Influence of Students' Personality Traits on Learning Style

Amala Jayanthi.M, Lakshmana Kumar.R, Hari Priya.K.P

Abstract: Students are the soul of Academics. The Goal of the education is students centric. The Motto of the education is to groom the students' knowledge, skillsets and behavior under well-trained academician supervision in academics. Bloom's theory on learning activity states, as the learning progress, a person's not only grows in his/her knowledge and mental skills (i.e. Cognitive) but also in his/her emotions (i.e. Affective). Educational Data Mining is one of the budding research area in educational sector. It helps to enhance the standard of the academic system by understanding the educational method and their involvement within the higher manner. Personality is a blend of an individual emotional, Attitudinal, Behavioral responses. Personality is an intrinsic influence of emotions. As personality preferred learning style also an influence of attitude/behavior. This research is to study the influence of the personality trait of students on their Learning Style. The personality is of the students is evaluated using Eysenck Personality Inventory. The Learning form of the students is decided by the Honey and Mumford Learning Inventory. This paper finds out the impact of personality on the Learning style preferences of the students in their learning process by employing the supervised and unsupervised techniques on the students' dataset. Navies Bayes Classification and K-Means clustering is utilized to classify the learners under their Learning and Personality classes. The study determines the existence of positive association between the students' Personality and Learning Style through descriptive and predictive modelling using mapping or function. This investigation allows the teaching community to understand students' Personality and Learning Style in the learning environment provide education with appropriate teaching style.

Keywords: Navies Bayes Classification, K-Means Clustering, Bloom's Taxonomy, Affective Domain, Eysenck Personality Inventory, Personality Types, Honey and Mumford Learning Styles and Inventory.

I. INTRODUCTION

EducationaldataMining is associatedegree rising analysis application in Data Mining. To have better understanding of students on their learning process various Data Mining methods used to explore the data values from educational environmental settings. Eysenck Personality Inventory has been used to identify the students' Personality Traits. With the scale obtained students' Personality is fixed. Honey and Mumford Learning Style theory has been used to figure out learners' preferred learning style. With the scale obtained by Honey and Mumford Learning Style Inventory [1,2] students learning style preference is determined. This paper deals with educational objectives which determine the students' Learning Style with respect to their Personality. K- Means clustering technique is used for categorizing the studentobjects based on their personality and Learning Style into clusters of similar students' objects [25]. Navies Bayes is used for classifying subcategory in the students' dataset. This paper finds the association between personality traits of the students and their category of preferred learning style [27] based on Supervised and Unsupervised Learning Process. Apriori Algorithm is employed to find the association between Learning Style and Personality.

II. MOTIVATION

A. Bloom's Taxonomy:

Benjamin Bloom and his Co-Workers devised the learning theory. They designated three domains of learning activity as Cognitive Domain (Intellectual), Affective Domain (Emotional), and Psychomotor (Skills).The affectional Domain contains learning skills that square measure mainly associated to emotional (affective) processes.. The Bloom's five levels of Affective Domain are: Receiving, Responding, Organizing, Valuing, and Internalizing. The learning process of information or stimuli various between individuals. Learning style is influenced by the attitude and the behaviour (Affective) of an individual. Learning style of the student participants is measured by Honey and Mumford Learning Style Questionnaire. Personality is key element of Affectivity. Personality of an individual is uniqueness in characteristic patterns, feelings and behaviour. Personality of a student participant is assessed by Eysenck Personality Inventory.

B. Honey and Mumford Learning Style Questionnaire:

Honey and Mumford Learning Style Questionnaire, world-wide accepted tool that contains of eighty things of type agree and disagree types. Based on the responses of 80 items, score is calculated and the participants are categorized as activist, theorist, reflector and pragmatist. Each participant responses describes the way he/she has been feeling over the past week.

C. Eysenck Personality Inventory:

Eysenck personality questionnaire (EPQ) could be a form [1,2] that assess the sort of a personality. Psychologists Hans Jurgen Eysenck and his wife Sybil B. G. psychologist devised the form.

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It includes of a hundred things of Yes/No queries.The responses are his/her feelings over a past week. The score is calculated based on the responses on 100 items, and the student participants are categorized under Extroversion, Neuroticism and Introvert.

