Analysis of Individuals Vulnerable To Substance Addiction Leading To Mental Illness: A Review of Machine Learning Approach

Bijoy Chettri[1], Lekh Nath Chettri[2], Devashish Sharma[3]andSudarshan Lawati[4]
[1]Lecturer, Dept of Computer Science and Technology
[2, 3, 4]Dept of Computer Science and Technology
[1, 2, 3, 4] Centre for Computers and Communication Technology, Chisopani, S. Sikkim, 737126

Abstract- *Substance abuse leading to addiction especially among our youth population has become one of the major problem in our society. The initiation of their addiction in most cases starts from the age of 15 to 19 while they are in their High School or in the Colleges.*

The proposed research work will focus on the study of neurocognitive characteristics of a subject abusing drug/marijuana leading to harmful impact on mental health of the subject. In addition, to devise and train a Support Vector Machine (SVM) as a screening tool to diagnose the level of addiction the subject has developed.

The tool will also wherein the characteristics will be both the symptoms (as of the screening tools requirement) as well the daily activities that tells about his/her personality traits of the particular patient. The training dataset to be used will have features as recorded symptoms (through record of screening) and daily activities as answers to predefined questionnaire (of personality trait screening tool). Machine Learning approaches will be applied in this project.

Keywords- Substance abuse, drug/marijuana, Machine Learning, Support Vector Machine, Learning Model.

I. INTRODUCTION

1.1 Mental Health

Mental health by definition includes one’s emotional, bio-psychological, implication from physical health and social well-being. It is that one factor responsible for how we think, feel, act and react to a given social, emotional, physical or any other stimuli. It also helps to determine how we cope up with various situations posing stress and pressure, relate and communicate to others, and make decisions in our individual lives. It is an important aspect of healthy living at every stage of our life cycle, from childhood, through adolescence (teenage) to adulthood and finally to our old age. [1]

Major factors that affect mental health of an individual at any instance of time are as follows:-

Biological factors such as genetic characteristics or brain chemistry(working of brain).

Life experiences, such as trauma or abuse in the past times.

Family history of mental health problems or working environment relations.

Bio-psychosocial factors are key determinant of one’s mental health. [1]

1.2 Machine Learning

Machine Learning, as the words simply suggests is about making the machine to learn from past-experience data using certain algorithms. To be precise, machine learning is a concept, using which we can give a task to the machine without programming it and is a subset of Artificial Intelligence. Machine learning algorithms devise a mathematical model or simply statistical model of sample dataset, known as training dataset, in order to make predictions or decisions. The process of learning actually begins with the machine’s observation of data, such as examples, direct experience in the past, or certain predefined instruction, so as to look for patterns in data and make optimized decisions in the future based on the examples provided. The primary idea behind the concept of Machine Learning is to allow the computers learn on their own without human assistance or interference and adjust the actions associated accordingly. [2]

1.3 Machine Learning Algorithms

Machine Learning algorithms are categorized mainly in three domains:-

1.3.1 Supervised Learning

In supervised learning, we are provided with a data set whose correct output is already familiar to us, having the idea beforehand that there is a relationship between the input parameters and the output parameters of the dataset. Supervised learning problems are broadly classified into regression and classification problems. Some examples of Supervised Learning are as follows: Regression, Random Forest, KNN, Logistic Regression, SVM, Decision Tree etc. [3]

1.3.2 Unsupervised Learning

In this algorithm, we do not have any target or outcome variable to predict / estimate. It is used for clustering population in different groups, which is widely used for segmenting customers in different groups for specific intervention. Examples of Unsupervised Learning: Apriori algorithm, K-means. [3]

1.3.3 Reinforcement Learning

Reinforcement Learning is, when exposed to an environment, how the machine train itself using trial and error. Machine mainly learns from past experiences provided in an interpretable and tries to perform best possible solution to a certain problem. In past couple of years, a lot of improvements in this particular area has been seen. Main example includes DeepMind's Alpha Go, beating the champion of the game Go in 2016, Markov Decision Process. [3]

1.4 Support Vector Machine (SVM)

Support Vector Machine (SVM) algorithm comes under Supervised Machine Learning and it is used for both Regression and classification problems.

