A Novel Fuzzy Geometric Naive Bayes Network for Online Skills Assessment in Training Based on Virtual Reality

Jodavid A. Ferreira[1,2] [a], Arthur R. R. Lopes[2], Liliane S. Machado[2,3] [b] and Ronei M. Moraes[2,4] [c]

[1] *Graduate Program in Decision Models and Health, Federal University of Paraíba, João Pessoa, Paraíba, Brazil*

[2] *Laboratory of Technologies for Virtual Teaching and Statistics, Federal University of Paraíba, João Pessoa, Paraíba, Brazil*

[3] *Departament of Informatics, Federal University of Paraíba, João Pessoa, Paraíba, Brazil*

[4] *Departament of Statistics, Federal University of Paraíba, João Pessoa, Paraíba, Brazil*

Keywords: Fuzzy Geometric Naive Bayes, Geometric Distribution, User's Assessment, Virtual Reality.

Abstract: Computational intelligence-based assessment systems have been proposed for implementation in virtual reality (VR) simulators to enhance technical proficiency in secure environments. Traditional training methods in healthcare, such as live subjects, cadavers, or mannequins, have limitations in reflecting realistic characteristics and deteriorate over time. Virtual reality-based assessment systems offer the advantage of check users skills in realistic and immersive training experiences, providing feedback at the end of the training. This paper presents a novel approach to assessment using a Single-User Assessment System (SUAS) that incorporates a Fuzzy Geometric Naive Bayes Network. The proposed method utilizes geometric distribution to model the fuzzy boundaries and assess the performance of gynecological examinations in a virtual reality simulator. The study evaluates the effectiveness of the proposed SUAS by comparing it with three other assessment methods. The results demonstrate the superior performance of the proposed method in accurately evaluating user performance in the simulated gynecological examinations.

1 INTRODUCTION

Computational intelligence-based assessment systems have been suggested for implementation in virtual reality (VR) simulators (Moraes et al., 2021), specifically designed to enhance technical proficiency of students and professionals in secure, 3D graphical and interactive environments. In the context of healthcare, practical training is typically conducted using live subjects, cadavers, guinea pigs or mannequins. However, these methods deteriorate over time and fail to fully reflect realistic characteristics, thereby impacting the effectiveness of the training. On the other hand, virtual reality-based assessment systems do not deteriorate over time and constantly strive to simulate the situation in the most realistic manner possible (Souza et al., 2006).

One notable benefit of assessment systems is its capacity to capture user interactions in real-time, enabling the assessment of user's skills based on this data (Moraes and Machado, 2009). Consequently, receive feedback just after the simulation becomes crucial and can be utilized to generate a comprehensive analysis of the user's abilities or to adjust the simulation's difficulty level. Earlier studies have proposed the integration of both single-user assessment systems (SUAS) and multi-user assessment systems (MUAS) with VR simulators for training (Moraes and Machado, 2012).

The assessment of a procedure necessitates the establishment of metric parameters and the tracking of user interactions. It is widely recognized that VR simulators offer realistic representations (Moraes et al., 2021). Protocols do not consider exact values for location and movements but include linguistic description for them. It makes fuzzy events modeling an appropriate approach for assessment purposes. Furthermore, each procedure has unique characteristics in terms of assessment metrics and, as consequence, interaction data follows specific statistical distributions. Thus, the quality of the assessment results can be enhanced by achieving a more accurate fit with the sta-

[a] https://orcid.org/0000-0002-2131-6464
[b] https://orcid.org/0000-0002-1182-2929
[c] https://orcid.org/0000-0001-8436-8950

Ferreira, J., Lopes, A., Machado, L. and Moraes, R.
A Novel Fuzzy Geometric Naive Bayes Network for Online Skills Assessment in Training Based on Virtual Reality.
DOI: 10.5220/0012211000003595
In *Proceedings of the 15th International Joint Conference on Computational Intelligence (IJCCI 2023)*, pages 395-401
ISBN: 978-989-758-674-3; ISSN: 2184-3236

tistical distribution. In the scientific literature, few fuzzy methods based on discrete random variables can be found. In fact, two methods based on Poisson (Moraes and Machado, 2015) and Binomial (Moraes and Machado, 2016) distributions were proposed by the same authors. However, other discrete distributions can be suitable to be embedded on assessment systems, as for instance, Geometric distribution.

