of predictive accuracy

First we use "split-validation", from which the BN model is tested using the validation data set $\mathcal{V}$ composed of $N = 285$ solved cases, each reporting the offender variables. For each of the test cases in $\mathcal{V}$, we use the values of the crime variables as evidence in performing inference on the arsonist variables. Then, compare the predicted values for the arsonist variables (which are the highest-probability predictions and always different from blank, as explained above) to non-blank

known case outcomes in $\mathcal{V}$, and take note of matches. If for a fixed case of $\mathcal{V}$ and a fixed arsonist variable, say A_i, the outcome of the variable is a blank, then the prediction of variable A_i for this case is not considered in order to compute the success rate of the BN in predicting. The success rate on predicting each arsonist variable from the evidence given by the crime variables for the N cases of $\mathcal{V}$ is called "IPA" (*Individual Predictive Accuracy*) (see column "Split-validation" in Table 1). It is obtained by dividing the number of correct predictions for each variable by the total number of predictions (excluding blanks).

Table 1: Individual Predictive Accuracy (IPA) and Overall Predictive Accuracy (OPA). "Mean" and "Deviation" columns correspond to $k-$fold cross validation.

Arsonist variable IPA (%)	Split-validation	Mean	Deviation
A_1 = age	27.57	30.30	3.06
A_2 = way of living	53.21	53.46	3.01
A_3 = kind of job	76.44	74.62	3.02
A_4 = employment status	34.68	37.74	3.34
A_5 = educational level	46.63	52.24	5.44
A_6 = income level	44.27	44.05	5.04
A_7 = sociability	69.19	66.70	4.45
A_8 = prior criminal record	80.07	79.41	4.45
A_9 = history of substance abuse	78.50	82.07	2.82
A_{10} = history of psychological problems	79.70	82.71	4.83
A_{11} = stays in the scene	49.10	49.35	4.36
A_{12} = distance from home to the scene	41.91	42.46	3.02
A_{13} = displacement means to commit arson	44.53	42.79	4.66
A_{14} = residence type	40.52	45.12	5.28
A_{15} = wildfire motive	61.05	62.94	4.12
Total OPA (%)	54.04	55.19	0.05

From this table we see the wildfire arsonist characteristics that are typically correctly predicted (IPA$\geq 60\,\%$): A_3, A_7, A_8, A_9, A_{10} and A_{15}, and then can be used to narrow the list of suspects. Specially important are A_8, A_9 and A_{10}. Indeed, they are operative variables that greatly help the researcher to identify the offender, which is precisely the aim of profiling. Also of major importance is A_{15}. Its key role is evidenced since all crime variables except C_3 are descendants of A_{15}. It should also be borne in mind that for any variable we choose as prediction the outcome that maximizes the probability, causing failures in prediction when the second most likely outcome has a close probability. Table 1 also shows the average percentage of global correct accuracy, for all the arsonist variables, named "OPA" (*Overall Predictive Accuracy*). It is obtained by dividing the total number of matches (1,914) on all predictions by the total number of predictions (excluding blanks), which is 3,542.

Secondly, we also use "$k-$fold cross validation" with $k = 10$. That is, we reuse the data set $\mathcal{D}$ generating k splits of $\mathcal{D}$ into non-overlapping training and validate sets with (approx.) proportions $(k-1)/k$ and $1/k$, respectively. For each split we obtain the IPA value as we did for the partition $\mathcal{T} - \mathcal{V}$. From

these $k = 10$ values we compute the mean, as well as the standard deviation (see columns "Mean" and "Deviation" in Table 1).

Finally, we computed the "DIPA" (*Disincorporate Individual Predictive Accuracy*), which is the percentage of correct predictions, for each arsonist variable, from the validation set $\mathcal{V}$, according to the prediction that we made for it from the evidence given by the crime variables. For example, if the prediction for A_{15} was "gross negligence", then the DIPA tells us that the accuracy rate would be 79 %, as can be seen in Table 2, while if the prediction for A_{15} was "revenge", this rate plummets to 16.67 %.

Table 2: Disincorporate Individual Predictive Accuracy (DIPA) for A_{15}.

If prediction was	% accuracy (DIPA)
profit	46.67
gross negligence	79.00
slight negligence	51.65
impulsive	54.79
revenge	16.67

5 Conclusion

We present BN as a novel methodology for profiling of arsonists in wildfires. We learn the BN from the database and validate it, by estimating the accuracy of predictions for each arsonist variable individually (IPA) and all together (OPA). We also check internal consistency of the database. Therefore, we can use learned BN to predict the profile of the offender from the information about a particular arson-caused wildfire, and obtain confidence levels for the predictions of the arsonist variables. Globally, the estimation of network's accuracy is 55.19% (but varies between 30.30 and 82.71% according to the variable; take into account the number of possible values for each variable, which is high for some of them). By comparing with partial results obtained from experts (approx. 40% of accuracy), this value seems high enough for a profile model.

We think this approach is really innovative and helpful. Our purpose in the future is going deeper in the study of the obtained model and its performance as profiler, as well as its behavior as new solved cases are incorporated into the database, and also apply this methodology to other crimes (e.g. against persons).

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Table 3: Outcomes of the variables in the database.

Variables	Outcomes
C_1 = season	spring/winter/summer/autum
C_2 = risk level	high/medium/low
C_3 = wildfire start time	morning/afternoon/evening
C_4 = starting point	pathway/road/houses/crops/interior/forest track/others
C_5 = main use of surface	agricultural/forestry/ livestock /interface/recreational
C_6 = number of seats	one/more
C_7 = related offense	yes/no
C_8 = pattern	yes/no
C_9 = traces	yes/no
C_{10} = who denounces	guard/particular/vigilance
A_1 = age	up to 34 / 35 to 45 / 46 to 60 / more than 60
A_2 = way of living	parents/in couple/single/others
A_3 = kind of job	handwork/qualified
A_4 = employment status	employee/unemployed/sporadic/retired
A_5 = educational level	illiterate/elementary/middle/upper
A_6 = income level	high/medium/low/without incomes
A_7 = sociability	yes/no
A_8 = prior criminal record	yes/no
A_9 = history of substance abuse	yes/no
A_{10} = history of psychological problems	yes/no
A_{11} = stays in the scene	no/remains there/gives aid
A_{12} = distance from home to the scene	short/medium/long/very long
A_{13} = displacement means to commit arson	on foot/ by car/ all terrain / others
A_{14} = residence type	village/house/city/town
A_{15} = wildfire motive	profit/gross negligence/slight negligence/impulsive/revenge

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