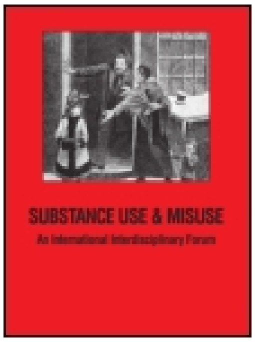
Using Classifiers to Identify Binge Drinkers Based on Drinking Motives



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ORIGINAL ARTICLE

Using Classifiers to Identify Binge Drinkers Based on Drinking Motives

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A representative sample of 2,844 Dutch adult drinkers completed a questionnaire on drinking motives and drinking behavior in January 2011. Results were classified using regressions, decision trees, and support vector machines (SVMs). Using SVMs, the mean absolute error was minimal, whereas performance on identifying binge drinkers was high. Moreover, when comparing the structure of classifiers, there were differences in which drinking motives contribute to the performance of classifiers. Thus, classifiers are worthwhile to be used in research regarding (addictive) behaviors, because they contribute to explaining behavior and they can give different insights from more traditional data analytical approaches.

Keywords classifiers, nonlinearity, identifying binge drinkers, drinking motives

INTRODUCTION

Behavioral scientists aim to explain human behavior by gaining more insight into risk and protective factors related to a certain behavior. For example, drinking behavior is known to be associated with cognitions, genetics, drinking situations, and availability of alcohol (Hawkins, Catalano, & Miller, 1992). Studies aiming to explain drinking behavior have led to valuable insights to identify populations at risk. For example, younger employees are more likely to report binge drinking (Matano et al., 2003), and initiating drinking at a younger age is related to binge drinking among young men who have sex with men (Wong, Kipke, & Weiss, 2008). These findings mostly assume a linear relationship: an increase in a factor X (used here to identify people at risk) leads to a proportional increase in behavior Y. An alternative is the existence of nonlinear relationships (Miller, 2004). This view is based on Chaos Theory, which stems from natural science, but has also been used to explain substance abuse (Warren, Hawkins, & Sprott, 2003). Resnicow and Vaughan (2006) state that "there may be common patterns of behavior change within and across individuals that follow certain complex, non-linear patterns." Testing this hypothesis in binge drinking is important: if the relationships between certain factors and binge drinking are nonlinear, then our current linear approaches would produce an error that could be reduced.

Classifiers are ways to identify people engaging in a certain behavior. Intuitively, a classifier is a function that assigns labels to individuals (e.g., binge drinker or not) based on their features (e.g., drinking motives, sociodemographics). The methodology to construct a classifier commonly consists of partitioning the feature space (e.g., all possible answers that participants can give to items in a questionnaire) into regions associated with a particular outcome (prediction). The example in Figure 1 partitions the feature space by cutting it horizontally or vertically (Figure 1, right). Each cut is recorded as a node in a tree (Figure 1, left), and the resulting classifier is a decision tree. The construction of a classifier needs to be done by means of a dataset in which individuals' labels are known (e.g., it is known whether someone is a binge drinker or not). Subsequently, the classifier can be used to label individuals (e.g., identify binge drinkers) based on their values regarding certain features (e.g., their scores on an item within a questionnaire). In the example of Figure 1, an individual could have a value of 1.5 for feature 1 and 3.5 for feature 2. To predict the label, the rules expressed in the decision tree need to be followed, starting from the top. In order, we have: feature $2 = 3.5 > 3$ (A), feature $1 = 1.5 > 1$ (C), feature $2 = 3.5 < 4$ (D), leading to "nonbinge drinker."

The current study aims to demonstrate the potential of using classifiers in research on addictive behaviors. Classifiers are used to identify binge drinkers based on drinking motives. Moreover, in light of the aforementioned view of nonlinear relationships, we explore evidence for both linear and nonlinear relationships between drinking motives and binge drinking. Finally, we explore whether specific answers to items are particularly indicative in terms of identifying binge drinkers.