SITEG 2.0 is an advanced virtual reality simulator designed specifically for gynecological examination training(Moraes et al., 2020). It offers realistic graphics and interactive tasks to enhance the learning experience.

The simulator provides a wide range of cases, including healthy patients, as well as patients with Herpes, HPV (Human Papillomavirus), and varying degrees of cervical cancer. As in real life, in this simulator users must visually analyse the vagina and use a haptic device to collect material from cervix. The haptic device acts as a spatula or cotton swab (Figure 1). This is a soft interaction and the force applied on cervix and the amount of material are relevant to achieve success in the procedure. To ensure effective assessment, SITEG 2.0 incorporates an embedded assessment system that monitors user interactions during the anamnesis (patient history) and physical examination stages of the simulation.

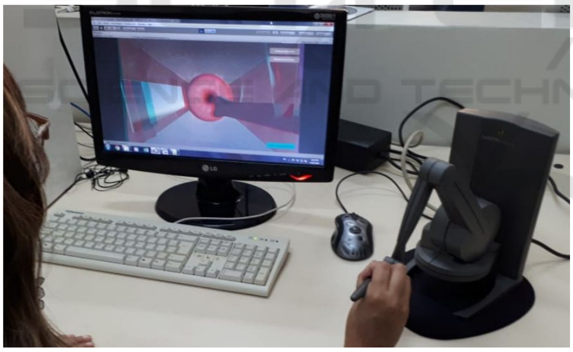


Figure 1: SITEG 2.0 with the haptic device acting as a spatula.

This paper presents a novel approach to assessment using a Single-User Assessment System (SUAS) based on a Fuzzy Geometric Naive Bayes Network to model the number of independent attemps of an user to successfully collect material from cervix using a spatula and a cotton swab. This collect must cover all region of the cervix and requires a specific range of force during the touch. The proposed method utilizes geometric distribution to model and assess the performance of the gynecological examination.

The SUAS implemented in SITEG 2.0 is responsible for evaluating the user's performance during the simulation. It provides valuable feedback and assessment based on the user's actions and interactions within the virtual environment (Figure 2).

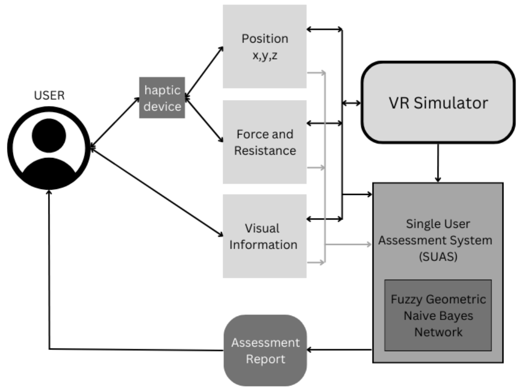


Figure 2: SUAS of the SITEG 2.0 simulator with the Fuzzy Geometric Naive Bayes Network.

The theoretical framework of this SUAS is elaborated upon in subsequent sections, along with the simulation results obtained using data from SITEG 2.0. Additionally, a comparative analysis of the SUAS with two other assessment methods is presented for a comprehensive evaluation.

The paper is structured as follows: Section 2 presents the statistical fundamentals of geometric distribution; Section 3 describes fuzzy probability in Zadeh approach and networks based on Naive Bayes hypothesis are described. Section 4 brings the accuracy measures used in this paper. The results obtained and the discussion can be seen on Section 5. Section 6 brings conclusions of this paper.

