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Approximation of Statistical Implicative Analysis to Learning Analytics: A systematic review

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ABSTRACT
The learning Analytics has been and is still an emerging technology, the amount of research on learning analysis are increasing every day. The integration of new tools, methods and theories is necessary. The aim of this paper is to study the approximation of Statistical Implicative Analysis theory (SIA) to Learning Analytics (LA). To this end, we have created an approximation framework based on the definition, stages, and methods used in LA. In total, three criteria approach and thirty-six sub-themes were compared. We use systematic review in the literature published in the last 66 months in bibliographic database ACM, EBSCO, Google Scholar, IEEE, ProQuest, Scopus and WOS. We started with 319 papers and finally 24 met all quality criteria. This document provides the themes by which SIA approximates to LA, also provides the percentages by category approach and identifies a number of future researches.

Categories and Subject Descriptors
• **Computers and education →Computer and Information Science Education →Information systems education.**
• **Computers and Society →Organizational Impacts →Automation.**
• **Mathematics of Computing →Probability and statistics →Statistical computing**

Keywords
learning analytics; statistical implicative analysis; systematic review; approximation; learning analytics definition; learning analytics methods; learning analytics stages.

1. INTRODUCTION
Learning Analytics has been and is still an emerging technology (specific learning analytics and adaptive learning) , it is published in the Horizon Report 2016 [27]. Time adoption Horizon is one year or less, but how many institutions, teachers, learners and their contexts, are you ready?

Learning Analytics in Enterprise Performance Management document [52], classified de organizations under three maturity levels based on where they stand in learning analytics application. In Generation 1 (Descriptive and partially Diagnostic): 90% of organizations; Generation 2 (partially Diagnostic, Discovery and partially Predictive): 5-9% of organizations; Generation 3 (partially Predictive and prescriptive): No organizations.

Bichsel, proposes an analytics maturity model used to evaluate the progress in the use of academic analytics and learning analytics. In the advances they have produced positive results but, most institutions are below 80% level. Most institutions also scored low for data analytics tools, reporting, and expertise [8].

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 [41].

In the following subsection, we show the construction steps of approximation framework based in definition and data source, stages, and methods of LA.

1.1 Approximation Framework of Learning Analytics

In this job, we use the definition set out in the first international Conference on Learning Analytics and Knowledge (LAK 2011) and assumed by the Society for Learning Analytics Research: "Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs."[1]

In the above definition we can notice the following three parts:
1)The inputs, according to Bernhardt. V.[2], data about learners and their contexts can be: student learning (How did students at the school score on a test?, Are there differences in student scores on standardized tests over the years?), demographics (How many students are enrolled in the school this year?, How has enrollment in the school changed over the past five years?), perceptions (How satisfied are parents, students, and/or staff with the learning environment?, How have student perceptions of the learning environment changed over time?), and school processes (What programs are operating in the school this year?, What programs have operated in the school in the past five years?)
2)The process, formed by four steps: measurement, collection, analysis and reporting. In addition, Campbell describe academic analytics as an "engine to make decisions or guide actions", and define five steps: capture, report, predict, act, and refine [11]. The Campbell stages are more generally and we use in this paper. The Analysis step in the definition (or report and predict in the Campbell steps), It can be detailed by the classification proposed first by Baker and Inventado [6] . They are based on the similarity of Educational Data Mining (EDM) and LA methods. The Baker and Inventado classification is as follows: Prediction (Classification, Regression, Latent Knowledge Estimation), Relationship Mining (Association Rule Mining, Sequential Pattern Mining, Correlation Mining, Causal Data Mining), Structure Discovery (Clustering, Factor Analysis, Domain Structure Discovery), Discovery with models. In a recent research, Papamitsiou and Economides [41] published the DM/LA methods adopted by authors to analyze the gathered data. They propose the follow organization: Classification, Clustering, Regression, Text mining, Association Rule Mining, Social Network Analysis, Discovery with models, Visualization and Statistics.
3) **The Output**, the definition indicate that the purposes are understanding and optimizing learning and the environments. Understanding and optimizing learning often uses simple, intuitive, dynamics and adaptable data analysis representations, for example maps, tables, dashboards, graphics, diagrams, etc.

