PAMELA-CL: Partition Membership Based on Lazy Classifier for Neuromarketing

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Abstract. Neuromarketing is one of the business strategies that has developed lately. The strategy studies the effect of product promotion on the brain. If the impact analysis on the brain is successfully carried out, the company can find a good and effective marketing strategy for potential customers. This study used electroencephalography (EEG) as data. 30 respondents were involved in data recording. The final goal in this study was to classify the emotions of respondents to the video simulations that were displayed. The video contains a number of products. There were 14 electrodes used for the recording process. Then the EEG data were preprocessed, and its characteristics were extracted before being classified. This study proposed PAMELA-CL for the classification. The classifier was compared with lazy classifier. The result was obtained that this new classifier has higher accuracy than the lazy classifier. The difference in accuracy between the two was above 25%. All experiments involving PAMELA-CL had accuracy above 85%. It showed that this new classifier could be recommended in solving neuromarketing problems, especially for the dataset used in this study.

1. Introduction
Humans were created as social creatures. They need each other in order to complement each other. This need requires them to interact with each other. The interaction to meet the needs of each life is called business activities. This activity becomes very important so that humans can survive. The scope of business includes services to goods and services both physically and spiritually. Over time, human needs are increasing and unlimited. It has led to an increase in business activities. All elements of society are competing to become both players and winners of the business. It gave rise to business competition. The business competition is an important economic activity. It is the main reason for the companies to improve their quality of production [1]. But this business competition must follow the existing procedures and sportsmanship between business players. In order to survive in the business world, players must be proactive to be creative in increasing resources and creating innovation [2]. Various strategies are needed to achieve this. One strategy to obtain consumers is through marketing [3].

Over time, marketing research is also growing rapidly. One marketing strategy that is rapidly developing is neuromarketing [4]. Researchers show a connection between brain signal reactions to product advertisements [5]. If advertisements offer discounts, the brain reacts by giving certain signals to the messages. These brain signals that will bring someone to take action on these advertisements for example by buying the product [6]. This strategy reinforces the opinion that spending decisions are often not determined by rational matters [7]. Therefore, marketing strategies need to pay attention to emotional
aspects so consumers buy the products offered [8]. This is the main reason neuromarketing was developed for the business world [9].

Neuromarketing has developed a lot lately. One of the supporting data comes from electroencephalography (EEG). EEG research has been developed, among others, for the stage of sleep [10], seizures [11], Alzheimer's disease [12], rapid eye movement behavior disorder [13], schizophrenia [14], and Parkinson's disease [15]. These studies process EEG data through machine learning. This technique studies data then to build models. This model is useful for classifying or recognizing data [16]. Because of its success in many cases, this study also used it for neuromarketing. This study uses a lazy classifier especially K-nearest neighbors. This classifier is called lazy because it does not build models [17]. Prediction is done by finding n nearest neighbors in determining predictions [18]. To improve the performance, this study developed it in combination with partition membership [19]. Partition membership was obtained through propositionalization [20].

2. Study literature

This research is related to propositionalization and K-nearest neighbors. Both are discussed in detail in this chapter.

2.1. Propotionalization

This method produces a membership partition. The process is carried out by transforming the attributes to produce new attributes. The mechanism is carried out through C4.5. The result is a decision test. This tree has leaves which are labels/classes from the dataset. A label can be obtained in various ways. A path produced from the root to one of the leaves becomes a new attribute in the dataset [21].

2.2. K-nearest neighbor

k-Nearest Neighbor (KNN) is a supervised learning algorithm. This method classifies based on data that has proximity. Predictions are based on the majority class of these data [22]. The amount of data that is close determines the performance of this method. Determination of neighbors based on Euclidean distances with the following calculation [23]:

$$d_i = \sqrt{\sum_{i=1}^{p}(x_{2i} - x_{1i})^2}$$ \hspace{1cm} (1)

Where:

- $x_{1i}$ as training data,
- $x_{2i}$ as testing data,
- $p$ as the number of attributes
- $d$ is distance or Euclidean

Several studies using KNN have been experimented repeatedly with several feature reduction scenarios to obtain features that affect the classification value. However, in this study, this mechanism was not repeated but added one additional process, the partition membership process.
3. Research design
The research design in this study is shown in Figure 1.

![Research design in this study](image)

**Figure 1.** Research design in this study

3.1. Data collecting

The data came from electroencephalography recordings (EEG) [24]. 30 respondents were involved in this recording. The stimuli of a number of products displayed to respondents when recording. Each respondent installed 14 electrodes (O1, O2, AF3, F3, AF4, F4, FC5, FC6, F7, P7, T7, F8, P8, T8) based on 10-20 international system standards. The respondents were asked to respond to stimuli in the form of "like" or "dislike". The response was recorded in the form of an EEG signal in this study.

3.2. Preprocessing

EEGs that had been successfully recorded must be preprocessed before entering the next stage. It was needed because the raw data contains low amplitude and frequency. It contained weak information. Therefore, this research processed it using a notch and 2nd-order band-pass filter. As for the notch filter with \( w_0 = 50 \times 2 / \text{side rate} \), and \( bw = w_0 / 30 \).