In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiate the two classes very well [4].
The proposed research based project focusses on prediction of possibilities of mental diseases based on features that includes both symptoms as well as daily activities that the subject indulges in. The aim is planned to be achieved through machine learning model and validation of the same model is to be done both theoretically using calculations as well as in real-time subject. And to compare and score the results shown by the subject as per the consultation of the medical specialist.

II. LITERATURE SURVEY

[1] Making Decision With Trees: Examining Marijuana Outcomes Among College Students Using Recursive Partitioning Adam D. Wilson, Kevin S. Montes, Adrian J. Bravo, Bradley T. Conner, Matthew R. Pearson, And the Marijuana Outcomes study team. Clinical Psychological Science
2018, Vol. 6(5) 744–754.

This large sample study targets to provide the impetus to develop intervention strategies targeting these factors. Exploratory analyses were used to identify a unique constellation of variables that are associated with marijuana use outcomes among college students. Recursive partitioning was used to examine more than 100 putative antecedents of lifetime marijuana user status, past-month marijuana user status, and negative marijuana-related consequences. Participants (N = 8,141) completed measures online across 11 sites in the United States. Norms (descriptive, injunctive, and internalized norms) and marijuana identity best distinguished marijuana users from nonusers (i.e., lifetime/past month), whereas marijuana use frequency, use of protective behavioral strategies, and positive/negative urgency best distinguished the degree to which users reported negative consequences. The results of this work demonstrate that tree-based modeling is a useful methodological tool in the selection of targets for future clinical research. The limitation of this work is that an additional research is needed to determine if these factors are causal antecedents, rather than consequences or epiphenomena.

[2] Decision-making in stimulant and opiate addicts in protracted abstinence: evidence from computational modeling with pure users.

Woo-Young Ahn, George Vasilev, Sung-Ha Lee, Jerome R. Busemeyer, John K. Kruschke, Antoine Bechara and Jasmin Vassileva.

Substance dependent individuals (SDI) often show decision making shortfall; however, it remains ambiguous whether the nature of the underlying decision making processes is the same in users of different classes of drugs and whether these deficits persist after discontinuation of drug use. The researchers have used computational modeling to address these questions in a unique sample of relatively "pure" amphetamine-dependent (N=38) and heroin- dependent individuals (N=43) who were currently in protracted abstinence, and in 48 healthy controls (HC). For the comparison of three cognitive models: (1) Prospect Valence Learning with decay reinforcement learning rule (PVL-Decay

RI), (2)PVL with delta learning rule (PVL-Delta), and (3) Value-Plus-Perseverance (VPP) model based on Win-Stay-Lose-Switch (WSLS) strategy, A Bayesian model comparison technique, a simulation method, and parameter recovery tests were used. The aforementioned model comparison results showed that the VPP model, a hybrid model of reinforcement learning (RL) and a heuristic strategy of perseverance had the best post-hoc model fit, whereas the two PVL models showed better simulation and parameter recovery performance. Computational modeling results suggested that overall all three groups depend more on RL than on a WSLS strategy. Heroin users displayed reduced loss aversion comparative to HC across all three models, which suggests that their decision-making shortfalls are long standing (or pre-existing) and may be driven by reduced sensitivity to loss. In contrast, amphetamine users displayed comparable cognitive functions to HC with the VPP model, whereas the second best-fitting model with relatively good simulation performance (PVL-Decay RI) revealed increased reward sensitivity relative to HC. These results suggest that some decision-making deficits persist in protracted abstinence and may be mediated by different mechanisms in subjects using opiate and stimulant.

[3] Does Marijuana Use at Ages 16–18 Predict Initiation of Daily Cigarette Smoking in Late Adolescence and Early Adulthood? A Propensity Score Analysis of Add Health Data.
Trang-Quynh Nguyen, Cyrus Ebnesajjad, Elizabeth A. Stuart, Ryan David Kennedy and Renee M. Johnson1.