2 STATISTICAL MODELING

2.1 Geometric Distribution

The geometric distribution finds its utility in various fields, ranging from reliability analysis to queueing theory, providing a mathematical framework to quantify the number of independent attempts required to achieve the first success in a Bernoulli experiment. In the SITEG 2.0, that distribution is suitable for modeling the number of trials until the successful execution of a given task. This is a good parameter for user's skills assessing, since that for a well trained user, this task should be performed with the shorter possible number of trials.

A discrete random variable X follows a geometric distribution $X \sim G(p)$ if its probability distribution function (pdf) has the following equation (1). This distribution is provided by one parameter, defined as p (Mendenhall et al., 2012).

$$f(x;p) = p(1-p)^x, \tag{1}$$

where $0 < p \leq 1$ and $x = 0,1,2,\ldots$

2.2 Mathematical Properties

The expectation and variance are important properties of the geometric distribution. Thus, let $X \sim G(p)$, its expectation is given by

$$E(X) = \frac{1-p}{p} \tag{2}$$

and the variance of geometric distribution is given by

$$\begin{aligned} V(X) =& E(X^2) - (E(X))^2 \\ =& \frac{1-p}{p^2} \end{aligned} \tag{3}$$

where $0 < p \leq 1$.

2.3 Parameter Estimation

Let $X_1,\ldots,X_n$ a random sample i.i.d. of a random variable $X \sim G(p)$, such that p is a geometric distribution scalar parameter, with the restriction $0 < p \leq 1$. Thus, we have that $\hat{p}$ is obtained by

$$\hat{p} = \frac{n}{n + \sum_{i=1}^{n} X_i} = \frac{1}{1+\overline{X}}, \tag{4}$$

where $\overline{X} = \sum_{i=1}^{n} X_i/n$.

3 A NEW FUZZY NAIVE BAYES GEOMETRIC NETWORK-BASED ASSESSMENT METHOD

A Naive Bayes network assumes that the variables are conditionally independent, i.e., the information about an event is not dependent on that of other events. Additionally, we assume geometric distribution for variables present in the training simulation. Initially, we describe the classical Geometric Naive Bayes Network and in the following the new SUAS based on Naive Bayes Network with geometric distribution for fuzzy events.

Thus, let $\mathbf{x}_i = \{X_{i1}, X_{i2}, \ldots, X_{ik}\}$ a random vector of data in the i-th sample with k-information (dimension/variables) obtained when training is performed and w_j, $j \in \Omega$ the performance class most likely to be chosen, since the set $\Omega = 1,...,M$ where M is the total number of performance classes for the assessment of a user in the simulator. The probability of the performance class w_j assuming that each variable X_{it} is conditionally independent of any other variable X_{il} for all $t \neq l \leq k$, is:

$$P(w_j|X_{i1},X_{i2},...,X_{ik}) = \frac{1}{S} P(w_j) \prod_{t=1}^{k} P(X_{it}|w_j) \tag{5}$$

where S is a scale factor.

3.1 The Geometric Naive Bayes Network

For better understanding, we present first the classical Geometric Naive Bayes Network. In this case, it is assumed for $P(X_{it}|w_j)$ in eq. (5) the conditional probability using Geometric distribution. Thus, after mathematical manipulations, the eq. (5) can be rewritten as a discriminating function g, as follows:

$$g(w_j|\mathbf{x}_i) = \log P(w_j|\mathbf{x}_i) \tag{6}$$

$$= \log P(w_j) + k \log p_j + \sum_{t=1}^{k} X_{it} \log(1-p_j) \tag{7}$$

where p_j is estimated by eq. (4).