3.3. Feature extraction

This stage aimed to find the characteristics that were able to represent the characteristics of the signal. The existence of these characteristics was useful to facilitate classification by looking for distinguishing features between classes. To achieve this goal, this study used wavelets as feature extraction.

3.4. Partition membership process

This process aimed to discover new features from the dataset. This feature was a transformation from the old feature. It was done to achieve classifier optimization. The result was the classifier can produce higher accuracy. In this research, this process was carried out through propositionalization. The trees were built based on the C4.5 algorithm with a confidence factor = 0.25 and batch size = 100.

3.5. Lazy classifier

Lazy classifier aimed to classify EEG signals into two classes namely "likes" and "dislikes". This study used KNN as a lazy classifier. The neighborhood search was done linearly based on the Euclidean distance. The batch size was 100. The number of neighbors used was tested in this study to find the most optimal parameters.
3.6. Evaluation

The performance of this study was based on accuracy and confusion matrix. The accuracy was based on the amount of data classified correctly divided by the whole data. Furthermore, the evaluation was through a confusion matrix. This matrix was a performance analysis of each classification process in identifying each class.

4. Results

This study examined the number of neighbors of KNN (K) from 1 to 3. This study offered a combination of lazy classifier and partition membership process. This combination was called Partition Membership based on Lazy Classifier (PAMELA-CL). Although the classifier was lazy, the combination was expected to have higher performance than before the combination occurred. The results can be proven in Table 1.

Table 1. System performance for neuromarketing

| Methods                          | Accuracy (%) |
|----------------------------------|--------------|
| Lazy Classifier with K=1        | 56.75        |
| Lazy Classifier with K=2        | 57.51        |
| Lazy Classifier with K=3        | 59.52        |
| PAMELA-CL with K=1              | 94.16        |
| PAMELA-CL with K=2              | 90.81        |
| PAMELA-CL with K=3              | 87.18        |

In Table 1, the lazy classifier with K = 1 has an accuracy = 56.75%. If K = 2, accuracy increases to 57.51%. The accuracy increases again with K = 3. The increase in accuracy can be seen in PAMELA-CL. The difference in accuracy above 25%. If the lazy classifier accuracy increases with an increase in K, but the accuracy of PAMELA-CL actually decreases. It is because the features of the lazy classifier were still not optimal in recognizing each class. The addition of neighbors was a supporting feature in achieving this. But at PAMELA-CL, the features possessed were optimal in recognizing class. Adding neighbors created bias and makes it more difficult to predict a class.

Table 2 shows dislike data classified as likes. It was as much as 213. But Table 3 was 92 and Table 4 was 198. The unstable number shows the inconsistency of the classifier even though it only changed the number of neighbors. The inconsistency was mostly caused by features that were still not optimal in finding the nearest neighbor which did have the same class. The different conditions can be seen in the performance of PAMELA-CL in Tables 5, 6, and 7. The increase in K caused decreased accuracy. But this decrease has a stable pattern in the confusion matrix.

Table 2. Confusion matrix of Lazy Classifier with K=1

|                  | Predicted: Dislike | Predicted: Like |
|------------------|--------------------|-----------------|
| Actual: Dislike  | 371                | 213             |
| Actual: Like     | 239                | 222             |

Table 3. Confusion matrix of Lazy Classifier with K=2

|                  | Predicted: Dislike | Predicted: Like |
|------------------|--------------------|-----------------|
| Actual: Dislike  | 492                | 92              |
| Actual: Like     | 352                | 109             |
Table 4. Confusion matrix of Lazy Classifier with K=3

|                | Predicted: Dislike | Predicted: Like |
|----------------|-------------------|-----------------|
| Actual: Dislike| 386               | 198             |
| Actual: Like   | 225               | 236             |

Table 5. Confusion matrix of PAMELA-CL with K=1

|                | Predicted: Dislike | Predicted: Like |
|----------------|-------------------|-----------------|
| Actual: Dislike| 565               | 19              |
| Actual: Like   | 42                | 419             |

Table 6. Confusion matrix of PAMELA-CL with K=2

|                | Predicted: Dislike | Predicted: Like |
|----------------|-------------------|-----------------|
| Actual: Dislike| 550               | 34              |
| Actual: Like   | 62                | 399             |

Table 7. Confusion matrix of PAMELA-CL with K=3

|                | Predicted: Dislike | Predicted: Like |
|----------------|-------------------|-----------------|
| Actual: Dislike| 537               | 47              |
| Actual: Like   | 87                | 374             |

5. Conclusion
This study proposed a combination of lazy classifier and partition membership and is called PAMELA-CL. This research proved that although the classifier used was lazy, the combination had high performance. The data used was neuromarketing based on EEG. The results were known that PAMELA-CL had an accuracy above 85%. The increase obtained compared without a combination was above 25%. It proves that PAMELA-CL is the optimal classifier for data neuromarketing in this study.

6. References

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