Assessment of the Relationship Between Attribute Coding and the Interpretability of Machine Learning Models: An Analysis in the Context of Children and Adolescents with Depression

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Abstract: Depression is a global public health challenge that affects approximately 300 million people. Artificial Intelligence and Machine Learning have revolutionized the healthcare sector, allowing the development of models to diagnose depression. Tabular data, shared in healthcare, requires preprocessing, including encoding categorical attributes into numeric values, as many Machine Learning algorithms only support numeric data. This study aims to investigate different coding methods for non-ordinal nominal categorical attributes in a dataset related to depression in children and adolescents suffering from Major Depressive Disorder (MDD). The comparison results revealed that the XGBoost algorithm with the Hash Encoding, Customized One Hot, Frequency, and Dummy coding techniques were more effective for the analyzed data set. However, not all of these encodings are interpretable. These results provide significant insights, highlighting the importance of choosing appropriate coding methods to improve the accuracy of Machine Learning models and the interpretability of these models in healthcare.

1 INTRODUCTION

Depressive disorder, called depression, represents a significant public health challenge on a global scale (Herrman et al., 2019). Around 300 million individuals worldwide face depression (PAHO, 2022).

The World Health Organization (WHO) states that depressive disorders, such as mental illness, are different from usual variations in mood or routine feelings. Major Depressive Disorder (MDD) is the most common type of depression in adolescents. It is characterized by sadness, loss of interest, tiredness, excessive guilt, sleep and appetite disturbances, moderate or sluggishness, and suicidal thoughts. In this article, the term depression refers to this form of MDD.

Depression in children and adolescents is a severe problem, with estimates of approximately 1.1% among adolescents aged 10 to 14 and 2.8% among adolescents aged 15 to 19 (WHO, 2021). In Brazil, the prevalence of depression in children over 14 years old varies from 0.2% to 7.5% (Coutinho et al., 2014).

Depression has several symptoms that affect somatic and psycho-emotional processes. This can be complicated during adolescence, as symptoms can be confused with age-typical behaviors, such as irritability, family conflicts, school problems, substance use, and problematic behavior (Bernaras et al., 2019).

Early diagnosis of depression is crucial to prevent the condition from worsening and to improve the effectiveness of treatment (Balázs et al., 2013). In Brazil, only 19.2% of children and adolescents treated in the Unified Health System (SUS) and diagnosed with depression sought or received any (Coutinho et al., 2014) treatment.

In an attempt to obtain a more accurate and early diagnosis as possible, many studies have focused on finding additional evidence, whether verbal, non-

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verbal, behavioral, linguistic, gestural, or social, that can help diagnose or alert to the future development of the depression in adolescence (Balázs et al., 2013).

On the other hand, the application of Artificial Intelligence (AI) has achieved significant advances in different areas of health (Yu et al., 2018). In the area of depression, we have several studies classifying patients with depression (Chu et al., 2018; Kim et al., 2019). Therefore, computational methods can provide valuable help in diagnosing and classifying people with depression.

Using Machine Learning (ML) algorithms is possible to assist in the prediction and decision-making processes related to depression, using data such as image, text, audio, and tabular data(Yu et al., 2018).

Tabular data, most common in healthcare, includes measurements and counts of clinical, laboratory, and historical values and must be represented appropriately so that results are consistent, organized, and can be used to create efficient ML models (Yu et al., 2018). In this case, the databases are composed of instances (observations) and attributes (characteristics), these can be numeric or nominal.

Data quality is essential for the excellent performance of ML algorithms, so data preprocessing is crucial due to common imperfections in raw data such as missing values *outliers*, high attribute dimensionality, and data balancing (Kotsiantis et al., 2006). An essential step in this process is encoding, which converts categorical attributes into numeric values, as most ML algorithms require this input type.

The distribution of categorical characteristics in health data plays an essential role in the interpretability of results(Vellido, 2020). This is because choosing appropriate coding can directly affect the ability to understand and extract meaningful insights from data, and some coding approaches can result in the loss of important information.

