Analysis of Psychological Test Data by using K-means Method

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Keywords: Stroop, Stress, Machine Learning, K-means, Clustering.

Abstract: The Stroop test also called the colors and words test, is a widely used attention test to detect neuropsychological problems. Moreover, the stress test is a psychological instrument used to diagnose the level of stress and to identify the most common symptoms. This research aims to evaluate whether there is a relationship between the score of the Stroop test and the participant's level of stress. Data are collected through a web application, where participants answered the stress test and completed the Stroop test. Several variables were collected, such as the precision of each answer, the time spent, and demographic information. The machine learning technique called k-means was applied to process the collected data; the results include clusters of unlabeled data to find relationships. The main findings show that a person's stress level is directly linked to the number of correct answers obtained in the Stroop test; according to the clusters that show higher stress levels, the number of correct answers decreased progressively.

1 INTRODUCTION

The Stroop test, also known as the color and word test, was first proposed in 1935 by the American Psychologist J. Ridley Stroop (Stroop, 1935). It is an efficient neuropsychological test, widely used for experimental and clinical purposes. This evaluation tool is designed to measure an individual's reaction time in a specific task, and the reaction time with the number of correct answers obtained by the participant. The application of the Stroop test is performed through the fastest possible reading of three different tables. The first two represent "Congruent Conditions", while the third represents an "Incongruent Condition" (Scarpina & Tagini, 2017). A congruent condition is a word whose color matches correctly, while an incongruous condition occurs when the word and the color represented are different (van Maanen et al., 2009).

There are two ways to score the Stroop test: the time it takes the subject to complete the entire test and the number of correct answers within a specific period of time (Golden, 2001). Although, several studies have shown that, in ordinary people, the results of both methods are the same (Scarpina & Tagini, 2017), (Geukes et al., 2015).

Stress is a feeling of physical or emotional tension in the life of the human being, which is experienced at some point, more or less frequently. For example, a person can experience stress when dealing with changes in their environment, feeling frustrated, finding themselves in a situation that cannot control, among others, which alter the mood (National Center for Biotechnology Information, 2005). According to Szabo and Somogyi (2012), Hans Selye points out that stress is human behavior based on demands that

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Sarango, A., Patiño, A., Acosta-Urigüen, M., Sanchez, J., Cedillo, P. and Orellana, M.
Analysis of Psychological Test Data by using K-means Method.
DOI: 10.5220/0011046900003188
In *Proceedings of the 8th International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2022)*, pages 236-243
ISBN: 978-989-758-566-1; ISSN: 2184-4984

specify several stages as a form of alarm, resistance, and exhaustion; therefore, it is an adaptive process and a moment of emergency, necessary for survival.

Machine learning is a data analysis method, which automates the construction of models. It will allow to generate predictions by analyzing the data, so unobserved results or future behaviors can be predicted (Orrù et al., 2020). According to Bleidorn & Hopwood (2019), one of the great uses of machine learning in psychological science is the developing of assessment tools that can predict a person's personality through information circulating on the Internet (e.g., Facebook, Twitter, Instagram). It allows to create predictions using supervised models, such as decision trees, Naive Bayes, neural networks, and unsupervised models like clustering (Yarkoni & Westfall, 2017). Monitored models are created from tagged samples; in contrast, unsupervised models are developed using unlabeled examples, consisting of grouping examples based on their similarities (Orrù et al., 2020). These models allow to classify and find relationships between different variables entered into the algorithm and generate predictions (Yarkoni & Westfall, 2017). Shatte et al. (2019), show that in recent years, the application of machine learning within mental health has developed multiple uses. Around 300 investigations that used this method to facilitate data analysis, obtained and generated predictions with extremely high reliability. Furthermore, these techniques let researchers better understand their results, and consider better future projects that may derive from them (Yarkoni & Westfall, 2017).

There are several studies about the Stroop test, van Maanen et al. (2009), Nishikawa et al. (2019), Kim et al.(2015). However, none of them show a direct relationship between the application of the Stroop test with stress. In this context, the use of machine learning is proposed as a tool that can find out the relationship between different variables (Nishikawa et al., 2019), (Shatte et al., 2019), (Srividya et al., 2018).