Using the definition, stages and methods of LA, we construct an approximation framework to LA. The figure 1, contain the components (definition, stages and methods) and subcomponents of each one.

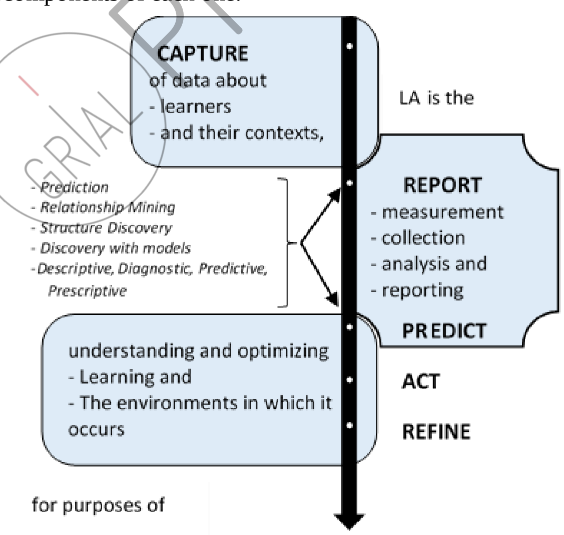


Figure 1: Approximation Framework

[1]https://tekri.athabascau.ca/analytics/

[2]http://www.eqao.com/en/Our_Data_in_Action/articles/Pages/ using-data-improve-student-learning.aspx

In the figure abode, the blue figures represent de three parts of the definition (input, process and output). The arrow represents the stages flow. The analysis methods act directly in report and predict stages. The figure also illustrates the relationship between the definition, stages and methods of LA. The figure represents graphically the approximation framework used in this document.

1.2 Statistical Implicative Analysis (SIA)

SIA was created for Regis Gras [21] and SIA is a statistical theory [20] and a set of data analysis tools that allows to approach knowledge on the basis of the information contained in the database (individuals and variables). SIA emerged to solve situations in mathematical didactics [49]. The main aim is to interpret the structure of data formed by subjects and variables, the determination of patterns among the variables, and following from these patterns to provide predictions [24]. The approach is performed starting from the generation of asymmetric rules [23] between variables and variables classes, represented by tables (clusters no hierarchical)[22], graphs (association rules) [25] and dendrograms (hierarchical clusters, hierarchical oriented clusters) [50]. The rules are called quasi implications since they are logical implications, but with exceptions. You can also determine and characterize the relationship between the subject and rules. SIA carries approximately 45 years of experience in solving educational problems [5] [55].

The nature of SIA is epistemological and didactic, the distribution of literature in computational research, theory research, Educational applications and others applications [43] up to the year 2014 is shown in Figure 2.

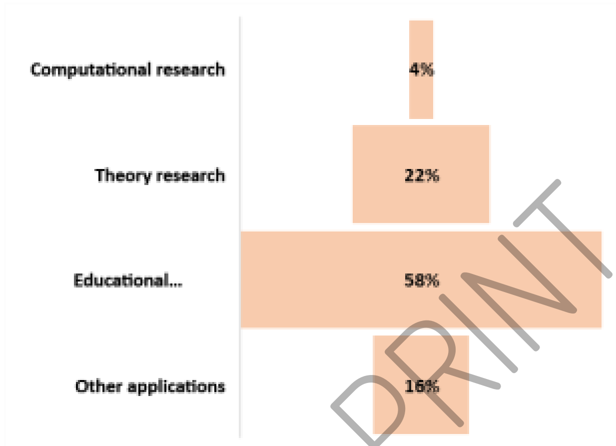


Figure 2: Distribution of SIA literature

Currently there are applications in text mining [30], Item Analysis [28] [14], and lately in image analysis [46]. The relationship between SIA and Probability Theory, Inductive Inference Theory, Nonparametric Statistics, Optimization Theory, Multivariate Statistics and Dynamical System Theory can be found in [26].