Given the weakening trend in adolescent cigarette smoking and increase in general access to marijuana, it is necessary to examine whether the marijuana use in adolescence is a risk factor for subsequent cigarette smoking in late adolescence and early adulthood. Preliminary evidence from a very small number of studies suggests that access to marijuana or its usage during adolescence is associated with later cigarette smoking; however, to control confounding, studies published before this work used regression adjustment, which is vulnerable to extrapolation when the confounder distributions vary between adolescent marijuana users and non-users. This study uses propensity score weighting, a causal inference method not previously used in this area of research, to weight participants based on their estimated probability of exposure given confounders (the propensity score) to balance observed confounders between marijuana users and nonusers. The sample consists of participants of Add Health (a nationally representative dataset of youth followed into adulthood) who were 16–18, with no background or history of daily cigarette smoking at baseline (2731 for male sub-samples and n = 2928 for female). The researchers in this work have assessed the effect of adolescent marijuana use (exposure, ascertained at wave 1) on any daily cigarette smoking during the subsequent 13 years (outcome, ascertained at wave 4). Analyses suggest that for females (but not males) who used marijuana in adolescence, marijuana use increased the risk for subsequent daily smoking: OR = 1.71, 95% CI = (1.13, 2.59). This work recommends that adolescent marijuana use may be viewed as a possible risk factor for subsequent initiation of daily cigarette smoking in women.

[4] Testing a machine-learning algorithm to predict the persistence and severity of major depressive disorder from baseline self-reports.

RC Kessler, HM van Loo, KJ Wardenaar, RM Bossarte, LA Brenner, T Cai, DD Ebert, I Hwang, J Li, P de Jonge, AA Nierenberg, MV Petukhova, AJ Rosellini, NA Sampson, RA Schoevers, MA Wilcox and AM Zaslavsky.

In this paper, complications in clinical decision-making due Heterogeneity of major depressive disorder (MDD) illness course has been focused. The past efforts to use symptom profiles or biomarkers to develop clinically useful prognostic subtypes have had limited success, a recent report showed that machine-learning (ML) models developed from self-reports about incident episode characteristics and comorbidities among respondents with lifetime MDD in the World Health Organization World Mental Health (WMH) Surveys predicted MDD persistence, chronicity and severity with good accuracy. This paper reports results of model validation in an independent prospective national household sample of 1056 respondents with lifetime MDD at baseline. The WMH ML models were applied to these baseline data to generate predicted outcome scores that were compared with observed scores assessed 10–12 years after baseline. In this work the cross-check of accuracy between ML models namely WMH ML models and conventional logistic regression models. Area under the receiver operating characteristic curve based on ML (0.63 for high chronicity and 0.71–0.76 for the other prospective outcomes) was consistently higher than for the logistic models (0.62–0.70) despite the latter models i.e. logistic regression models including more predictors. A total of 34.6–38.1% of respondents with subsequent high persistence chronicity and 40.8–55.8% with the severity indicators were in the top 20% of the baseline ML-predicted risk distribution, while only 0.9% of respondents with subsequent hospitalizations and 1.5% with suicide attempts were in the lowest 20% of the ML-predicted risk distribution. The results from this study confirmed that clinically useful MDD risk-stratification models can be generated from baseline patient self-reports and that ML methods improve on conventional methods in developing such models.

[5]Machine Learning identifies substance behavioral markers for opiate and stimulant and stimulant dependence.Woo-Young Ahn, Jasmin Vassileva.

The goal of this study was to identify multivariate substance specific markers classifying heroin dependence (HD) and amphetamine dependence (AD) by using machine learning approaches. For this purpose the participants included 39 amphetamine mono-dependent, 44 heroin mono-dependent, 58 polysubstance dependent, and 81 non-substance dependent individuals. The majority of substance dependent participants were in protracted abstinence. For the predictors in machine-learning algorithm the following features were taken: demographic features, personality (impulsivity trait, trait psychopathy, aggression, sensation seeking), psychiatric (attention deficit hyperactivity disorder, conduct disorder, antisocial personality disorder, psychopathy, anxiety, depression), and neurocognitive impulsivity measures(Delay discounting, Go/No-Go, Stop Signal, Immediate Memory, Balloon Analogue Risk, Cambridge Gambling, and Iowa Gambling tasks).The approach used in this work i.e. machine-learning approach revealed substance-specific multivariate profiles that classified AD and HD in many new samples with a higher margin of accuracy. Among the 54 aforementioned predictors used in this research, psychopathy was the only classifier found to be common to both types of addictions.

[6] Impact of adolescent marijuana use on intelligence:Results from two longitudinal twin studies.