The decision rule for the vector $\mathbf{x}_i$ and a performance class w_j is given by:

$$\hat{w}_j = \arg \max_{j \in \Omega} g(w_j|\mathbf{x}_i).$$

3.2 The Fuzzy Geometric Naive Bayes Network

The new Bayesian Network named Fuzzy Geometric Naive Bayes Network is proposed from union of the Zadeh's definition of probability of fuzzy events (Zadeh, 1968) and geometric distribution. Formally, let ($\mathbb{R}^k$, B, P) a probability space, where B is σ-field of Borel subsets in $\mathbb{R}^k$ and P is probability measure of $\mathbb{R}^k$. Let F in B a fuzzy event with membership function $\mu_F : \mathbb{R}^k \rightarrow [0,1]$, then the probability of a fuzzy event F is defined by the Lebesgue-Stieltjes integral presented in the eq. (8).

$$\begin{aligned} P(F) &= \int_{F \subseteq \mathbb{R}^n} \mu_F(x) dP = E(\mu_F) \\ &= \int_{F \subseteq \mathbb{R}^n} \mu_F(x) f(x) dP \end{aligned} \tag{8}$$

where $f(x)$ is a density function of a random variable X (Zadeh, 1968). Thus, let a random vector $\mathbf{x}_i = \{X_{i1}, X_{i2}, \ldots, X_{ik}\}$, such that each X_{it}, $t = 1, \ldots, k$ is a fuzzy random variable with membership function $\mu_j(X_{it})$, $j = 1, \ldots, M$, so we have:

$$P(w_j|X_{i1}, X_{i2}, ..., X_{ik}) = \frac{1}{S_f} P(w_j) \prod_{t=1}^{k} P(X_{it}|w_j)\mu_j(X_{it}). \tag{9}$$

where S_f is a scale factor.

As in the case of the Geometric Naive Bayes Network, assuming that $P(X_{it}|w_j)$ follows a geometric distribution, and applying some mathematical manipulations, the Fuzzy Naive Bayes Geometric Network can be described by a discriminating function g_f:

$$\begin{aligned} g_f(w_j|\mathbf{x}_i) &= \log P(w_j|\mathbf{x}_i) \\ &= \log P(w_j) + k \log p_j + \sum_{t=1}^{k} X_{it} \log(1 - p_j) \\ &\quad + \log \mu_j(X_{it}) \end{aligned} \tag{10}$$

where p_t are estimated using the training data of for each class $w_j, j \in \Omega$ and the estimator given by the eq. (4). When compared equation (10) to equation (6) it is worth noting the membership function of X_{it} for the performance class w_j is modelling the fuzzy information.

The vector $\mathbf{x_i}$ will be assigned to the performance class w_j, according to the decision rule:

$$\hat{w}_j = \arg \max_{j \in \Omega} g_f(w_j|\mathbf{x}_i).$$

4 ACCURACY MEASURES

In this section, the performance of the assessment methods is measured. The accuracy (α) and Kappa coefficient (κ) are adopted as comparison criteria, which are defined as follows.

The accuracy (α) is a metric that relies on the confusion matrix, depicted in Table 1. It is determined by the following definition:

$$\alpha = \frac{\sum_{i=1}^{g} n_{ii}}{\sum_{i=1}^{g} \sum_{j=1}^{g} n_{ij}}, \tag{11}$$

where $\sum_{i=1}^{g} n_{ii}$ is the sum of the main diagonal terms of the confusion matrix, $\sum_{i=1}^{g} \sum_{j=1}^{g} n_{ij}$ is the sum of all its entries and g represents its pre-defined partitions.

Another assessment measure that is commonly used is the Kappa coefficient (K), as proposed by Cohen (Cohen, 1960). This coefficient is defined based on the confusion matrix as follows:

Table 1: Confusion matrix.

		Real class (c)			
		1	2	$\cdots$	g
Assigned class ($\hat{c}$)	1	n_{11}	n_{12}	$\cdots$	n_{1g}
	2	n_{21}	n_{22}	$\cdots$	n_{2g}
	$\vdots$	$\vdots$	$\vdots$	$\ddots$	n_{3g}
	g	n_{g1}	n_{g2}	n_{g3}	n_{gg}

$$\kappa = \frac{P_0 - P_c}{1 - P_c}, \tag{12}$$

where $P_0 = N^{-1} \sum_{i=1}^{g} n_{ii}$, $P_c = N^{-2} \sum_{i=1}^{g} n_{i+} n_{+i}$, n_{ii} is the sum of elements at the main diagonal of the confusion matrix, n_{i+} is the sum of its elements at ith row, n_{+i} is the sum of its elements at ith column and N represents the total number of decisions at the confusion matrix. Variance of Kappa (σ_K^2) was also calculated. According to (Landis and Koch, 1977), the Kappa coefficient may interpreted by means of concordance percentage in Table 2.