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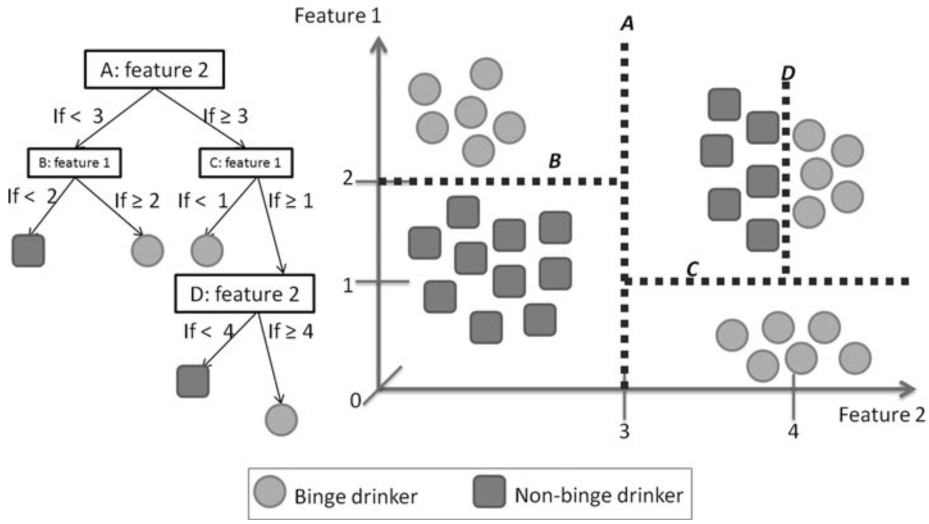

FIGURE 1. Example of partitioning the feature space.

Case: Identifying Binge Drinkers by Means of Drinking Motives

In the motivational model of alcohol use (Cox & Klinger, 1988), drinking motives are the most proximal factors for drinking behavior. There are two dimensions underlying the classification of drinking motives (Cooper, 1994; Cox & Klinger, 1988): the valence (positive or negative) and the source (internal or external) of the outcomes people expect to achieve by drinking. Combining these two dimensions results in four drinking motive categories: enhancement (internal, positive), social (external, positive), coping (internal, negative), and conformity (external, negative).

An international review of drinking motives has revealed that most young people reported drinking for social motives, some indicated enhancement motives, and only a few reported coping motives (Kuntsche, Knibbe, Gmel, & Engels, 2005). Furthermore, it has been demonstrated that the effects of drinking motives on alcohol outcomes are robust across populations (including adolescents, college students, emerging adults, adults) and across important life stages (e.g., the transition from adolescence into adulthood) (Cooper et al., 2008; Littlefield, Sher, & Wood, 2010).

A previous study, using full cross-lagged regression models (i.e., a linear approach), demonstrated the value of drinking motives in predicting drinking behavior among adults (Crutzen, Kuntsche, & Schelleman-Offermans, 2013): social motives positively affected the number of drinks on the heaviest drinking day, whereas enhancement motives positively affected the number of drinking days. Coping motives positively affected both measures of drinking behavior, whereas conformity motives were not related to drinking behavior when using full cross-lagged regression models.

METHODS

Data were collected through the LISS panel (Longitudinal Internet Studies for the Social sciences; www.lissdata.nl) (Scherpenzeel, 2009). The reference population for the LISS panel is the Dutch speaking adult population permanently residing in the Netherlands. In co-operation with Statistics Netherlands addresses were randomly drawn from the nationwide address frame including individuals who do not have Internet access. These were provided equipment to access the Internet via a broadband connection to ensure representativeness of the sample. Those with small band Internet access were provided with broadband. There was ethics approval for the umbrella project, which was conducted by an external party (CentERdata; http://www.centerdata.nl/en). Relevant ethical safeguards were met with regard to the participant confidentiality and consent.

Participants

Drinking motives can only be assessed for individuals who drink alcohol. Therefore, we focused on the panel members who indicated in November 2010 that they drank alcohol during the past year. A sample of 3,192 respondents was selected at random from these panel members. They were invited for the assessment of drinking motives and drinking behavior in January 2011. Of those invited, 2,861 responded (89.6% response rate) and 2,844 fully completed the measures (99.4% retention rate). The final sample consisted of 47% women; the average age was 52 years ($SD = 17$). Of these participants, 34% had a low level of highest completed education, 32% an intermediate level, and 34% a high level (according to the definitions of Statistics Netherlands; http://statline.cbs.nl/statweb/).