The statistical theory [4] and application of SIA are in continuous expansion and development. The SIA informatics tool is called CHIC[12] [13], the last windows version is 6.x, the CHIC free multiplatform version is called RCHIC[3] and is used from 2015. SIA has an international group of active researchers from 2000[4].

When analyzing a large samples containing the entropy calculation option [33]. It is possible to know what are the subjects, or classes of subjects more responsible for computed implications, we can introduce supplementary variables in statistical database such as gender, social category, economical category, professional category, academic category. The contribution, indicates which subjects pay more to an implication. The typicality indicates the typical subjects of the population.

The principal aim of this paper is to study and determine the approximation topics of SIA to LA and identifies a series of future researches in both Learning Analytics and Statistical Implicative Analysis.

In section 2, we describe the systematic review steps: Research Questions and PICO method, Bibliographic database and search characteristics, Inclusion and Exclusion criteria and Quality of Literature used in the methology. In the section 3 we show de results in four tables with frequency analysis. In the section 4 you can found new research questions about ASI approximation to LA.

2. METHODOLOGY

2.1 Research questions and PICO method

The methodology used was a systematic literature review of empirical research [39] about Statistical Implicative Analysis literature. This work, which aims to collect and summarize descriptive information about the approximation of SIA to LA, addresses for three principal research questions[34]:

RQ1: What are the parts of Learning Analytics definition observed from educational research using an SIA approach?

Table 1: PICO methodology for first question

[3] http://members.femto-st.fr/raphael-couturier/en/rchic

[4] http://sites.univ-lyon2.fr/asi8/

P	24 pieces of literature
I	Parts of Learning Analytics definition (https://tekri.athabascau.ca/analytics/)
C	No comparison
O	Learning Analytics definition (one or more than one part, What part?)

RQ1.A: What are Learning Analytics data source observed from educational research using an SIA approach?

Table 2: PICO methodology sub question, data source

P	24 pieces of literature
I	Learning Analytics, data source (http://www.eqao.com/en/Our_Data_in_Action/ articles /Pages/ using-data-improve-student-learning.asp)
C	No comparison
O	Learning Analytics, data source (one or more than one part, What source?)

RQ2: What area Learning Analytics stages observed according to the Five Stages of Analytics from educational research using an SIA approach?

Table 3: PICO methodology for second question

P	24 pieces of literature
I	Learning Analytics stages. Campbell, five stages: capture, report, predict, act, and refine
C	No comparison
O	Learning Analytics stages (one or more than one stage, What stage?)

RQ3: What area Learning Analytics methods observed from educational research using an SIA approach?

Table 4: PICO methodology for third question

P	24 pieces of literature
I	Learning Analytics methods. Baker and Inventado classification and Papamitsiou and Economides methods classification.
C	No comparison
O	Learning Analytics methods (one or more than one method, What method?)

2.2 Bibliographic database and search characteristics

This document aims to examine the research papers about SIA. The source of SIA papers was seven electronic databases: ACM Digital Library, EBSCO, Google Scholar, IEEE Digital Library, ProQuest, Elsevier's Scopus abstract and citation database and Web of Science from international databases (WOS). The Review was limited to studies published in the last 66 months, between 2011 and 2016 (first semester). The data sources and search characteristics are summarized in Table 5.

Table 5. Bibliographic database and search characteristics

BIBLIOGRAPHIC DATABASE		ACM, EBSCO, Google Scholar, IEEE, ProQuest, Scopus, WOS
SEARCH	**Principal Search Criteria**	Statistical Implicative Analysis
	PSC's Results (applying exclusion criteria and time):	24 pieces of literature
	Time	66 months, between 2011 and 2016 (first semester)
	Topics:	• LA definition and data

	Approximation criteria	source • LA stages • LA methods

While searching, the subtopic (or synonym) has been guided to Table 6.