This research aims to apply machine learning techniques to data obtained from the Stroop test to find patterns affected by stressful situations. Then, the Stroop test will be applied to a group of individuals, forming a dataset to apply a machine learning algorithm. Finally, the data will be analyzed to generate predictions through unsupervised learning, leaving the proposed model to classify the common characteristics among them. Also, patterns of anxiety or depression are expected to be found within the group to be tested.

The structure of this document is as follows: Section 1 presents the introduction. Section 2 discusses the related work. Section 3 presents the methodology used in this research. Section 4 deals with the results obtained by the investigation. Finally, Section 5 presents the conclusions and future work.

2 RELATED WORK

The Stroop test has significant importance in psychology, because it allows to evaluate individual’s ability to inhibit cognitive interference, when processing characteristics that affect a simultaneous stimulus of another attribute of the same stimulus (Stroop, 1935). In this context, Tulen et al. (1989) demonstrate in their research the existence of significant changes in feelings of anxiety and tension based on data obtained about the heart rate. Likewise, De Paula et al. (2020), applied this test to older people, highlighting its potential to serve as cognitive exercises, which could be a helpful tool for the prevention and treatment of aging diseases. On the other hand, Karthikeyan et al. (2012) affirmed that there is a significant change in the results obtained between an individual's normal state and the state of stress after applying the Stroop test, with a precision level of 79.17%. Regarding the methods of its application, Wu et al. (2010) show a way of executing it: through a cognitive performance evaluation test of reality, the user faces a driving simulation. Here, people read words written in different colors, coherent or not, with their semantic meaning. In this way, the researchers obtain reaction time and user error data gathered from users’ different stimuli. Likewise, Prado et al. (2021) show a comfortable way to apply the Stroop test for the user when performing it through a simple application connected to an eye tracker, that allows automating data collection.

In psychology, Lu et al. (2012) proposed a method to detect stress, based on the analysis of the variations of the articulation of speech using smartphones. The authors reported a predictive stress accuracy of 81% and 76% for indoor and outdoor environments, respectively, using the vocal production of 14 subjects. Likewise, Maxhuni et al. (2017) used an intermediate method to represent a person's mood and use it to build a predictive stress model that obtained an accuracy of 78.2%. On the other hand, Arriba-Pérez et al. (2019) show alternative ways to detect stress through new technologies, such as smart bracelets. In this way, the data collection can be automated to estimate a person's stress without the need for clinical measurements supervised by health professionals.

While in the field of machine learning, according to Shatte et al. (2019), mental health applications for machine learning were identified in four key domains: detection and diagnosis of mental health conditions; prognosis, treatment and support; public health; and research and clinical administration. In these aspects, Khoury et al. (2019) worked on the diagnosis of Alzheimer's through the use of supervised and unsupervised machine learning approaches. After comparing them with three studies of the same data set using traditional techniques, valid results could be reached. On the other hand, Seo et al. (2019) showed that it is possible to apply machine learning and deep learning techniques to multiple data sets of information to recognize mental stress within the workplace. Likewise, Ho et al. (2019) demonstrate that stress analysis using machine learning and deep learning is effective since conventional machine learning algorithms, such as SVM and AdaBoost, produced results with a precision of 64.74% ± 1.57% and 71.13% ± 2.96%, respectively. In contrast, deep learning algorithms, such as deep belief networks and convolutional neural network models, have obtained results with an accuracy of 84.26% ± 2.58% and 72.77% ± 1.92%, respectively.

According to the research of Xu et al. (2015), the k-means algorithm provides good results in the analysis of stress-related data. Additionally, Laird et al. (2005) demonstrate that clustering in data analysis, obtained from the Stroop test generates optimal results. The clustering k-means is one of the most widely used algorithms to find hidden or theoretically suspected groups in an unlabeled data set. Furthermore, it also allows discovering relationships between data groups, which would not have been recognized manually (Xu et al., 2015).

Even though stress and Stroop's test concepts have been widely studied separately, there is no research evidence based on the relationship between them. Multiple scenarios can be analyzed to determine if environmental variables affect the Stroop test results based on this relation.