Measures

Drinking Motives

The Drinking Motives Questionnaire Revised (DMQ-R) was used to measure drinking motives. Cooper (1994) developed the DMQ-R, which has become the most widely used questionnaire to measure drinking motives (Kuntsche et al., 2005) and was shown to be a valid and reliable instrument to assess drinking motives across cultures (Crutzen & Kuntsche, 2013; Kuntsche, Stewart, & Cooper, 2008). This questionnaire assesses the strength of each of the four categorical motives (enhancement, social, coping, and conformity) with five items per category. Participants indicate the relative frequency of occasions in which each item promoted drinking, on a scale from one ("never") to five ("almost always"). The list of all items, including their means, is provided in the Appendix.

Drinking Behavior

Drinking behavior was assessed by the number of drinks on the heaviest drinking day during the past week (open-ended). To increase validity, respondents were asked to report each type of beverage separately (e.g., strong beer, extra strong beer, strong drinks/liqueur, sherry/martini, wine, and premixes). The type of serving was also assessed (e.g., a regular glass, a pint, a small or large can, a small or large bottle). These drinks were converted into standard drinks based on the alcohol content in most on-premise locations in the Netherlands: a standard drink contains 10 g alcohol (Lemmens, 1994). Participants were categorized as binge drinkers if the amount of standard drinks consumed on the heaviest drinking day during the past week is at least four (for women) or five (for men). A total of 33.45% of the final sample engaged in binge drinking in the week prior to filling out the questionnaire; 26.65% of women and 39.50% of men.

Analyses

The types of classifiers considered in this study are among the most popular, and include regressions, decision trees, and support vector machines (SVMs). Regressions assume that a linear combination of the features can be used to predict the behavior, which is often known as assuming a "linear relationship." Both linear logistic regression and multinomial logistic regression were used. Decision trees do not aim at directly combining features to predict the behavior; instead, they partition the feature space using the simple cuts illustrated in Figure 1. A consequence is that decision trees are not as linear as regressions: intuitively, a feature can be increased with no changes on the behavior to be predicted as long as one stays in the same region of the partition (e.g., in Figure 1, varying feature 1 from 0 to 2 and feature 2 from 0 to 3 does not change the categorization). Logistic model tree, J48, and functional tree were the decision trees used in this study. SVMs also divide the feature space, but they are not restricted to horizontal or vertical cuts as in decision trees. Instead, SVMs with a linear kernel can use all possible straight cuts (e.g., diagonal), and SVMs with nonlinear kernel such as polynomial or (Gaussian) radial basis function use cuts other than lines. Furthermore, building a classifier on real data can potentially result in a list of thousands of varying cuts to represent a model, which cannot be easily displayed. Therefore, we have provided the names of the learning techniques that were used to develop the classifiers along with key technical choices, instead of graphical depictions of the resulting classifiers. Besides the SVM mentioned above, we have also used normalized training data (both with sequential minimization algorithm using a radial basis function kernel and a normalized polynomial kernel) and no normalization standardization (with sequential minimization algorithm using a radial basis function kernel). Technical details about these classifiers can be found elsewhere (Heykin, 2008; Kecman, 2001; Rokach & Maimon, 2008). Age, gender, and educational level were taken into account besides drinking motives to classify binge drinkers.

A key outcome measure of this study is the performance of each classifier in using drinking motives to infer whether a participant is a binge drinker. This performance was measured using a standard procedure known as 10-fold cross-validation, in which "the data set is split into 10 parts of approximately equal sizes, and each part is used in turn for testing of a classifier built on the pooled remaining 9 parts" (Kuncheva, 2004). The main advantage of this procedure is that the performance of a classifier is evaluated on different instances than those used to build it, in which case it could perform artificially high. Indicators of performances were the percentage of correctly classified binge drinkers and nonbinge drinkers, the weighted percentage of correctly identified participants (higher indicates better performance), and the mean absolute error (lower indicates better performance).

RESULTS

Table 1 provides an overview of the performances of classifiers. Performances are sorted by the percentage of correctly identified binge drinkers, which is of practical relevance as well as a better indicator of overall performance than correctly identified cases (Giabbanelli & Crutzen, 2013).