Table 6. Examination criteria used

RQ	**TOPIC: APPROXIMATION CRITERIA**	**SUBTOPIC**
1	SIA Approximation to LA definition and Data source	**LA** **Input:** *Learners *Learners Context ***Data source:** -Student learning -Demographics -Perceptions -School processes **Process:** *Measurement *Collection *Analysis *Reporting **Output:** *Understanding *Optimizing
2	SIA approximation to LA Stages	*Capture *Report *Predict *Act *Refine
3	SIA Approximation to LA methods: Baker and Inventado classification	**Prediction:** *Classification *Regression *Latent Knowledge Estimation **Relationship Mining:** *Association Rule Mining, *Sequential Pattern Mining *Correlation Mining *Causal Data Mining **Structure Discovery:** *Clustering *Factor Analysis *Domain Structure Discovery **Discovery with models**
	SIA Approximation to LA methods: Papamitsiou and Economides classification	**LA/EDA methods:** *Classification *Clustering *Regression *Text mining *Association Rule Mining *Social Network Analysis *Discovery with models *Visualization *Statistics

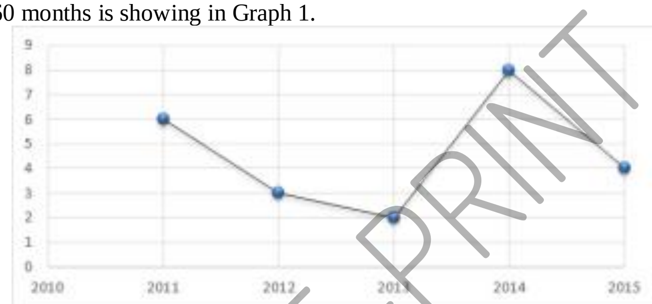
2.3 Inclusion and Exclusion criteria

At the end of the stage of collection of data, is applied rigorously the criteria of inclusion and exclusion (see Table 7).

Table 7. Inclusion and Exclusion criteria

INCLUSION	EXCLUSION
• Articles published in digital libraries: ACM, EBSCO, Google Scholar, IEEE, ProQuest, Scopus, WOS. • Articles published about Statistical Implicative Analysis and Education • The articles must be to present quantitative results. • Papers presented in Spanish, Italian, French and Portuguese language are considered if English translation exist.	• Book chapters • Articles published about Statistical Implicative Analysis and (computational research or theory research or others applications) • Articles that do not present empirical data • Papers presented in language different of English.

We started with 319 of the 111 jobs which were in education, 42 were duplicate records and, finally, 24 met all quality criteria. The Graph of selected SIA papers in the first 60 months is showing in Graph 1.



Graphic 1: SIA papers selected by year

In the first search we use de keyword: "Statistical Implicative Analysis" in digital libraries, after we use EndNote (standard software tool for publishing and managing bibliographies, citations and references) for detect the duplicate records, the dates criteria, educative area and subtopics (see Table 8)

Table 8. Results of search and inclusion criteria

BIBLIOGRAPHIC DATABASE	PRINCIPAL SEARCHING: SIA	PAPERS THAT MEET INCLUSION CRITERIA	NO DUPLICATE	TIME
ACM	1	0	0	0
EBSCO	12	6	4	2
Google Scholar	224	86	49	11
IEEE	1	1	1	1
ProQuest	15	8	8	6
Scopus	60	6	4	1
WOS	6	4	3	3
Total	319	111	69	24

2.4 Quality of Literature

The quality criteria used in the selection of collected literature are shown below:

- Clarity in the methodology used: objective, data, population of study, methods of analysis, software, results, publication of results.
- Sufficient results: graphics, figures, tables and discussion.

We proceeded with the reading and analysis of the articles that met quality criteria. We design the database in an electronic data sheet. We registered the subtopics found, for the definition, stages and methods of LA. Descriptive statistical methods were used to analyze, represent and interpret the results. Finally, non-statistical methods for the synthesis of the revision were used.

3. RESULTS

In this paper, the selected literature on SIA for the research has been analyzed for three approximation criteria and thirty-six subtopic described above in Table 6, and the results can be summarized as follows.

3.1 SIA approximation to LA definition and data source

Table 9, shows the papers reference, quantity and frequency of RQ1' subtopics.

