

# Scrutinization of Student Knowledge by Pearson and Spearman Technique

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**Abstract-** This informational index is utilized to evaluate the knowledge of the student in the context of study time and exam execution of every student. We perform the software metric analysis on the given data set. In perspective of the spearman attribute analysis and Pearson correlation of data, we can separate each student in light of the learning level.

**Keyword:** Pearson Correlation, Spearman Correlation, User Knowledge.

### Introduction

Pearson model is utilized to discover the connection between the traits x and y in view of the estimation of r. Pearson helps us to discover how intently an attribute is related to different attributes. We have a dataset of almost 100 clients portraying their review time and exam execution with the assistance of 5 attributes. In view of the examination of information, we can choose which attribute can be considered and which attribute can be dismissed. For instance, in Pearson technique, if the estimation of r is more than 0.5 then the attributes are thought to be emphatically related and if it is beneath 0.3 the traits are inadequately related. Correlation between two variables in Spearman is equivalent to the rank estimation of two variables in Pearson correlation; while linear relationships are assessed in Pearson correlation, monotonic relationships are evaluated in spearman’s correlation.

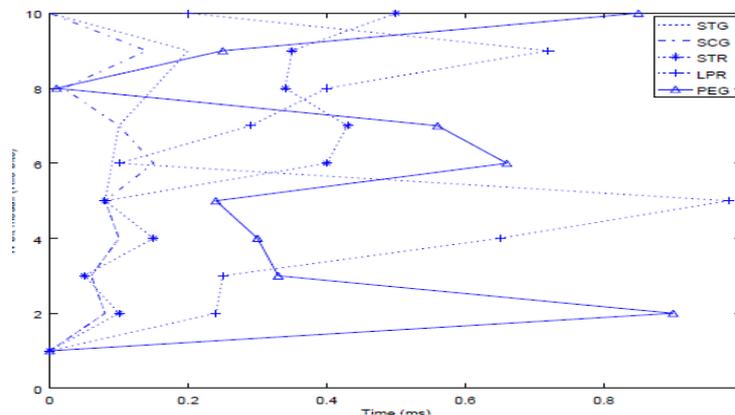


Figure 1. User Knowledge

TABLE I. SAMPLE USER PERFORMANCE DATA

<i>USER</i>	<i>STG</i>	<i>SCG</i>	<i>STR</i>	<i>LPR</i>	<i>PEG</i>
A	0	0	0	0	0
B	0.08	0.08	0.1	0.24	0.9
C	0.06	0.06	0.05	0.25	0.33
D	0.1	0.1	0.15	0.65	0.3
E	0.08	0.08	0.08	0.98	0.24
F	0.09	0.15	0.4	0.1	0.66
G	0.1	0.1	0.43	0.29	0.56
H	0.15	0.02	0.34	0.4	0.01
I	0.2	0.14	0.35	0.72	0.25
J	0	0	0.5	0.2	0.85

**Introduction**

A. Pearson based Attribute Clustering

$$r = \frac{N \cdot \sum xy - \sum x \cdot \sum y}{\sqrt{(N \cdot \sum x^2 - (\sum x)^2) \cdot (N \cdot \sum y^2 - (\sum y)^2)}}$$

All the relations with r value less than 0.5 are considered as weak relations and the related attributes can be ignored and only strongly related attributes are considered. This decreases the overall number of attributes.

TABLE II. PEARSON SIMILARITY MATRIX

	<i>STG</i>	<i>SCG</i>	<i>STR</i>	<i>LPR</i>	<i>PEG</i>
<i>STG</i>	1	0.62	0.26	0.53	-0.25
<i>SCG</i>	0.62	1	0.18	0.34	0.2
<i>STR</i>	0.26	0.18	1	-0.1	0.39
<i>LPR</i>	0.53	0.34	-0.1	1	-0.29
<i>PEG</i>	-0.25	0.2	0.39	-0.29	1

**B. Spearman based Attribute Clustering**

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Here,  $\rho$  is the spearman co-efficient;

$\sum d_i^2$  is the sum of square of paired scores;

TABLE III. SPEARMAN SIMILARITY MATRIX

	<i>STG</i>	<i>SCG</i>	<i>STR</i>	<i>LPR</i>	<i>PEG</i>
<i>STG</i>	1	0.66	0.37	0.65	-0.13
<i>SCG</i>	0.66	1	0.33	0.35	0.27
<i>STR</i>	0.37	0.33	1	-0.01	0.5
<i>LPR</i>	0.65	0.35	-0.01	1	-0.32
<i>PEG</i>	-0.13	0.27	0.5	-0.32	1

**C. Linear Regression Method:**

Replace the sum values in the following form, to get the optimized cost of  $\theta$  value.

$$J(\theta_1) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^i) - y^i)^2$$

Based on Linear Regression we will get the optimized  $\theta$  value, and for this  $\theta$  attribute value can be effectively relapsed after the Pearson similarity measure (where  $r > 0.5$ ). This strategy is utilized for cost optimizing which implies enhancing the variable. This is one of the techniques utilized for accomplishing machine learning Table III consists of  $\theta$  value along with cost function for each attribute relation.