3 METHODOLOGY

For the experiment, a stress test will be carried out to determine the stress levels in the testing subjects. Subsequently, a web page will be developed in which the Stroop test will be applied. Afterward, a machine learning algorithm known as k-means will be applied to the data to analyze them. Due to the characteristics described in section 2, the k-means algorithm has been selected for the data analysis because of its wide application in research and ease of implementation.

The project's development is shown in Figure 1, which specifies the research process following the parameters of the Software Process Engineering Meta-Model (SPEM). SPEM is a “meta-model” and a UML 2.0 profile used to define software development processes and systems and their components (Ruiz-Rube et al., 2013). Therefore, it is a standardized scheme for describing development processes managed by the Object Management Group (Omg, 2008).

To apply the stress and Stroop tests, a group of 110 individuals between 19 and 30 years old was selected. The data obtained were processed and stored in a database on the cloud.

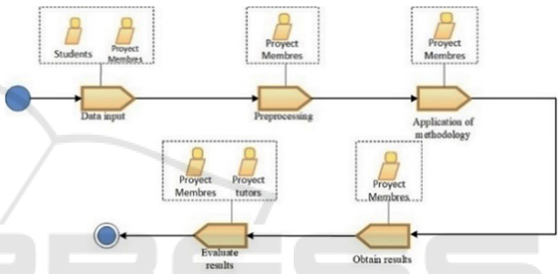

Figure 1: SPEM Diagram.

3.1 Data Entry

Data will be obtained with the application of both the stress test and the Stroop test.

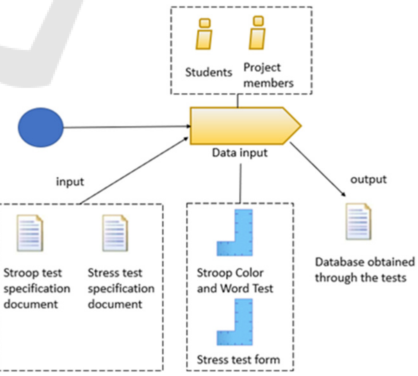

Figure 2: SPEM Diagram.

3.2 Stress Test

First, a stress test composed of 12 specific questions will be applied to determine the stress level. The questions are related to aspects such as physical and psychological conditions. This type of test is a derivative of the psychosomatic problems questionnaire that has already been used with good results by Rincón (2019).

The questionnaire asks if the participant has felt any of twelve symptoms in the last three months. The answers are evaluated through a Likert's scale with six possible values in terms of frequency (1=Never; 2= Rarely; 3=Occasionally; 4= Sometimes; 5= Relatively often; 6= Very often) (Rincón, 2019). Therefore, by adding results, it is possible to calculate the stress level of the participant, as shown in Table 1.

Table 1: Stress levels.

Total sum	Stress level
Sum<24	No stress
24>=Sum<36	Low stress
36>=Sum<48	Medium stress
48>=Sum<60	High stress
60>=Sum	Critical stress

3.3 Stroop Test

Prado et al. (2021) proposed an application based on the Stroop test containing only the last section of the original one, related to concentration. The test classification carried out considering the hits performed at a specific time (van Maanen et al., 2009). For this test, a total of 95 seconds is selected.

3.4 Data Processing

Once the data has been collected, a process based on the proposed by Seid & Pooja (2019) is defined. The information obtained from the tests will be debugged and standardized; the missing values and outliers were not considered. The inter-quartile range analysis method was used to find and eliminate outliers, as shown in Figure 3 and Figure 4.

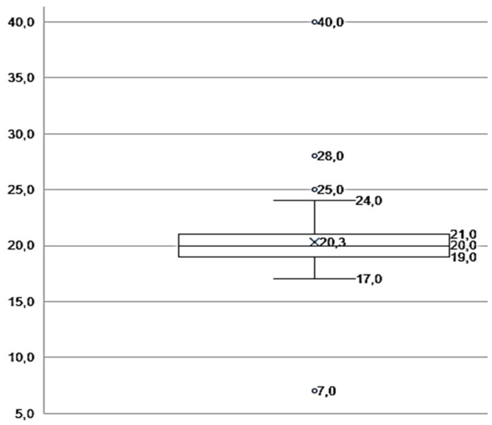

Figure 3: Inter-quartile range analysis to age variable.