D. K-Means Clustering:

Cluster investigation portrays the items and their connections by gathering the information objects in light of the data found in information. The goal of bunch examination is to gather objects. K-Means Clustering is a partitional bunching approach. Essential K-Means Clustering Algorithm is as per the following,

1: Select K poits as the underlying centroids

2: repeat:

3: From K Clusters by doling out all focuses to the nearest centroid of each group.

4: until: The centroids don’t change.

E. Navies Bayes Classification *:*

Classification is administered learning. Characterization is the supervised form of arranging the new information under known class names. Navie Bayes Classifier is most valuable for extensive sets. It depends on the bayes theorem.

Algorithm:

Bayes hypothesis figures back likelihood, P(c|x), from P(c), P(x), and P(x|c). Bayes classifier expect that the impact of the estimation of an indicator (x) on a given class(c) is autonomous of the estimations of different indicators.

This assumption is called class conditional independence.

Likelihood

Class Prior Probability

$$P(c \mid x) = \frac{P(x \mid c)P(c)}{P(x)}$$

Posterior Probability

Predictor Prior Probability

$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

- *P*(*c*|*x*) is the posterior probability of *class* (*target*) given *predictor* (*attribute*).
- *P*(*c*) is the prior probability of *class*.
- *P*(*x*|*c*) is the likelihood which is the probability of *predictor* given *class*.
- *P*(*x*) is the prior probability of *predictor*.

III. EPHML APPROACH

In Phase 1, the Eysenck Personality Inventory for personality is pretested. Analyze test is conducted for post-graduation students to determine their personality. According to the resultant scale the student participants are grouped under Extrovertism, Neuroticism, Introvert categories [28,29,30].

Likewise in Phase 2, Analyze test for learning style has been conducted to the similar set of students. Based on the output scale of the Analyze test, the student participants are categorized under Activist, Reflector, Theorist and Pragmatist. The final student dataset that contains the result of the Analyze tests of Eysenck Personality Inventory and Honey & Mumford Learning Style Inventory of the students.

In Phase 3 and 4, Data Mining Techniques, K-Means clustering and Naive Bayes Classification are applied to find the association between the Learning Style and Personality. Each Cluster categorize the students based on their personality traits and designates the cluster as Extroversion, Introvert and Neuroticism. Similarly students are grouped under their respective clusters of learning style using similar method. Naive Bayes classification technique is used to categorize the Learning Style and Personality of the students.

In Phase 5, Apriori Algorithm is applied to discover the association between the Learning Styled and Personality of the student respondents.

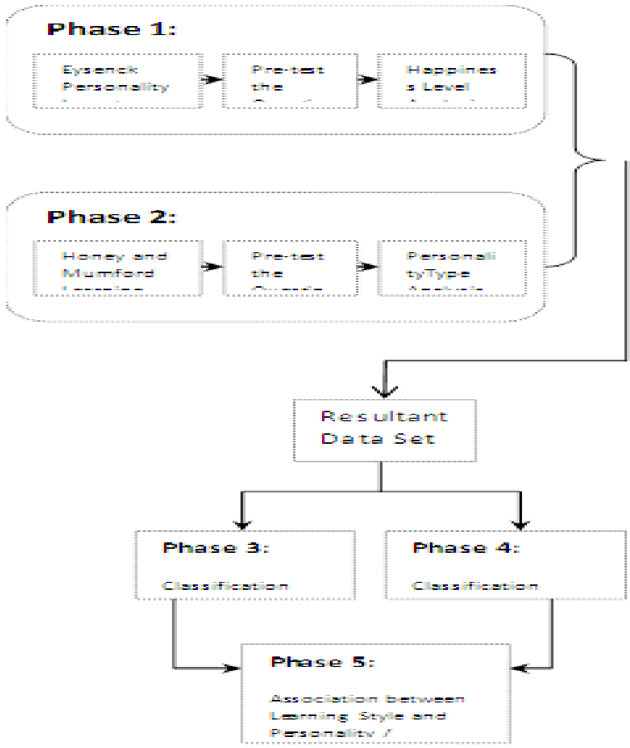

Figure 1 Bayes Classifier

IV. RESULTS AND DISCUSSIONS

From the dataset containing 148 dataset, the relationship between learners’ Personality Type, Learning Style and academic performance is studied

Table I depicts the various clusters and corresponding Learning Style. It reveals that the students are grouped in cluster 0(Activist), cluster 1(Pragmatist), cluster 2(Theorist) and cluster 3(Reflector) respectively based on their Learning Style.