Table 1 confirms that classifiers have potential in identifying binge drinkers based on drinking motives: close to 70% of participants were correctly identified as binge drinker or nonbinge drinkers by the various techniques used here.[1] It should be noted, however, that classifiers were constantly better at identifying nonbinge drinkers than binge drinkers. In particular, logistic regressions (i.e., assuming a linear combination of motives predicting binge drinking) were the most successful in identifying nonbinge drinkers, while being some of the least successful in identifying binge drinkers. Several decision trees were constructed (J48, Functional tree, Logistic model tree) but they did not significantly improve the performances. Using SVM, the mean absolute error was minimal, although performances on identifying binge drinkers improved. Further examination showed that cutting through the feature space in straight lines (i.e., linear

[1] All classifiers shared a confidence interval of ±5% with 95% confidence. The percentage of correctly classified participants over each of 10 repeated tests on subsets of the data had a standard variation of up to 2%.

TABLE 1. Summary of performances

Correctly classified binge drinkers (%)	Correctly classified nonbinge drinkers (%)	Correctly identified cases (%)	Mean absolute error	Type of classifier	Technical specification[a]
68.2	70.4	70.2	.30	SVM[b]	Normalized training data[c]
67.4	68.9	68.6	.31	SVM	Linear kernel
66.3	70.1	69.7	.30	SVM	Radial basis function
64.4	71.3	70.3	.30	SVM	No normalization standardization[c]
64.2	73.0	71.4	.38	Decision tree	Logistic model tree
64.2	73.0	71.4	.38	Regression	Linear logistic regression
64.0	70.8	69.9	.30	SVM	Normalized training data[d]
63.2	70.0	69.3	.31	SVM	Polynomial kernel
61.2	73.5	71.0	.38	Regression	Multinomial logistic regression
54.9	71.6	68.4	.40	Decision tree	J48
49.3	72.8	66.1	.37	Decision tree	Functional tree

[a]Classifiers assuming a linear relationship between input and output are shaded gray; classifiers using linear cuts are shaded black; nonlinear classifiers are shaded white.
[b]SVM = Support vector machines.
[c]Sequential minimization algorithm using a radial basis function kernel.
[d]Sequential minimization algorithm using a normalized polynomial kernel.

kernel) was almost as efficient as cutting using complex nonlinear shapes.

Finally, when comparing the structure of classifiers, we found that no specific features consistently contributed to their performance. For example, when performing a multinomial logistic regression, all top five coefficients were based on conformity motives[2] and accounted for 90% of the weight of all coefficients. However, in a linear logistic model, conformity motives were not used and instead the model draws primarily on enhancement and social motives.

DISCUSSION

We used the technique of classifiers to explore how binge drinking could be predicted from drinking motives, which are the most proximal factors in the motivational model of alcohol use (Cox & Klinger, 1988). Our key finding is that 70% of participants could be correctly identified as binge drinkers or nonbinge drinkers based on drinking motives and demographic information assessed by short questionnaires. Therefore, using classifiers can contribute to explaining human behavior, one of the main research areas of behavioral scientists.

Comparing this result to that of other studies faces two methodological challenges. First, there is currently no standard dataset on which the ability to correctly identify binge drinkers can be evaluated. This forces researchers to compare the efficiency of their techniques across different populations, which can sometimes have drastically different demographics: for example, a number of studies focus on young populations, although the average age in our sample was 52 years. Second, the indicators of performances reported by researchers are commonly tied to the technique that was employed, and do not directly speak to the percentage of participants that could be correctly identified. This is illustrated by reporting correlations and R^2 when using regression techniques (Sheeran, 2002), where a review showed the average R^2 for behaviors to be .28; a recent example of this approach in binge drinking is provided by Cooke, Sniehotta, and Schüz (2007), who had R^2 at .33 based on intentions and previous binge drinking. Although our performance of 70% can be deemed high given the complexity of the behavior and the small size of the questionnaire used to assess it, creating standard datasets and providing unified performance measure will be a key step to allow systematic comparison.

In light of the possibility that drinking motives can be connected in nonlinear ways to binge drinking (Warren et al., 2003), we compared the performances when undertaking a linear approach (e.g., a regression) versus a nonlinear approach (e.g., an SVM with nonlinear kernel). This case study finds that the latter was more successful in identifying binge drinkers in comparison with more traditional regression approaches, while keeping the mean absolute error to a minimal. Therefore, there is potential in utilizing nonlinear approaches to explore the complex connections between drinking motives and binge drinking.