In view of the Pearson correlation attribute analysis of performance dataset which is shown in the above Table II, it is evident that the discoveries give (STG versus SCG, LPR); (SCG versus STG); (LPR versus STG) are the essential cluster attributes. From the above dataset, we are choosing STG, SCG, PEG under the constraint of  $\geq 0.50$ . From the above dataset, we are choosing STG, SCG under the constraint of  $\geq 0.60$ .

In view of the Spearman correlation attribute scrutinization of execution dataset which is appeared in the above Table III, it is very clear that the discoveries give (STG versus SCG, LPR); (SCG versus STG); (LPR versus STG) are the essential cluster attributes. The attributes are rehased as like Pearson under corresponding constraints.

TABLE IV. COST VALUE

	<i>STG</i>	<i>SCG</i>	<i>STR</i>	<i>LPR</i>	<i>PEG</i>
<i>STG</i>	0	0.24	0.37	1.06	1.79
<i>SCG</i>	0.02	0	0.42	1.3	1.59
<i>STR</i>	0.09	0.07	0	1.45	0.99
<i>LPR</i>	0.1	0.07	0.59	0	1.86
<i>PEG</i>	0.1	0.07	0.3	1.65	0

TABLE V. OPTIMIZED COST

	<i>STG</i>	<i>SCG</i>	<i>STR</i>	<i>LPR</i>	<i>PEG</i>
<i>STG</i>	0	0.001	0.01	0.05	0.08
<i>SCG</i>	0.001	0	0.02	0.06	0.07
<i>STR</i>	0.004	0.003	0	0.07	0.04
<i>LPR</i>	0.005	0.03	0.02	0	0.09
<i>PEG</i>	0.005	0.01	0.01	0.08	0

TABLE VI. CORRESPONDING OPTIMIZED THETA

	<i>STG</i>	<i>SCG</i>	<i>STR</i>	<i>LPR</i>	<i>PEG</i>
<i>STG</i>	1	1	2	2	2
<i>SCG</i>	1	1	2	2	2
<i>STR</i>	0.5	0	1	1	1.5
<i>LPR</i>	0	0	0.5	1	0.5
<i>PEG</i>	0	0	0.5	0.5	1

### Conclusion

Based on the Pearson correlation and Spearman attribute analysis of performance dataset which is shown in the above Table II and III, it is very certain that the discoveries give (*STG* versus *SCG*, *LPR*); (*SCG* versus *STG*);(*LPR* versus *STG*)are the primary cluster attributes. Machine learning based decision-making Table IV is applied to anticipate the 'y' attribute from 'x'.

**References**

- [1] Xiao, Chengwei, et al. "Using Spearman's correlation coefficients for exploratory data analysis on big dataset." *Concurrency and Computation: Practice and Experience* (2015).
- [2] P. Dhavachelvan, Chandra Segar T, K. Satheskumar, "Evaluation of SOA Complexity Metrics Using Weyuker's Axioms," *IEEE Int. Ad. Comp. (IACC)*, India, pages. 2325 – 2329, March 2009
- [3] Alam, Md Ashad, Bangladesh Dinajpur, and Mohammed Nasser. "Simulation Based Comparison among Fifteen Estimators of Correlation Coefficient."
- [4] Xu, Nuo, Xuan Huang, and Samuel Huang. "A Measure of General Functional Dependence between Two Continuous Variables." *Communications in Statistics-Theory and Methods* just-accepted (2016): 00-00.
- [5] Smith, Reginald. "A mutual information approach to calculating nonlinearity." *Stat 4.1* (2015): 291-303.
- [6] E Malathy, Chandra Segar Thirumalai, "Review on non-linear set associative cache design," *Int. Jnl. Ph. Tech*, Dec-2016, Vol. 8, Issue No.4, pp. 5320-5330
- [7] Chandrasegar Thirumalai, Rashad Manzoor, "Cost Optimization using Normal Linear Regression Method for Breast Cancer Type I Skin," *IEEE IPACT 2017*. .
- [8] Rodgers J.L. & Nicewander W.A., 1988. Thirteen ways to look at the correlation coefficient. *The American Statistician* 42 (1): 59–66.
- [9] Spearman, Charles E. "charles e. Spearman (1863–1945) i faktorska analiza posle 110 godina."
- [10] Maugis, P. A. "Event conditional correlation: Or how non-linear linear dependence can be." *arXiv preprint arXiv:1401.1130* (2014).