Given the above, this article aims to investigate different types of coding for nominal categorical attributes in a healthcare database. The aim is to analyze the performance and effectiveness of different encodings in this data set and investigate whether there is an encoding that presents more effective results, in addition to observing whether or not it helps with the interpretability of the results.

To carry out this analysis, we used a database of children and adolescents with different symptomatic presentations of depression and eight different codings. One Hot (OHE), Dummy, and Customized One Hot encodings ensure explicit representations of categories, while Frequency and Count ensure the frequency of attribute options. Ordinal and Rank Hot maintain the order and relationship between categories, and Hash reduces dimensionality while preserving part of the information.

The remainder of this text follows the following structure: Section 2 brings the reference, containing the techniques usually used to convert nominal attributes. Section 3 reviews some studies related to coding techniques for categorical attributes and cardinality. Section 4 presents the methodology adopted in this study. Section 5 explores the results achieved during the experiments. Finally, Section 6 brings final considerations and points to future work.

2 BACKGROUND

2.1 Depression in Children and Adolescents

MDD is characterized by sadness much of the day, almost every day. Symptoms include significant loss of interest or pleasure in activities, changes in weight, sleep problems, agitation or psychomotor retardation, fatigue, feelings of worthlessness or excessive guilt, difficulty concentrating, thoughts of death, and suicidal ideation. MDD not only affects adults, but also children and adolescents. Although they may vary depending on age, symptoms are similar to those seen in adults (Bernaras et al., 2019).

Depression in children leads to adverse effects on socioemotional skills, resulting in relationship irritability, social isolation, low school attendance, and self-harm risk. Additionally, it disrupts personality development, potentially leading to personality disorders (Herrman et al., 2019).

The origin of depression in adolescence is multifactorial, involving several processes and risk factors of a biological, interpersonal, cognitive, emotional and personality. There is no single necessary and sufficient cause for depression, and therefore, a complete understanding requires the simultaneous assessment of multiple elements (Hankin, 2006).

For adequate treatment of depression, an accurate diagnosis is necessary. Therefore, professionals who care for children and adolescents and treat depression should be familiar with the Diagnostic and Statistical Manual of Mental Disorders V (DSM-V). This manual presents essential criteria for diagnosing depression. The primary feature for diagnosing MDD is the presence of 5 of 9 critical symptoms on most days for two weeks, with at least 1 being depressed mood or loss of interest/pleasure (Association et al., 2014).

Treating and preventing depression in children and adolescents is crucial. Many of the treatments for depression in this age group were initially developed based on treating adults. Essential evidence-based treatments include pharmacotherapy, cognitive behavioral therapy, and interpersonal therapy. A combination of therapies and medications may also be considered (Balázs et al., 2013).

2.2 Techniques for Encoding Categorical Attributes

Often, datasets are organized in a tabular or matrix structure in which rows and columns represent instances and attributes, respectively.

For the encodings described in the following subsections, consider the following notation: Let a database be $B = (I, A, C)$, where I is a set of instances, A is a set of attributes, and C is the set of target classes. The total number of instances is denoted by m.

Furthermore, another term used is the cardinality of the categorical attribute to evaluate the performance of coding methods.

Cardinality in categorical variables indicates how many unique values an attribute can have $(card(a_i) = N)$. High cardinalities, with many different values, are challenging in ML modeling.

2.2.1 Indicator Encoding

It is a generic concept that refers to two standard methods of encoding categorical attributes, One Hot Encoding and Dummy Encoding (Pargent et al., 2022).

- **One Hot Encoding:** The method creates a new column for each N level of a categorical attribute, representing them as binary values (0 or 1) in each row. The process generates a binary matrix with columns corresponding to the number of variations of this attribute (N) (cardinality). In other words, high attribute cardinality results in high-dimensional feature vectors in (Pargent et al., 2022) databases.

  Dummy Encoding: Dummy is an improved version of OHE. However, unlike OHE, it uses $N - 1$ columns to represent an attribute with cardinality N.