Table 2: Levels of correlation of Kappa coefficient.

κ	Kind of concordance
< 0.00	Poor
0.00 |— 0.20	Small
0.20 |— 0.40	Standard
0.40 |— 0.60	Moderate
0.60 |— 0.80	Good
0.80 |— 1.00	Excellent

5 RESULTS

The Fuzzy Geometric Naive Bayes Network was implemented in the FuzzyClass package ((Ferreira and Moraes, 2023)) of the R software, available at https://cran.r-project.org/web/packages/FuzzyClass/index.html and used to produce the results that follows.

Two simulation studies were conducted in order to know the performance of the new Fuzzy Geometric Naive Bayes Network. The first study aimed to verify the maximum likelihood estimator presented in Section 2, while the second study focused on generating a dataset to assess the proposed new training assessment method. Both results are presented throughout this section.

Table 3 presents the results of parameter estimation for the geometric distribution, specifically for the parameter p. Accurate parameter estimates in statistical distributions are crucial for obtaining reliable and precise results in analysis and inference. Appropriate parameter estimation enables a correct description and understanding of the data, as well as it also enables evidence-based decision making supported by robust statistical evidence.

In this case, four values for the parameter p were randomly selected to cover the entire parameter space, adhering to the constraint $0 < p \leq 1$. The values of p used in this study were $p = [0.05, 0.20, 0.60, 0.95]^\top$. Additionally, the sample size was varied to assess whether the estimation converges to the true parameter value with increasing sample size. In this case, sample sizes of $n = [10, 30, 100, 1000]^\top$ were employed.

Table 3: Performance of the estimation of parameter for the Geometric distribution.

n	$\hat{p}$ $\left(MSE_{\hat{p}}\right)$	
	p=0.05	p=0.20
10	0.0553 (2.8×10^{-2})	0.2153 (2.3×10^{-1})
30	0.0523 (5.3×10^{-3})	0.2050 (2.5×10^{-2})
100	0.0506 (3.7×10^{-4})	0.2020 (4.2×10^{-3})
1000	0.0501 (1.8×10^{-5})	0.1999 (1.7×10^{-6})
	p=0.60	p=0.95
10	0.6255 (6.5×10^{-1})	0.9556 (3.1×10^{-2})
30	0.6110 (1.2×10^{-1})	0.9532 (1.0×10^{-7})
100	0.6022 (5.1×10^{-3})	0.9501 (1.7×10^{-5})
1000	0.6001 (1.8×10^{-6})	0.9501 (1.0×10^{-5})

The results obtained from this simulation study reveal that a Monte Carlo simulation with 1,000 replications was conducted for each case. The average value of $\hat{p}$ across the 1,000 replications and the mean squared error ($MSE_{\hat{p}}$) were calculated. The results indicate that as the sample size increases, the estimates converge to the true parameter value. For instance, when $p = 0.05$ and $n = 10$, the estimated value of $\hat{p}$ is 0.0553 with $MSE_{\hat{p}} = 2.8 \times 10^{-2}$. However, with $n = 1000$, the estimated values for $\hat{p}$ and $MSE_{\hat{p}}$ are 0.0501 and 1.8×10^{-5}, respectively. This behavior is observed consistently across all other cases.

The performance assessment of the proposed Fuzzy Naive Bayes Geometric Network in a SUAS (Single-User Assessment System) was conducted through a Monte Carlo simulation consisting of 1,000 replications. In each replication, a sample of 1,500 observations was generated, representing three classes of performance that correspond to different assessments of the procedure. These classes include: Class 1, indicating that "the procedure was performed well"; Class 2, indicating that "the user needs more training"; and Class 3, indicating that "the user needs much more training".

