

SIA's asymmetric rules approximation to hierarchical clustering in Learning Analytics: mathematical issues

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Brief Abstract.

Bichsel, proposes an analytics maturity model used to evaluate the progress in the use of academic and learning analytics. In the progress, there are positive results but, most institutions are below 80% level. Most institutions also scored low for data analytics tools, reporting, and expertise” [1]. In addition, a task with the methods of Data Mining and Learning Analytics is analyze them (precision, accuracy, sensitivity, coherence, fitness measures, cosine, confidence, lift, similarity weights) for optimize and adapt them [4]. Learning Analytics was and continues to be an emerging technology [2]. The time to adoption Horizon is one year or less but, how many institutions, teachers, learners and data analytics tools, are ready?

Statistical Implicative Analysis (SIA) was created for Regis Gras [7], 45 years ago, SIA is a statistical theory which provides a group of data analytics tools to extract knowledge. The approach is performed starting from the generation of asymmetric rules [3] similar to dendrograms used in the hierarchical clusters [6]. But, the asymmetric rules can be used like a hierarchical clusters? An intuitive approximation between asymmetric rules and hierarchical clusters was given in [5]. The principal aim of this paper is to give mathematical issues of asymmetric rules to hierarchical clustering in Learning Analytics.

Acknowledgements: University of Salamanca and PhD Programme on Education in the Knowledge Society.

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