Table 9. SIA approximation to LA definition

SUBCATEGORY OF LA DEFINITION	PAPER REFERENCE (See References)	FREQ (%)
Input: Learners	[1], [2], [3], [9], [10], [14], [16], [17], [18], [19], [57], [28], [31], [32], [35], [36], [38], [42], [44], [47], [54], [56]	22 91.7%
Input: Learners Context	[40], [45]	2 8.3%
Process: Measurement	[[1], [2], [3], [9], [10], [14], [16], [17], [18], [19], [57], [28], [31], [32], [35], [36], [38], [40], [42], [44], [45], [47], [54], [56]	24 100%
Process: Collection	[[1], [2], [3], [9], [10], [14], [16], [17], [18], [19], [57], [28], [31], [32], [35], [36], [38], [40], [42], [44], [45], [47], [54], [56]	24 100%
Process: Analysis	[[1], [2], [3], [9], [10], [14], [16], [17], [18], [19], [57], [28], [31], [32], [35], [36], [38], [40], [42], [44], [45], [47], [54], [56]	24 100%
Process: Reporting	[14], [57], [40], [42], [44]	5 20.8%
Output: Understanding	[1], [2], [3], [9], [10], [16], [17], [18], [19], [57], [28], [31], [32], [35], [36], [38], [45], [47], [54], [56]	20 83.3%
Output: Optimizing	[14], [40], [42], [44]	4 16.7%

The most frequent subtopics in the SIA approximation to LA definition are on measurement, collection and analysis (100%), on Learners (91.7%) and on understanding (83.3%). Fewer frequent are the subtopics reporting (20.8%), optimizing (16.7%) and Learners context (8.3%), (See Table 9).

Table 10, shows the papers reference, quantity and frequency of RQ1.A subtopics.

Table 10. SIA data source

SUBCATEGORY OF LA DATA SOURCE	PAPER REFERENCE (See References)	FREQ (%)
Student learning	[1], [2], [3], [9], [10], [14], [16], [17], [18], [19], [57], [28], [31], [32], [36], [38], [42], [44], [47], [54], [56],	21 87.5%
Demographics	[40],	1 4.2%
Perceptions		0
School process	[35], [42], [45],	3 12.5%

The most frequent subtopics in the SIA approximation to LA data source are student learning (87.5%) and on school process (12.5%). Fewer frequent are the subtopics demographics (4.2%) and perceptions (0%). (See Table 10)

The answer to the question **RQ1** is: Learning analytics is the measurement (100%), collection (100%), analysis (100%) and reporting (20.8%) of data (Student learning (87.5%) and school process (12.5%)) about learners (91.7%) and their contexts (8.3%), for purposes of understanding (83.3%) and optimizing (16.7%) learning and the environments in which it occurs.

3.2 SIA approximation to LA stages and Types

Table 11, shows the papers reference, quantity and frequency of RQ2' subtopics.

Table 11. SIA approximation to LA stages and Types

SUBCATEGORY OF LA STAGES	PAPER REFERENCE (See References)	FREQ (%)
Capture	**[[1], [2], [3], [9], [10], [14], [16], [17], [18], [19], [57], [28], [31], [32], [35], [36], [38], [40], [42], [44], [45], [47], [54], [56]**	**24** **100%**
Report	**[[1], [2], [3], [9], [10], [14], [16], [17], [18], [19], [57], [28], [31], [32], [35], [36], [38], [40], [42], [44], [45], [47], [54], [56]**	**24** **100%**
Predict	**[14], [18], [31], [40], [42], [47]**	**6** **25%**
Act	**[40]**	**1** **4.2%**
Refine		**0**

Table 11 shows that the most frequent subtopics in the SIA approximation to LA stages are on capture and report (100%), on predict (25%) and on act (4.2%). Fewer frequent are the subtopics refine (0%).

The answer to the question **RQ2** is: The LA stages most observed in SIA papers are: capture and report (100%). Fewer frequent are the subtopics Act (4.2%), and refine (0%).

3.3 SIA approximation to LA methods

Table 12, shows the papers reference, quantity and frequency of RQ3 subtopics.

The most frequent subtopics in the SIA approximation to LA methods are Association Rule Mining (95.8%), Clustering (37.5%), Statistics (20.8%) and Causal Data Mining (4.2%), (See Table 12).