2.2.2 Rank Hot Encoding

Rank Hot encoding is a variation of OHE in which all attributes, including the current and previous categories, are set to "hot" (1), and the remaining categories are set to cold (0). This technique is proper when there is some ordinal or hierarchical relationship between categories, and the order of the categories plays a relevant role (Buckman et al., 2018).

2.2.3 Frequency Encoding

This coding assigns a numerical value to each level (N) of the categorical attribute according to its frequency about the total occurrences (m) to that data set column. Therefore, the most frequent values receive higher numerical values, and the less frequent values receive lower values. However, according to (Roy, 2019), it is possible to lose important information if two distinct categories have the same occurrence rate.

2.2.4 Count Encoding

Count coding consists of counting the number of occurrences of a given categorical feature (N) in a specific attribute and replacing the names of these features with the count performed. As with coding by frequency, it is possible to lose important information if two distinct categories have the same value of occurrences (Roy, 2019).

2.2.5 Ordinal Encoding

This coding transforms options for a categorical attribute into a column of integers based on knowledge of the number of existing categories (Pargent et al., 2022). It is possible to provide a mapping to define a specific order; otherwise, integer values are assigned randomly. The result is a column of integers ranging from 1 to N.

2.2.6 Hashing Encoding

The method transforms categorical data into a numerical value using a hash function. It reduces extensive data sets into smaller structures of fixed size. However, hash functions are unidirectional, making it impossible to recover the original values after the hash values are generated. Furthermore, the risk of complications when different keys result in the same hash value can compromise data interpretability in critical situations (Kuhn and Johnson, 2019).

3 RELATED WORKS

Kovalerchuk and McCoy (2023) discuss the challenge of generating accurate and interpretable ML models for datasets with numeric and categorical attributes. The authors suggest using numerical coding for non-numeric attributes and present an algorithm called

Sequential Rule Generation (SRG). The SRG algorithm is successfully introduced to generate explainable rules in categorical data and is evaluated in several computational experiments.

In another study, the authors evaluate the influence of encoding numeric attributes on two highly unbalanced fraudulent transaction data sets. Six coding methods were employed, belonging to Agnostic Methods and Target-Based Methods. The study highlights the importance of choosing the appropriate encoding technique for imbalanced datasets, as target-based encodings can have significant performance in the (Breskuvienė and Dzemyda, 2023) model.

Cerda and Varoquaux (2022) investigated statistical coding approaches for categorical attributes for automated methods suitable for categories with high cardinality. Two coding approaches, Min-hash Encoder, and Gamma-Poisson Factorization, were compared with other approaches on different databases. The results showed that if interpretability is required, Gamma-Poisson factorization is the most suitable alternative, while if scalability is essential, the Min-hash encoder is the most efficient option.

4 MATERIALS AND METHODS

4.1 Database Description

To conduct this analysis, we used a database provided by the Federal University of Minas Gerais related to depression in children and adolescents aged between 10 and 16 years old, 158 males and 219 females, totaling 377 instances. The database comprises 74 attributes that contain essential information for analyzing depression in children and adolescents between 10 and 16 years old. These attributes cover several aspects, including demographic, social, and mental health-related data.

Furthermore, we categorized depression into two groups based on percentile calculation, where 63 individuals were classified as having high depression, while the rest were classified as having low depression. The cutoff point for this classification was defined as the 85th percentile.

During pre-processing, two textual attributes and 27 attributes related to the CDI questionnaire totaled 45 input attributes. The description of the attributes is detailed in Table 1.

4.2 Description of Methods

To evaluate different coding techniques for categorical attributes, we created a *pipeline* for ML in the language *Python*, employing several libraries widely used in data science projects, such as *Scikit-learn*[1] *Pandas*[2] and *Category Encoders.*[3]. Figure 1 illustrates the pipeline used to carry out this study.