During the simulation, 70% of the sample was utilized for training the new SUAS based on the Fuzzy Geometric Naive Bayes Network, while the remaining 30% was allocated for testing purposes. In Table 4, we present the estimated values of p that were used to generate the samples for this portion of the study.

Figure 3 displays a scatter plot of the first two dimensions of the simulated data. In this case, the classes are distinguished by different colors. The Class 1 is represented by light gray, Class 2 by dark gray, and Class 3 by black. It is worth noting the concentration of Classes 1 and 2 points in the lower left corner of that scatter plot. Densities with parameters of Table 4 can be observed in the Figure 4, according to the geometric distribution defined in equation (1). It is evident that assessment methods with data exhibiting such behavior is challenging due to the overlapping distributions.

The proposed network, named Fuzzy Geometric Naive Bayes (FGeomNB) was compared with the classical Geometric Naive Bayes (GeomNB), the Naive Bayes (NB) and the Fuzzy Naive Bayes (FNB) networks. The results can be found in Table 5, where the best assessment method was FGeomNB, achieving a total accuracy of 0.81 and a Kappa coefficient of 0.72. GeomNB followed closely with an accuracy of 0.77 and a Kappa coefficient of 0.67. The NB and FNB assessment methods obtained the same accuracy and Kappa coefficients, which were 0.60 and 0.40, respectively.

Table 4: Parameters used in the simulation by Monte Carlo.

Estimated Parameters	Class 1 p	Class 2 p	Class 3 p
Dimension 1	0.01	0.50	0.90
Dimension 2	0.01	0.50	0.70
Dimension 3	0.01	0.50	0.50

In Tables 6 and 7, the confusion matrices of the analyzed methods are found. Table 6 presents the re-

Table 5: Simulation results by Monte Carlo, where α is accuracy, κ is Kappa coefficient, σ^2_κ is Kappa coefficient variance.

Methods	α	κ	σ^2_κ
NB	0.60	0.40	1.1×10^{-3}
FNB	0.60	0.40	1.1×10^{-3}
GeomNB	0.77	0.67	7.7×10^{-4}
FGeomNB	0.81	0.72	7.3×10^{-4}

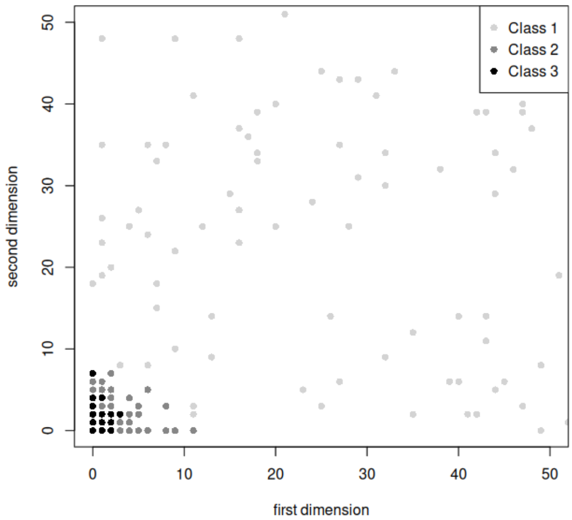


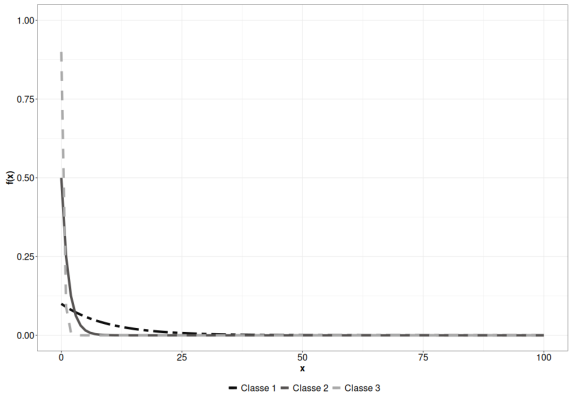
Figure 3: Scatter plot depicting the first and second dimensions of the simulated data of a Monte Carlo iteration.

sults for FGeomNB (left) and GeomNB (right). In Table 7, can be found the results for FNB (left) and NB (right).