The answer to the question **RQ3** is: The LA methods most observed in SIA papers are: Association Rule Mining (95.8%), Clustering (37.5%) and Statistics (20.8%)

4. DISCUSION AND CONCLUSIONS

In the introduction on LA and SIA, we could observe that the area for both is education. This shows us a first compatibility that justifies this work. LA and SIA papers are growing constantly, see for example temporal serie in Graph 1.

Table 12. SIA approximation to LA methods

SUBCATEGORY OF LA METHODS	PAPER REFERENCE (See References)	FREQ (%)
BAKER AND INVENTADO CLASSIFICATION		
Classification		**0**
Regression		**0**
Latent Knowledge Estimation		**0**
Association Rule Mining	**[1], [2], [3], [9], [10], [14], [16], [17], [18], [19], [57], [28], [31], [32], [35], [36], [38], [40], [42], [44], [45], [47], [56]**	**23 95.8%**
Sequential Pattern Mining		0
Correlation Mining		0
Causal Data Mining	[54]	1 4.2%
Clustering	[2], [9], [14], [17], [57], [28], [32], [40], [54]	9 37.5%
Factor Analysis		0
Domain Structure Discovery		0
Discovery with models		0
PAPAMITSIOU AND ECONOMIDES CLASSIFICATION		
Social Network Analysis		0
Text Mining		0
Visualization		0
Statistics	[1], [17], [57], [31], [36]	5 20.8%

LA has some definitions, we have worked with the most common: LA definition of the first international Conference on Learning Analytics and Knowledge (LAK 2011). The first research question is about the SIA approximation to this definition and data source, the results obtained are shown below.
We obtained a global SIA approximation to LA definition between 59.3% and 67.6%, the percentage depends on the selected data source. The approximation is good and we can note that SIA has as a source the learners and some the learning context. With the calculated percentages, SIA could contribute to LA in measurement, collection and analysis about learners, for purposes of understanding learning.

Campbell, define five stages: capture, report, predict, act, and refine [11], with the calculated percentages of LA stages, SIA could contribute in capture and report, but SIA would contribute little in Act stage and no could contribute in Refine stage.

Analyzing the third research question can be determined that the SIA could contribute very much in Association Rule Mining, SIA could contribute much in Clustering and SIA and could contribute little in Statistics.

From the above analysis some research questions are obtained, that can be studied by researchers of SIA or LA:

- SIA could contribute very much in Learners part of LA definition. But, how to use this result in LA contribution?
- SIA does not contribute in Learners Context part of LA definition. What are the reasons? What are the strategies to contribute in Learners Context part of LA definition?
- Why SIA contribute a little in learning optimization part of LA definition? How increment the contribution?
- Why SIA do not use demographics and perceptions data part of LA definition? How increment the contribution?
- SIA could contribute very much in capture and report steps of LA stages. But, how to use this result in LA contribution?
- How increment the SIA contribution to Act step of LA stages?

- SIA could contribute in Refine step of LA stages?
- SIA could contribute very much in Association Rule Mining. But, Are there advantages? When is possible to use SIA Association Rule Mining? Are there differences between SIA Association Rule Mining and traditional methods uses in LA?
- SIA could contribute much in Clustering. But, Are there advantages? When is possible to use SIA Clustering? Are there differences between SIA Clustering and traditional methods uses in LA?

In conclusions, SIA could contribute very much in learners, collection, analysis, understanding and student learning of LA definition and data source; SIA could contribute very much in capture and report of LA stages; SIA could contribute very much in association rule mining and clustering of LA methods. Here is important to answer the next question, how to use this result in LA contribution?

SIA could contribute much in optimizing, analysis, school process of LA definition and data source; SIA could contribute much in predict of LA stages; SIA could contribute much in statistics of LA methods. Here is important to answer the next question, how increment the contribution?

SIA does not contribute in Learners Context, Optimizing, Reporting, Analysis, School process of LA definition and data source; SIA does not contribute in demographics, perceptions and school process of LA stages; SIA does not contribute in causal data mining of LA methods. Here is important check this statement.

Finally, I hope that this work has motivated to researchers to answer the questions raised.

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