Nicholas J. Jackson, Joshua D. Isen, Rubin Khoddam, Daniels Irons, Catherine Tuvblad, William G. Iacono, Matt Mcgue, Adrian Raine, and Laura A. Baker.

The purpose of this study was to examine the associations of marijuana use with changes in intellectual performance in two longitudinal studies of adolescent twins (n = 789 and n = 2,277). The researcher in this study used a quasi-experimental approach to adjust for participants' family background characteristics and genetic propensities, in turn helping them to assess the causal nature of any potential associations. Standardized measures of intelligence were administered to the subjects at ages 9–12 y, before marijuana involvement, and again at ages 17–20 y. Marijuana use was self-reported at the time of each cognitive assessment as well as during the intervening period. Marijuana users had lower test scores relative to nonusers and showed a significant decline in crystallized intelligence between preadolescence and late adolescence. However, there was no evidence of a dose–response relationship between frequency of use and intelligence quotient (IQ) change. Furthermore, marijuana-using twins failed to show significantly greater IQ decline relative to their abstinent siblings. Evidence from these two samples suggests that observed declines in measured IQ may not be a direct result of marijuana exposure but rather attributable to familial factors that underlie both marijuana initiation and low intellectual attainment.

[7] Impact of Drug Addiction on Mental Health.
Wani MS* and Sankar R, Department of psychology, Annamalai University, Tamil Nadu India.

This research paper explored the impact of drug addiction on mental health. Wherein mental health is defined as the individual's adjustment with a maximum of effectiveness, satisfaction, happiness and socially considerate behavior and the ability to face and accept the reality of life. Therefore excess use of drugs largely affects individual's mental health. The methodology in this work consists of 60 subjects randomly selected among which 30 were adolescents (15 males and 15 females) and 30 adult's (15 males and 15 females). The P.G.I Health Questionnaire N-I devised by Varma, Wing and Pershad was used to measure the mental health status of drug addicts. The effect of two experimental variables namely age and gender were studied on one criterion variable i.e. mental health. For data analysis, mean and two way ANalysis Of VAriance (ANOVA) were applied which yielded the results that revealed that age and gender have significant effect on mental health of drug addicts. Also the work inferred that adult addicts and female addicts show better mental health than adolescent addicts and male addicts. This work concludes that age and gender are the influential factors in mental health in relation with drug addiction.

[8]The Five Factor Model of personality and evaluation of drug consumption risk.

Elaine Fehrman, Evgeny M. Mirkes, Awaz K. Muhammad, Vincent Egan, Alexander N. Gorban.

This paper focuses on the highly important problem of evaluating an individual's risk of drug consumption and misuse. For this work an online survey methodology was employed to collect data including Big Five personality traits (NEO-FFI-R), impulsivity (BIS-11), sensation seeking (ImpSS), and demographic information. The data set contained information on the consumption of 18 different central nervous system psychoactive drugs. Existence of groups of drugs with strongly correlated consumption patterns was demonstrated in Correlation analysis. Three correlation Pleiades were found, name by the central drug in the pleaide: ecstasy, heroin and benzodiazepines Pleiades. An exhaustive search was performed by the researchers in this work to select the most effective data mining methods and subset of input features to classify users and non-users for each drug and pleaid. Various classification methods namely decision tree, random forest, k-nearest neighbors, linear discriminant analysis, Gaussian mixture, probability density function, logistic regression and naïve Bayes were employed and the most effective classifier was selected for each drug. The quality of classification yielded was surprisingly high with sensitivity and specificity (evaluated by leave-one-out cross-validation) being greater than 70% for almost all classification tasks. The best results with sensitivity and specificity achieved were greater than 75% were for cannabis, crack, ecstasy, legal highs, LSD and volatile substance abuse (VSA).

[9] Associations of personality traits with marijuana use in a nationally representative sample of adolescents in the United States.

Angela E. Lee-Winn□, Tamar Mendelson, Renee M. Johnson.This work has used data from the National Comorbidity Survey: Adolescent Supplement, a nationally representative, cross-sectional study of 8495 U.S. adolescents aged 14 to 18 years. The calculations of adjusted prevalence ratios and odds ratios to assess associations of the five personality scales with lifetime use and frequencyof past 12-month use and examined gender as a potential moderator of these associations have been done.