It is worth mentioning, however, that classifiers were constantly better at identifying nonbinge drinkers than binge drinkers. A possible explanation is that event-level drinking contexts are important, besides drinking motives, to explain binge drinking. People drink more, for example, on days following elevated sadness when being motivated to drink to cope (Hussong, 2007), but also when they are internally motivated to increase positive affect (Birch et al., 2008). Additional contextual data could further increase the potential of classifiers as well as allowing a richer exploration of nonlinearity. It also needs to be stressed that classifiers are likely to be constantly better at identifying nonbinge drinkers than binge drinkers because of the larger proportion of Dutch adult drinkers who are nonbinge drinkers (Giabbanelli & Crutzen, 2013).

[2]Con1 = 5, Con2 = 4, Con1 = 4, Con4 = 5, Con3 = 5 (conform description in Appendix)

When comparing the structure of classifiers, it is striking to see the importance of conformity motives in a multinomial logistic regression, because conformity motives had no predictive value regarding drinking behavior in previous studies using linear models (Crutzen et al., 2013; Schelleman-Offermans, Kuntsche, & Knibbe, 2011). So, even though participants score at the lower-end of the scale regarding conformity motives (see Appendix), these motives do contribute when explaining binge drinking among adults. Furthermore, these low scores are representative of the Dutch speaking adult population, which allow generalization of the findings.

The take home message of the current study, over and above the findings of this specific case, is that classifiers are worthwhile to be used in research regarding (addictive) behaviors in general, because (1) they contribute to explaining behavior and (2) they can give different insights from more traditional data analytical approaches.

Declaration of Interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the article.

THE AUTHORS

Rik Crutzen, Ph.D., is a psychologist and e-communication specialist by background and obtained his Ph.D. within the field of health promotion. Dr. Crutzen is based at the Department of Health Promotion, which is part of CAPHRI—the School for Public Health and Primary Care, Maastricht University, The Netherlands. The overarching theme of his work is how technological innovations can be used to greatest effect in the field of health promotion to increase the public health impact of these innovations. An up to date overview of his publications can be found at www.crutzen.net.

Philippe J. Giabbanelli, M.Sc., is a computational modeler who focuses on applying simulations to health behaviors. His primary interest is in the modeling of chronic diseases, and particularly on the role that peers and the environment play in driving one's behavior. Philippe has published in some of the leading journals in the area, such as Advances in Complex Systems, Applied Soft Computing, the Journal of Computational Science, and the Journal of Artificial Societies and Social Simulation. He regularly teaches both computing science and health at Simon Fraser University, Canada.

GLOSSARY

Classifier: A computational model that assigns a label/category to participants based only on their features (e.g., gender, drinking motives). The model is trained using participant data with known label and features. The training repeatedly divides/cuts across features (e.g., divide across age or educational attainment) in order to isolate groups of participants with similar labels.

Decision tree: A linear classifier in which each successive cut in the data is based on the value of one feature (e.g., select participants with age >50 and successively select those for whom educational attainment is at most high school).

Motivational model of alcohol use: According to this model, drinking motives are the most proximal factors for drinking behavior. There are two dimensions underlying the classification of drinking motives: the valence (positive or negative) and the source (internal of external) of the outcomes people expect to achieve by drinking.

Support vector machine (SVM): A classifier able to perform both linear (as a decision tree) or nonlinear classification depending on a kernel function.

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APPENDIX
Item Means

Item	How often do you drink	Mean
Enh1	Because you like the feeling?	2.69
Enh2	Because it's exciting?	1.12
Enh3	To get high?	1.14
Enh4	Because it gives you a pleasant feeling?	2.33
Enh5	Because it's fun?	2.17
Soc1	Because it helps you enjoy a party?	1.77
Soc2	To be sociable?	2.20
Soc3	Because it makes social gatherings more fun?	1.91
Soc4	Because it improves parties and celebrations?	1.82
Soc5	To celebrate a special occasion with friends?	2.57
Cop1	To forget your worries?	1.21
Cop2	Because it helps you when you feel depressed or nervous?	1.23
Cop3	To cheer up when you're in a bad mood	1.23
Cop4	Because you feel more self-confident or sure of yourself?	1.17
Cop5	To forget about your problems?	1.18
Con1	Because your friends pressure you to drink?	1.04
Con2	So that others won't kid you about not drinking?	1.02
Con3	You drink to fit in with a group you like?	1.06
Con4	To be liked?	1.04
Con5	So you won't feel left out?	1.05