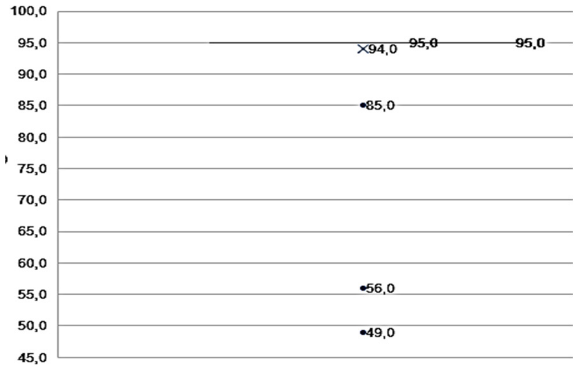

Figure 4: Inter-quartile range analysis to time variable.

The z-transform method is executed to obtain standard range among the entire data set.

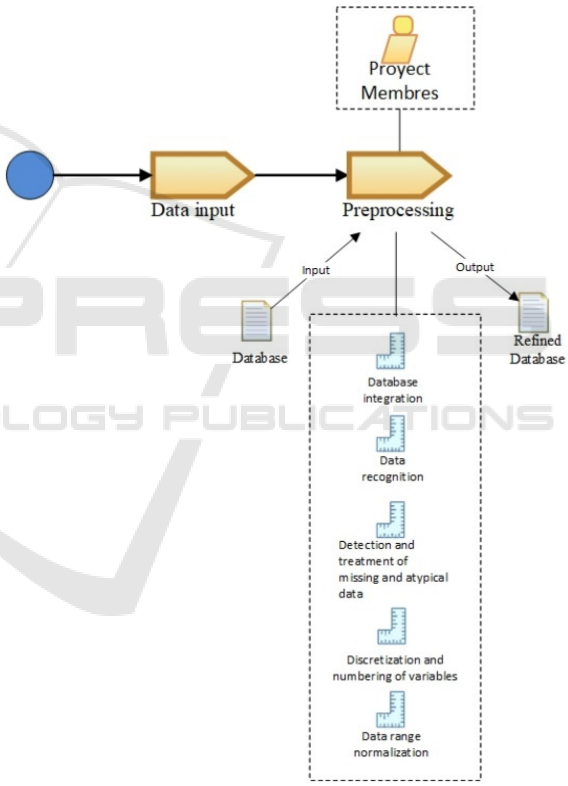

Figure 5: Preprocessing diagram.

3.5 The K-means Method

The machine learning algorithm k-means is applied, where the distance is used to calculate the k-groups. In order to determine the number of clusters, a Silhouette's coefficient method is applied. This method combines the cohesion and separation factors of the clusters. Cohesion is the average distance to the examples they find inside the same cluster.

Separation is the average distance to the closer cluster (Yuan & Yang, 2019). It is calculated as follows:

$$s(x)=(b(x)-a(x))/(\max(a(x),b(x))) \quad (1)$$

The resulting value is in the range [−1, +1]. If the value is near 1, it indicates a close relationship between the object and the cluster.

RapidMiner software was used for data analysis and data mining.

4 RESULTS

This study uses 105 records from the Stroop and stress test. To apply the k-means method, three different data configurations were used. The variables referring to stress levels and Stroop test results were used in the first form. Occupation and age were added in the second and third forms, respectively. The Figure 6 shows the Silhouette coefficient calculated for every configuration.

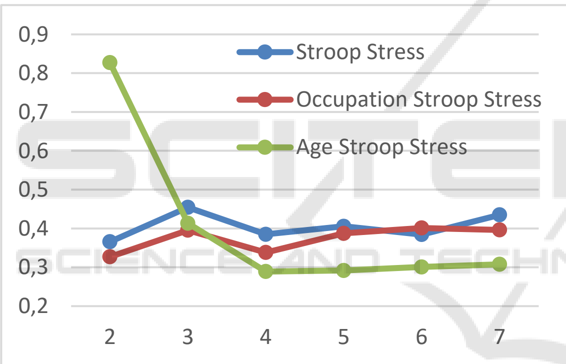

Figure 6: Silhouette's coefficient for every configuration of Clusters.