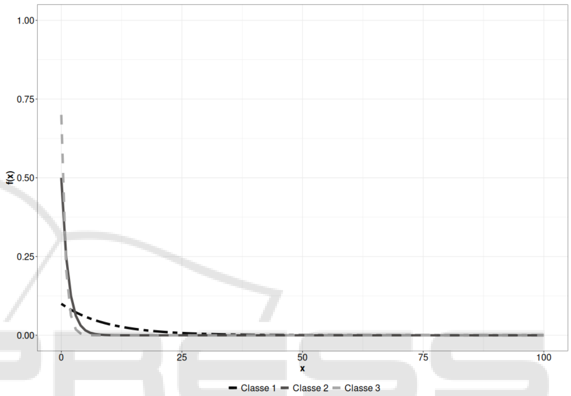
The 30% of the test sample represents that out of the 450 observations, 158 observations were selected for class 1, 146 for class 2, and 146 for class 3. In Table 6, can be observed that for FGeomNB, it correctly predicted 156 out of 158 possible instances of class 1, 82 instances of class 2, and 128 instances were correctly predicted of class 3. For the GeomNB method, it achieved higher accuracy, correctly predicting 158 out of 158 possible instances of class 1, 47 instances of class 2, with 99 errors, and 145 instances of class 3.

Similar interpretations can be drawn from Table 6, as they obtained the same discrimination with the same quantities of correct predictions and errors for each class. This may demonstrate the difficulty of this method in correctly classifying data with geometric behaviors. For class 1, the NB and FNB methods correctly predicted 152 out of 158 possible instances. For class 2, the methods struggled to make accurate predictions, correctly assigning only 36 out of 146 possible instances. For class 3, the methods correctly predicted 91 out of 146 possible instances.

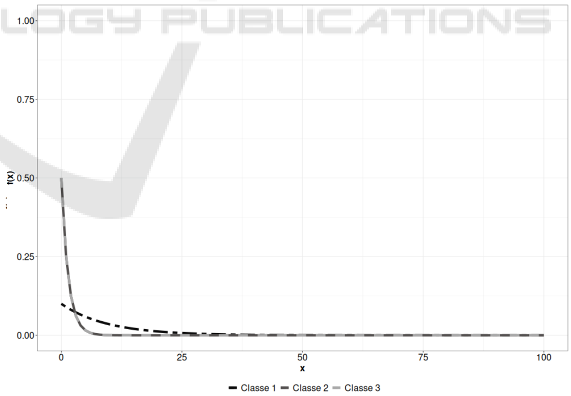
The FGeomNB method demonstrated superior accuracy and Kappa coefficient performance. However, upon observing the results for each class in tables 6 and 7, it is evident that FGeomNB did not outperform GeomNB in correctly allocating observations for classes 1 and 3. In this case, the utilization of fuzzy information aided in correctly classifying observations in class 2, where FGeomNB correctly allocated approximately twice instances with respect to



(a) Dimension 1.



(b) Dimension 2.



(c) Dimension 3.

Figure 4: Geometric distribution by dimension (variable) distinct by classes.

GeomNB. Therefore, the choice of the best training method also depends on the specific interest in the optimal assessment of a particular training case.

Fuzzy information provided improvements in the SUAS based on Fuzzy Geometric Naive Bayes when compared to the SUAS based on Geometric Naive Bayes. However, the same did not occur with SUAS based on Fuzzy Naive Bayes when compared with the

SUAS based on Naive Bayes. In this case, both SUAS provided the same results.

Table 6: Confusion matrix of FGeomNB (left) and GeomNB (right) assessment methods.