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TABLE I. CONFUSION MATRIX FOR LEARNING STYLE

Cross Validation		Predicted				
		a	b	c	d	Learning Style
Actual	A	96	0	0	0	Activist
	B	0	108	0	0	Pragmatist
	C	0	0	168	0	Theorist
	D	0	0	0	24	Reflector

Table II shows the confusion matrix for the learning styles. The confusion matrix reveals that there exists students of 4 classes with 4 sigmoid nodes.

TABLE II. CLUSTER ASSIGNMENTS AND PERSONALITY

Cross Validation		Predicted			
		a	b	c	Personality
Actual	A	96	0	0	Extrovert
	B	0	168	0	Neuroticism
	C	0	0	60	Introverts

TABLE III DEPICTS THE VARIOUS CLUSTERS AND CORRESPONDING PERSONALITY TYPES AS EXTROVERSION, NEUROTICISM AND INTROVERT ARE GROUPED IN CLUSTER 0, CLUSTER 1 AND CLUSTER 2 RESPECTIVELY.

TABLE III. CONFUSION MATRIX FOR PERSONALITY

Table IV shows the Confusion Matrix for Personality.

C0	C1	C2	Personality
96	0	0	Extrovert
0	168	0	Neuroticism
0	0	60	Introverts

The Confusion Matrix reveals the existence 3 different personality categories using 3 sigmoid nodes .

TABLE IV. ASSOCIATION RULES MINED

1. personality category=Neuroticism 168 ==> Learning category=Theorist 168 <conf:(1)>
2. Learning category=Theorist 168 ==> personality category=Neuroticism 168 <conf:(1)>
3. Learning category=Theorist 168 <conf:(1)>)
4. Learning category=Theorist 168 ==> <conf:(1)>
5. personality category=Neuroticism 168 <conf:(1)>
6. personality category=Neuroticism 168 ==> <conf:(1)> l
7. personality category=Neuroticism Learning category=Theorist 168 <conf:(1)>
8. Learning category=Theorist 168 ==> personality category=Neuroticism 168 <conf:(1)>
9. Learning category=Theorist personality category=Neuroticism 168 ==> <conf:(1)>
10. Learning category=Theorist personality category=Neuroticism 168
11. personality category=Neuroticism 168 ==> Learning categor <conf:(1)>
12. Learning category=Theorist 168 ==> personality category=Neuroticism <conf:(1)>
13. Learning category=pragmatist 108 ==> personality category=Extraversion 108 <conf:(1)>
14. Learning category=pragmatist 108 ==> <conf:(1)>
15. personality category=Extraversion ==> Learning category=pragmatist 108 <conf:(1)>
16. Learning category=pragmatist Performance=Average 108 ==> personality category=Extraversion 108 <conf:(1)>

Table V reveals the best association rules discovered. It shows the strong association between Learning Style, Personality and Performance with confidence 1.

TABLE V. TABLE V: CLUSTER ASSIGNMENTS AND LEARNING STYLES

C0	C1	C2	C3	Learning Style
96	0	0	0	Activist
0	108	0	0	Pragmatist
0	0	168	0	Theorist
0	0	0	24	Reflector

V. CONCLUSION

In this research study, it is proven that Learning style of the student is strongly associated with his/her personality. Association between the student's personality and learning style is discovered using .K-Means clustering technique and Navie Bayes classification technique. K-Means clustering is an effective technique to group the student under their respective cluster of learning style (Reflector, Theorist, Activist, Pragamatist) and personality (Extrovert, Neuroticism and Introvert) .The classifier reveals that each individual student's Learning Style is associated with his/her Personality. Hence the following observations are

made Neuroticism Personalities' preferred to be Theorist Learners. Introvert personalities are Reflecting learners. Extrovert personalities are either Pragmatist Learners or Activist Learners. This research depicts the positive correlation between the Learning Style and Personality trait during students' Learning Process and suggests the recommendation to have combination of teaching styles so that all learning style personalities will excel.

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