When the results are analyzed, the most significant value of cohesion and separation in the clusters is achieved when k=3. Table 2 and Figures 7, 8, and 9 show the distribution of the cluster.

Table 2: K-means results.

	Stress-Stroop	Occupation-Stress-Stroop	Age-Stress-Stroop
Cluster 0	29 items	51 items	26 items
Cluster 1	51 items	29 items	20 items
Cluster 2	15 items	15 items	49 items

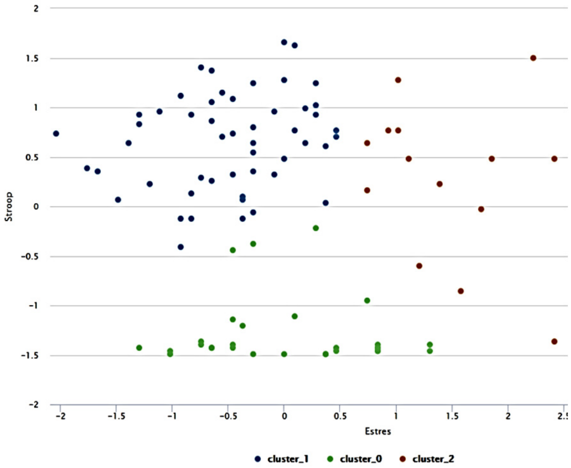

Figure 7: Clusters resulted of the Stroop Stress.

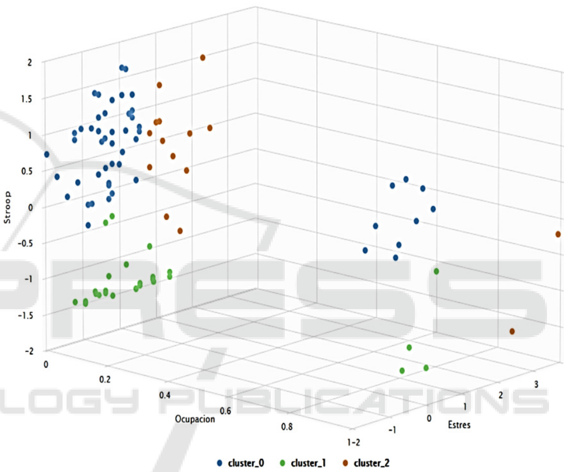

Figure 8: Clusters Occupation Stroop Stress.

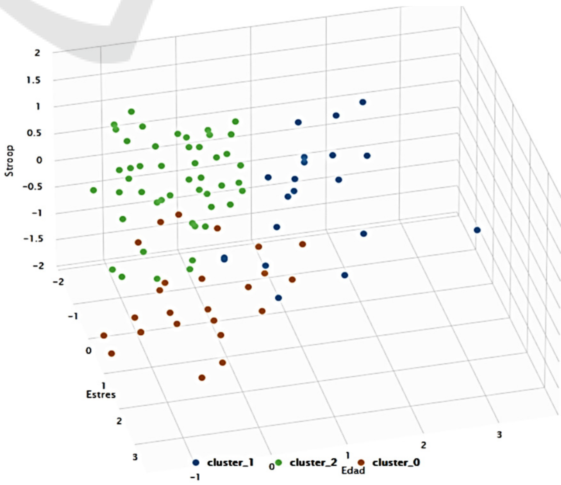

Figure 9: Clusters of Age variable.

Figure 7 shows how "Cluster 0" groups most of the data with a low score on the Stroop test regardless of the person's stress level.

While in "Clusters 1" and "Cluster 2" the best results of the Stroop test are divided by the level of stress presented by the people, being "Cluster 1" the one that groups the results with the lowest level of stress and "Cluster 2" those with the highest level of stress.

Figure 8 shows a distribution similar to the one gotten in Figure 7 with the difference that the names of "Cluster 0" and "Cluster 1" are changed. This is due to the fact that the occupation variable divides the data without any change in the distribution of the clusters, when it has fewer classes. Table 2 presents the described results.