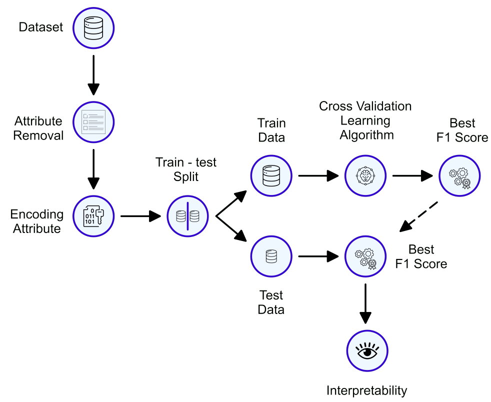


Figure 1: Pipeline adopted.

4.2.1 Preprocessing

1. **Attribute Removal**

   Initially, the database contained two attributes with insufficient information, "What medicine does the father take?" and "What medicine does the mother take?". Due to this limitation in data quality, we decided to exclude these attributes.

   Furthermore, textual attributes that referred to the medication the individual's parents took were removed. We made this decision considering the specific nature of this data and the complexity of integrating it into our analysis.

   Other attributes excluded from the analysis were related to the CDI (Children's Depression Inventory) questionnaire. This exclusion was due to the high correlation between these attributes and the class attribute.

2. **Categorical Attribute Coding**

   We use a specific coding, Ordinal Encoder, to carry out the coding for ordinal categorical attributes.

   To deal with the non-ordinal nominal categorical attribute "Lives_with_Who", we employ eight unsupervised categorical coders. Furthermore, we adapted the OHE for coding that would transform each family member option into a new attribute, assigning the value one if the individual

[1]Official documentation can be found at: *Scikit-learn*, the version used was 1.2.2

[2]The official documentation can be found at: *Pandas*, the version used was 2.0 .2

[3]Official documentation can be found at: *Category Encoders*, the version used was 2.6.1.

Table 1: Description of the dataset and used attributes.

	Description	Attribute Type	Possible Values
Demographics	Time spent with the mother/father per day during the week?	Discrete	Minimum = 0, Maximum = 24
	Time spent with the mother/father per day on the weekend?	Discrete	Minimum = 0, Maximum = 24
	Patient in psychological or psychiatric treatment?	Binary	Yes, no
	Parents live together or separated	Binary	Together, Separated/divorced
	Father's/mother's education level?	Ordinal Categorical	Did Not Study, Incomplete Primary School, Complete Primary School, Incomplete High School, Complete High School,Incomplete College, Complete College, Don't Know
	Has the mother/father or anyone in their family been in psychological or psychiatric treatment?	Binary	Yes, no
	Is the mother/father taking any continuous medication?	Binary	Yes, no
	Time the mother spends with her child(ren) per day during the week	Discrete	Minimum = 2, Maximum = 24
	Time the mother spends with her child(ren) per day on the weekend	Discrete	Minimum = 4, Maximum = 24
	Time the father spends with his child(ren) per day during the week	Discrete	Minimum = 0 , Maximum = 24
	Time the father spends with his child(ren) per day on the weekend	Discrete	Minimum = 0 , Maximum = 24
Social	Gender	Binary	Male, female
	Age	Discrete	Minimum = 10, Maximum = 16
	Mother's age	Discrete	Minimum = 26, Maximum = 54
	Is the mother/father working?	Binary	Yes, no
	Father's age	Discrete	Minimum = 25, Maximum = 78
	Who lives with the patient in their home?	Nominal Categorical	[Father], [Mother], [Siblings], [Grandparents], [Father and Mother], [Father, Mother, and Siblings], [Mother and Siblings], [Mother, Siblings, and Others], [Father, Sibling, and Others], [Mother and Others], [Father, Mother, Siblings, and Others], [Father and Siblings], [Father, Mother, and Others], [Siblings and Others], [Others], [Father and Stepmother], [Father, Stepmother, and Others], [Mother and Stepfather], [Mother, Stepfather, and Others], [Father and Others]
Questionnaire	Youth Self-Report (YSR)	Discrete	Minimum = 25, Maximum = 100

lives with that member and 0 if he does not. To clarify, let us take as an example the option I live with "father, mother and siblings": each of them was transformed into three new separate attributes, with an exclusive column for "father", another for "mother" and a third for "siblings".