The result indicated that each of the aforementioned personality traits was positively associated with lifetime use (all $p < 0.001$). Impulsivity (the total scale and both subscales) and aggression (all $p < 0.05$) were positively associated with frequency of past 12-month use. The neuroticism–lifetime use association was found to be stronger among girls ($p < 0.001$) than boys ($p < 0.05$), and the associations of lack of planning with frequency of use and impulsivity were significant only among girls, with moderate female users reporting higher levels of the personality scales than infrequent users (both $p < 0.01$).This study highlights the potential importance of identifying personality traits, specifically disinhibition-related traits such as impulsivity and aggression, to reduce and ultimately prevent adolescent marijuana use.

INFERENCES DRAWN

Table 2.1: Inferences drawn from Literature Survey

Author name and Publication	Title of the paper	Technique Used	Limitation
Adam D. Wilson, Kevin S. Montes, Adrian J. Bravo, Bradley T. Conner, Matthew R. Pearson, And the Marijuana Outcomes study team. Clinical Psychological Science2018, Vol. 6(5) 744–754	Making Decision With Trees: Examining Marijuana Outcomes Among College Students Using Recursive Partitioning	Recursive Partitioning Model, 1-Minus Standard Error Rule for cross-validation to check overfitting	Additional research is required to determine if these factors are casual antecedents, rather than consequences or epiphenomena
Woo-Young Ahn, George Vasilev, Sung-Ha Lee, Jerome R Busemeyer, John K. Kruschke, Antoine Bechara and Jasmin Vassileva.Drug and alcohol dependence 161 (2016): 247-257.	Decision-making in stimulant and opiate addicts in protracted abstinence: evidence from computational modeling with pure users.	Bayesian Data Analysis Models, Bayesian Model Comparisons.	Differentexperimental paradigms proving different aspect decision making will be necessary to examine subject different stages of the addiction cycle.

Table 2.2: Inferences drawn from Literature SurveyContinued.

Name of author and publication	Title of the paper	Techniques Used	Limitations
Woo-Young Ahn, Jasmin Vassileva	Machine Learning identifies substance behavioral markers for opiate and stimulant and stimulant dependence.	Machine learning algorithms for prediction and classification	Methodology not defined properly.
RC Kessler, HM van Loo, KJ Wardenaar, RM Bossarte, LA Brenner, T Cai, DD Ebert, I Hwang, J Li, P de Jonge, AA Nierenberg, MV Petukhova, AJ Rosellini, NA Sampson, RA Schoevers, MA Wilcox and AM Zaslavsky.05 January 2016, https//doi.org/	Testing a machine-learning algorithm to predict the persistence and severity of major depressive disorder from baseline self-reports.	World Mental Health (WMH) Machine Learning Model, Logistic Regression Models	A tiered risk assessment is required for the reliability of the outcome of the model.
Nicholas J. Jackson, Joshua D. Isen, Rubin Khoddam, Daniels Irons, Catherine Tuvblad, William G. Iacono, Matt Mcgue, Adrian Raine, and Laura A. Baker. Proceedings of the National Academy of Sciences, 113(5), pp.E500-E508.	Impact of adolescent marijuana use on intelligence: Results from two longitudinal twin study.	Co-twin Control Methods. Mixed Effect Model.	No direct effect of marijuana on intellectual skills of a subject was found
Wani MA and Sankar R. Wani and Sankar, J Ment Disord Treat 2016, 2:1	Impact Of Drug Addiction On Mental Health	Analysis of Variance (ANOVA)	Two features may underfit.
Elaine Fehrman, Evgeny M. Mirkes, Awaz K. Muhammad, Vincent Egan, Alexander N. Gorban.	The Five Factor Model of personality and evaluation of drug consumption risk.	An online survey to collect data. Correlation Analysis.	Different methodologies applied for different drugs.
Trang-Quynh Nguyen, Cyrus Ebnesajjad, Elizabeth A. Stuart, Ryan David Kennedy and Renee M. Johnson1. Prevention Science (2018): 1-11.	Does Marijuana Use at Ages 16–18 Predict Initiation of Daily Cigarette Smoking in Late Adolescence and Early Adulthood? A Propensity Score Analysis of Add Health Data.	Data Analysis through Propensity Score (PS) Weighing Method	Feature subset selection process needs to be done.
Angela E. Lee-Winn□, Tamar Mendelson, Renee M. Johnson.	Associations of personality traits with marijuana use in a nationally representative sample of adolescents in the United States.	Cross-sectional study of data from the National Comorbidity Survey: Adolescent Supplement.	Hypothesis made is not clearly presented.