		FGeomNB			GeomNB		
		Assigned Class			Assigned Class		
		C1	C2	C3	C1	C2	C3
Real class	C1	156	2	0	158	0	0
	C2	0	82	64	0	47	99
	C3	0	18	128	0	1	145

Table 7: Confusion matrix of FNB (left) and NB (right) assessment methods.

		FNB			NB		
		Assigned Class			Assigned Class		
		C1	C2	C3	C1	C2	C3
Real class	C1	157	1	0	157	1	0
	C2	95	10	41	95	10	41
	C3	38	3	105	38	3	105

In summary, it is found that the proposed network based on the geometric distribution achieved good correct allocations for the data used in this study. The network surpassed previously proposed networks in the literature such as Naive Bayes and Fuzzy Naive Bayes, indicating that they can serve as viable alternatives for assessment methods.

6 CONCLUSION

In this paper, a novel approach called the Fuzzy Geometric Naive Bayes Network was introduced to handle multidimensional intervals by modeling them using geometric distributions. This network served as the foundation for SUAS specifically designed for Virtual Reality (VR) simulators, such as SITEG 2.0.

Simulations were conducted using data that followed a geometric distribution and compared against Naive Bayes and Fuzzy Naive Bayes SUAS. The simulation results demonstrated that the SUAS based on the geometric distribution has superior discrimination capabilities, outperforming the traditional Naive Bayes and Fuzzy Naive Bayes approaches.

Moreover, the Fuzzy Geometric Naive Bayes Network proposed in this study can also be effectively utilized for datasets that involve intersections with values close to zero.

ACKNOWLEDGEMENTS

This research is supported by the National Council for Scientific and Technological Development - CNPq (Grants 305914/2021-9 and 315298/2018-9) and Fundação de Apoio à Pesquisa do Estado da Paraíba - FAPESQ-PB.

REFERENCES

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and psychological measurement*, 20(1):37–46.

Ferreira, J. A. and Moraes, R. M. (2023). Fuzzyclass: A family of fuzzy and non-fuzzy probabilistic-based classifiers. *Journal of Open Source Software*, 8(88):5613.

Landis, J. R. and Koch, G. G. (1977). The measurement of observer agreement for categorical data. *biometrics*, pages 159–174.

Mendenhall, W., Beaver, R. J., and Beaver, B. M. (2012). *Introduction to Probability and Statistics*. Cengage Learning, 14th edition.

Moraes, R. and Machado, L. (2009). Online training evaluation in virtual reality simulators using possibilistic networks. In *Proc. Safety Health and Environmental World Congress*, pages 67–71. Citeseer.

Moraes, R., Silva, I. L. A., and Machado, L. (2020). Online skills assessment in training based on virtual reality using a novel fuzzy triangular naive bayes network. In *Proc. FLINS*, pages 446–454. World Scientific.

Moraes, R. M., Ferreira, J. A., and Machado, L. S. (2021). A new bayesian network based on gaussian naive bayes with fuzzy parameters for training assessment in virtual simulators. *International Journal of Fuzzy Systems*, 23(3):849–861.

Moraes, R. M. and Machado, L. S. (2012). A new architecture for assessment of multiple users in collaborative medical training environments based on virtual reality. In *Uncertainty Modeling in Knowledge Engineering and Decision Making*, pages 1119–1124. World Scientific.

Moraes, R. M. and Machado, L. S. (2015). A fuzzy poisson naive bayes classifier for epidemiological purposes. In *2015 7th International Joint Conference on Computational Intelligence (IJCCI)*, volume 2, pages 193–198. IEEE.

Moraes, R. M. and Machado, L. S. (2016). A fuzzy binomial naive bayes classifier for epidemiological data. In *2016 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pages 745–750. IEEE.

Souza, D. F., Valdek, M. C., Moraes, R. M., and Machado, L. S. (2006). Siteg–sistema interativo de treinamento em exame ginecológico. In *VIII Symposium on Virtual Reality SVR*, volume 12.

Zadeh, L. A. (1968). Probability measures of fuzzy events. *Journal of mathematical analysis and applications*, 23(2):421–427.