Table 2 presents the Python coders and libraries used to implement them.

Table 2: Libraries and methods used to implement the encodings.

Encoding	Library	Methods
Count Encoding	Category_Encoders	CountEncoder
Customized One Hot	Pandas	-
Dummy Encoding	Pandas	get_dummies
Frequency Encoding	Pandas	-
Hashing Encoding	Category_Encoders	HashingEncoder
One Hot Encoding	Pandas	get_dummies
Ordinal Encoding	Category_Encoders	OrdinalEncoder
Rank Hot Encoding	Category_Encoders	RankHotEncoder

During the coding process of categorical attributes, we use the default settings of the coding methods except for the *Dummy Encoding* coding. For the *Dummy Encoding* technique, the *drop_first* pattern was changed, which removes the first level of each column. This change results in N-1 columns representing an attribute with a N cardinality.

4.3 Learning Algorithms

This research employed six machine learning algorithms to compare and determine the most effective organization method among those presented. The algorithms and their respective approaches were: Decision Tree - DecisionTreeClassifier, Random Forest - RandomForestClassifier, Support Vector Machine (SVM) - svm, Adaboost - AdaBoostClassifier, XGBoost - XGBClassifier, and Neural Network - MLPClassifier. During testing, all settings were changed to their default settings, as the focus is on evaluating the encodings, not the learning algorithms themselves.

We adopted a proportion of 80% for training and 20% for testing to divide the data.

We evaluated the model's generalization using a 10-fold cross-validation. We use *Python 3.10.9* at every stage, from pre-processing to hypothesis testing.

Taking into account that the problem analyzed is classification, the evaluation metric F1 Score[4].

4.4 Interpretability

To assist in the interpretability of the model, we adopted the SHAP (Lundberg and Lee, 2017) method, through which it was possible to understand how the model's predictions are influenced by different resources (attributes). We use the Dependence Plot as

[4] $F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$

Table 3: Machine Learning Algorithm Metrics Results for Each Encoding.

Results for F1 Score (Mean/Standard Deviation)						
Encoding	**AdaBoost**	**Decision Tree**	**Neural Network**	**Random Forest**	**SVM**	**XGBoost**
Count	0.6778/0.127	0.7106/0.1054	0.4547/0.0005	**0.7698/0.1435**	0.5725/0.1031	0.7202/0.1323
Customized One Hot	0.6993/0.0736	**0.7475/0.1228**	0.6752/0.164	**0.7722/0.1565**	**0.6297/0.1056**	**0.7819/0.1011**
Dummy	**0.7119/0.0956**	0.7390/0.1234	**0.7022/0.1488**	**0.7687/0.1504**	**0.6297/0.1056**	**0.7761/0.0988**
Frequency	0.6846/0.0746	0.7405/0.1017	0.4547/0.0005	0.7479/0.1471	**0.6395/0.1205**	**0.7781/0.1071**
Hash	**0.7082/0.0894**	**0.7570/0.1159**	**0.6869/0.1438**	0.7403/0.1640	**0.6297/0.1056**	**0.7883/0.0935**
One Hot	**0.7123/0.0735**	0.7395/0.1321	0.656/0.1034	0.7375/0.1563	**0.6297/0.1056**	0.761/0.1017
Ordinal	0.6954/0.0921	**0.7605/0.1045**	0.4547/0.0005	0.7585/0.1421	**0.6395/0.1205**	0.764/0.1013
Rank Hot	**0.7036/0.1136**	0.7366/0.1071	**0.6879/0.1158**	**0.7646/0.1529**	**0.6297/0.1056**	0.765/0.0981

a visual tool to deepen understanding of interpretable and non-interpretable encodings.

5 RESULTS AND DISCUSSIONS

Table 3 presents the results of tests with six categorical attribute encoding methods and ML algorithms. The proper choice of encoding is crucial for accurate outcomes, given the significance of nominal attributes and the necessity of numeric data for ML algorithms.