III. PROPOSED METHODOLOGY

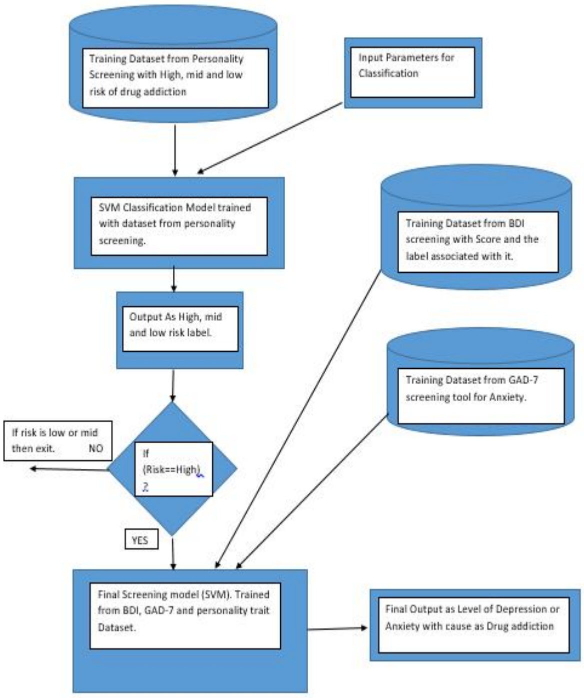

Fig 3.1: Flowchart for our proposed system

Fig 3.1 is the flowchart of our proposed system. The figure depicts how our proposed system will run. The System basically classifies the subject on risk of getting into drug addiction associated with him/her at first. Once the classification is done, subjects with low or medium risk are not take into consideration for further analysis. Subjects with high risk indicated by the classifier are further passed on to another level wherein a final model trained from dataset from screening tool of two main mental illness namely Beck's Depression Inventory known in short as BDI (for depression) and Generalized Anxiety Disorder-7 known in short as GAD-7 (for Anxiety). The Final model will give the output as the level of mental illness specifically Depression and Anxiety with root cause as Drug Addiction.

Steps to developing the Machine Learning Models:

Step 1: Devise a SVM classification model and train it using dataset from Personality trait Screening tool.
Step 2: Discard the Subjects classified as medium or low risk to drug addiction by the SVM classifier.
Step 3: Consider the subjects classified as high risk to drug addiction for the next model for the final output.
Step 4: Train the final model with the datasets consisting of records from BDI, GAD-7 and Personality trait Score. .
Step 5: Interpret the final output labelbased on the parameters or features as a pre-defined report with suggestive statement.
Step 6: Cross-Check and validate the Accuracy Score of the ML Models.

IV. CONCLUSION

With the advancement in machine learning technology, it can be a boon to medical science. Researches in intervention of computational technology and data science in medical science is one of the major inter-disciplinary field of research. Recent trend has mainly focused on the predictions as well as optimization of diagnosis through analysis of Electronics Medical Records (EMR). Mental health has been one widely researched and developing domain wherein work of optimization has been growing tremendously.The proposed system as a whole can provide reference as a support to individuals other than Medical specialists working in educational institutions like School and colleges to tap and tackle drug addiction at its initial phase.

The current work has focused on two main mental illness namely Depression and General Anxiety Disorder. Therefore, many of the mental illness except for the aforementioned two can be considered and worked upon through this methodology. The ML models applied in this work needs optimization on accuracy validation score. We have focused on the subject's personality trait as primary classifier for Drug addiction but in order to achieve higher accuracy, many other features such as Neurocognitive approaches, testimonies of individuals addicted to a particular drugs can be taken for an effective feature selection keeping them in abstinence.The major shortfall of appropriate training datasets posed a major problem since no such records are kept by the local authorities including the De-addiction and Rehabilitation Centers. Lastly, we hope that this work may put some light on dealing Mental Health issues in relation with Substance/Drug addiction (Abuse) and assist future work in this field. A standardized Data recording system is required for further advancement of this research

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