In Figure 9, it can be seen that the age variable causes to change completely the distribution of clusters data. This can be interpreted as the results of the stress test are low with an older age while at a younger age, the level of stress of the person can vary more.

A comparative analysis of the results was performed to detect whether the stress levels (detailed in Table 1) generate significant changes of the possible results of the Stroop test.

Table 3: Table of centroids Stress-Stroop.

	Stress	Stroop
Cluster 0	0.025	-1.281
Cluster 1	-0.488	0.656
Cluster 2	1.610	0.247

Table 4: Table of centroids Occupancy.

	Occupation	Stress	Stroop
Cluster 0	0.176	-0.488	0.656
Cluster 1	0.138	0.025	-1.281
Cluster 2	0.133	1.610	0.247

Table 5: Table of centroids Age.

	Age	Stress	Stroop
Cluster 0	-0.444	1.185	-0.656
Cluster 1	1.458	-0.468	-0.222
Cluster 2	-0.376	-0.422	0.435

The Stress-Stroop relationship (Table 3) shows that "Cluster 1" has a positive correlation; however, "Cluster 0" and "Cluster 2" show an inverse trend. This shows that people who have a lower stress level at the time of taking the Stroop test will obtain higher scores on it than people whose stress level is moderate or high.

Figure 10: Stress-Stroop Relation.

Adding the Occupation variable to the analysis, shows that "Cluster 0" and "Cluster 1" exchange their trends, while "Cluster 2" remains unchanged. This is due to the fact that the data referring to the occupation of the people were centralized for the most part in one type of occupation, which caused the distribution of the data not to change and the relationship shown in Figure 11 to be the same than in Figure 10, with the only change in the "Cluster 0" and "Cluster 1".

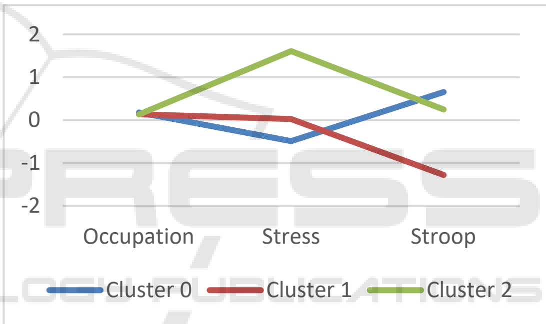

Figure 11: Occupancy-Stress-Stroop Relation.

Finally, by adding the age variable to the analysis, "Cluster 0" and "Cluster 1" maintain their original trends, but the relationship of "Cluster 2" is reversed. This is because the age variable causes the distribution of the Stress and Stroop data vary. It can be seen in Table 5 and Figure 12 where lower levels

Figure 12: Age-Stress-Stroop Relation.

of stress correspond to older age. While at lower age values, the distribution of the reference data remains similar to the two previous study cases, since the relationship of lower stress level with higher results in the Stroop test is maintained.

5 CONCLUSIONS

In this research, the analysis of the data obtained through applying the stress and Stroop tests were carried out. First, the dataset was cleaned, and then the k-means method was applied, from which data clusters were obtained for analysis. It is observed that the relationship between the Stroop and stress tests does not maintain a fixed correlation.

With the intention of analyzing if the inclusion of demographic variables alters or not the results of the clusters, different combinations were used. The variables “occupation” (person activity) and “age” were considered to perform this data analysis.

The results show that the age variable does not alter the trends of the clusters, while the occupation variable exchanges the labels of the clusters. This demonstrates that the inclusion of demographic variables does not change the relationship between the two tests.

In the future, other machine learning techniques could be applied to obtain the relationship between demographical variables and the Stress-Stroop test. It is also considered a larger dataset that includes more diverse demographic variables.

ACKNOWLEDGMENTS

The authors wish to thank the Vice Rectorate for Research of the Universidad del Azuay for the financial and academic support. We thank our colleagues from Laboratorio de Investigación y Desarrollo en Informática (LIDI) who provided insight and expertise that greatly assisted this work. As well as the Grupo de Investigación e Innovación Tecnológica (GIIT) from the Departamento de Ciencias de la Computación de la Universidad de Cuenca for allowing us to be part of this area of study.

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