The results are organized alphabetically based on the encodings and learning algorithms. Additionally, we highlight in bold the best encodings for each ML algorithm. Considering the t-test, all tests were performed with 95% confidence.

The study analyzed different encodings of categorical attributes in a database related to depression in children and adolescents provided by the Federal University of Minas Gerais. The algorithms used were AdaBoost, Decision Tree , Neural Networks, Random Forest, SVM, and XGBoost.

"The learning algorithm that proved most effective in achieving the best encoding results was XGBoost. The encodings Hash, Customized One Hot, Frequency, and Dummy yielded the highest F1 scores, as confirmed through a t-test [5] with this algorithm."

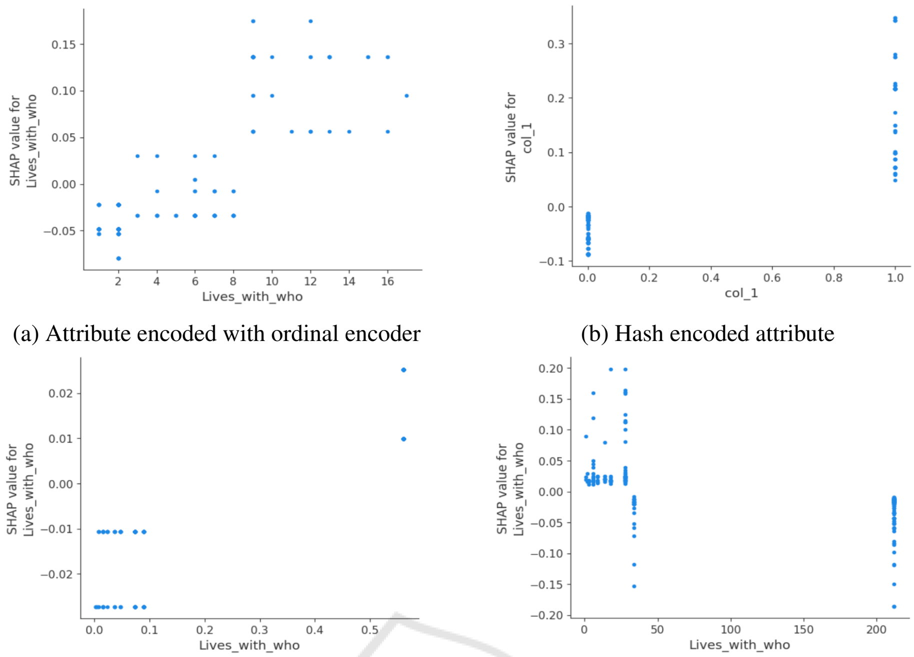
We use a method to assist with interpretability, as it is essential to understand the meaning of each attribute. In this case, how the attribute was encoded can contribute to or harm the interpretability of the explanations: both Hash, Frequency, and Count encoding have problems in terms of interpretability. For example, in Figure 2, we present one of the SHAP graphs, the Dependence Plot, with possible encodings for the attribute "Lives_with_Who" from the Depression base. This graph aims to analyze the impact of a given attribute on a set of database instances. On the graph, each point presented represents an instance of the base impacted by the attribute in the different encodings. Such impact, measured by the SHAP value, can be positive, negative, or null. In this case, the instances whose SHAP value is negative are those in which the attribute value hurts high depression. On the other hand, instances with a positive SHAP value are those whose attribute value contributes to high depression symptoms.

In Figure 2a, in which the attribute was coded with Ordinal Encoder, it is possible to notice the cases in which the attribute "Lives_with_Who" always contributed to the classification as low symptomatology for depression (cases 1 – Mother and brothers, 2 - Father, mother and brothers, 5 - Father and brothers, 8 - Mother) and the cases in which always favored classification as high symptoms (cases 9 - Mother, brothers and others, 10 - Father, mother and others, 11 - Father, stepmother and others, 12 - Mother, stepfather and others, 13 - Brothers and others, 14 - Father, 15 - Others, 16 - Father and others, 17 - Father, brothers and others). In the remaining cases (3 – Grandfather and grandmother, 4 – Mother, siblings, and others, 6 – Father and mother, 7 – Mother and others), the attribute sometimes contributes to low symptoms and, in others, to high symptoms. Primarily, we highlight that in this encoding, it is possible to interpret the model results with the behavior of the attribute.

In Figure 2b, observing the entry "col_1" generated in the Hash encoding, it is clear that when "col_1" is equal to 0 (zero), we have negative values of SHAP value indicating favor low symptomatology for depression. On the other hand, when "col_1" is equal to 1 (one), the attribute contributes to high depression symptoms. However, Hash functions are unidirectional, making it impossible to revert to the original values, which leads to the fact that "col_1" has no meaning in the context of the problem, compromising the interpretability of the explanations to be presented to the user and, possibly, its acceptance.

Finally, we work with the frequency and count encodings in Figures 2c and 2d. It is possible to extract interpretations of the attribute values as long as different values represent different response options. In frequency coding, each option is coded based on how often it appears in the attribute, while in count

[5]Hash: *p-value: [0-0.0029]*, Customized One Hot: *p-value: [0-0.0375]*, Frequency: *p-value: [0-0.0447]*, and Dummy: *p-value: [0]*



(a) Attribute encoded with ordinal encoder

(b) Hash encoded attribute

(c) Frequency encoded attribute

(d) Attribute encoded with count

Figure 2: Dependence plot with different encodings for the attribute "Lives_with_Who"

coding, the value represents the number of times the answer option appears in the attribute. For example, when we find the value 0.0158 in the frequency coding and the value 6 in the count coding for the attribute "Lives_with_Who" it could be any of the response options: 'Grandfather and Grandmother', 'Father, Mother and Others', 'Mother, Stepfather and Others' and 'Siblings and Others', and it is not possible to determine which specific response option is represented by these values in their respective encodings.

Regarding cardinality, it is essential to note that Hash, Customized One Hot, and Dummy coding techniques increase the dimensionality of the data set. For example, Hash encoding turns a single column into eight columns, Customized One Hot encoding into nine columns, and Dummy encoding into 19 columns. This increase in dimensionality can become a problem due to increased computational cost, overfitting, and analysis complexity.

The Neural Network and SVM learning algorithms did not perform satisfactorily for this database, considering the majority of encodings used.

Given the above, when it comes to coding, in the case of this specific database, the best algorithm to use is XGBoost. Furthermore, the user can choose between Hash, Customized One Hot, Frequency, and Dummy encodings, depending on what they want: a higher F1 Score or the interpretability of the results.

6 FINAL CONSIDERATIONS

This study aimed to investigate the existence of a technique for coding non-ordinal nominal attributes that demonstrates consistent results when applied to ML algorithms in a healthcare database linked to depression in children and adolescents, as well as observe whether it is interpretable. Several unsupervised coding techniques were explored, each with its advantages and limitations.

Analyzing each algorithm's metrics and applying the t-test made it possible to evaluate the performance of the different coding techniques. In the tests carried out, it was observed that the Hash, Customized One Hot, Frequency, and Dummy encodings achieved superior performance, although not all of them were interpretable. However, there is room to improve the pipeline used in order to obtain more satisfactory results. This includes fine-tuning the parameters of ML encodings and algorithms. Pay special attention to hash encoding, exploring different types of Hash encoding, and adjusting the number of bits used.

Encoding nominal categorical attributes is an efficient solution to deal with the qualitative nature of these attributes. It transforms categories into suitable numeric representations, effectively using this information in ML algorithms. This leads to more accurate and efficient solutions, advances in data analysis, and assists in decision-making, especially in the healthcare sector.

For future research, it is recommended to investigate broader healthcare datasets to validate different hit techniques, varying in size and complexity. These analyses should include databases with high cardinality to compare supervised and unsupervised approaches, improving programming techniques in machine learning projects in healthcare.

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