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Towards adaptive systems for automatic formative assessment in virtual learning communities

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***Abstract*—This paper presents a model for structuring shared resources, proposed to activate learners' formative and proactive assessment processes by enhancing the sharing-workflow among instructors. The model is based on the features of a Virtual Learning Community (VLC), and provides for the development and reuse of ontologies. The adoption of the model for the implementation of an adaptive system for the dispatching of materials is discussed on the basis of the results from clustering analyses. Semantic-similarity measures are compared by their application for clustering a collection of mathematical questions for automatic assessment, created by instructors within a national-wide VLC for Secondary Schools.**

Keywords—adaptive system; formative automatic assessment; ontology; semantic similarity clustering; virtual learning community.

I. INTRODUCTION

The present research proposes the adoption of semantic-capturing methods for implementing a communication mean between the communities of students and instructors: a system for adaptively providing digital materials shared within a virtual learning community, to increase the possibilities of activating formative and proactive assessment processes, operating on the basis of automatic detection of the semantic similarity in accordance with learning objectives and prerequisites, formulated as metadata in an empirically controllable way thanks to the model here presented. Ontologies are proposed as structured knowledge representation scheme to be referenced by the system, to generate – adaptively to the learner – networks of resources ("learning paths") connected by learning intentions and success criteria.

This paper inquiries how semantic clusterings generated on the basis of the proposed metadata are related to each other, and whether they are in accordance with clusterings from content-based similarity.

II. STATE OF THE ART

The increasing availability of mathematical ontologies is part of the recent advances on Semantic Web models and technologies that help solving new challenges in Mathematical Knowledge Management. This contrast the main limitation of the adoption of knowledge-based measures, namely their strong dependence on the availability of an ontology [1]. The development of recommender systems [2] and adaptive learning systems [3], based on semantic relations defined in domain ontologies, highlights the necessity of making mathematics more computable and its representation more robust and standardized. Nevertheless, the community of experts in semantic language design and markup for mathematics doesn't agree on how to create a semantic language for mathematics, despite the common target of achieving a Global Digital Mathematics Library [4]. This led to the proposal of increasing the interoperability between existing systems and languages.

Ontologies differ from other formalizing knowledge resources by their degree of formalization [5]. In the context of cognitive domains in mathematics education, several taxonomies have been published and largely used, especially involving the design and interpretation of achievement tests [6] [7] [8] [9]. Assuming that all cognitive levels could be tested using objective test questions [10], this paper proposes an ontological implementation of Anderson and Krathwohl's taxonomy, to be used together with an Italian translation of OntoMath^{PRO} ontology [11] to infer and distinguish the main thinking skills and types of knowledge implicit in mathematical problems.

III. THE MODEL

In order to obtain a more varied, and still effective, formative evaluation, it is proposed to make available to students additional materials for automatic assessment created

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by the whole community of teachers, adapting them to learners according to their learning habits. A system integrated to a Learning Management System (LMS) will enable to consult digital maps automatically generated from the collection of resources shared by a community of instructors, who work adopting a common framework of learning objectives. The maps will provide "learning object trajectories" (or "learning paths"), that are paths composed of nodes and edges: a node is a reference to a resource available in the LMS, while an edge between two nodes is created by matching commonalities between learning intentions and success criteria related to the two learning objects referenced by the nodes. The system will provide the community of teachers with aggregate analyses on the results of the community of students. It is expected that this will foster discussions on the effectiveness of the materials and methodologies proposed.

The model features are presented as follows in the next subsections: an introduction of the system's recipients is given (Virtual Learning Communities); is presented (Measurable Material); the method for enabling the matching of semantic similarity in terms of learning intentions and success criteria among two learning materials is proposed; the actions for the implementation of formative assessment process are summarized.

A. Virtual Learning Community

The area of application of the present research are Virtual Learning Communities [12]. A VLC is a system where

- instructors (discipline experts) manage one or more courses dedicated to a group of learners;
- tutors (discipline and ICT experts) help instructors in experimenting innovative methodologies for teaching, creating digital materials, peer collaboration, sharing resources and best practices, using advanced tools integrated to the LMS that hosts the online courses;
- instructors and tutors agree upon a framework of competences expected to be achieved by the learners at the end of the learning process.

A VLC is a "community of communities" [13]: the online courses held by teachers are communities themselves; the community of instructors is the place where teachers assume the role of "students" - by learning new methodologies and the use of advanced tools with the support of tutors. This research identifies the community of students as a further actor for continuously improving the technology-enhanced teaching & learning process of the community.

B. Measurable materials

The development of materials for automated assessment is part of a VLC, where students can access resources and activities at their own pace according to their needs [14], and teachers are free to design learning products. The products for Computer Aided-Assessment can widely vary depending on the AAS adopted. Whatever the type of response area taken into consideration, two definitions for the object of this study are proposed:

- A *measurable learning objects* (MLO) is defined as a digital resource containing one (and only one) response area dedicated to automated assessment [15].
- A *measurable learning material* (MLM) is any grouping of learning objects.

The definition of a learning material into its 'atomic' components is proposed to foster the reflection on the multimodal possibility for implementing automatic assessment. A single learning objective can be tested through several distinct types of questions. Moreover, teachers could implement assignments with different features accordingly to the educational strategy.

C. Descriptors for relating MLOs to competency frameworks

Clarifying, sharing, and understanding learning intentions and criteria for success are fundamental requirements for activating learners' reasoning on their own objectives achievement (*formative* assessment) and for stimulating the learner to undertake appropriate learning paths to achieve the objectives (*proactive* assessment). To connect MLMs to the competency framework agreed among the VLC, it is proposed to associate MLOs to natural language descriptions, which explicate the learning intentions and success criteria that the MLO was designed for. Associating descriptors to MLOs is not considered a distinct phase of MLO authoring, it instead should increase the educational validity of the whole instructors' work, from the design phase to the sharing and finding of different resources. In particular, the presence of descriptors shall favour teachers who joining the VLC for the first time, as they might not be familiar with advanced tools yet.

A triple of descriptors (*Performance*, *Requisites*, *Objectives*) is proposed to strengthen instructors' reasoning on the selection of contents, development of an instructional strategy, and construction of tests and other instruments for assessing and then evaluating student learning outcomes. The triple to be included in a MLO's metadata is defined as follows.

- *Performance* (also known as "instructional objectives", "behavioural objectives" or "learning objectives") is a specific statement of the observable behaviour required to who attempts performing the MLO.
- *Requisites* (or "prerequisites") states the instructor's belief of the necessary and sufficient condition to attempt performing the MLO.
- *Objectives* (or "goals") specifies what learners are required to be able to do as a result of the learning activity related to the MLO.

Performance is proposed to activate a reflection on the structure of the materials used online, therefore should be useful to the teacher both in the design phase, and during the research and afterwards. A well-written performance should meet the following criteria: describe a learning outcome (what the student will be able to do, that *can be observed* directly), be student-oriented (describing the conditions under which the student will perform the task), be observable (indicating criteria for evaluating student's performance). Optionally, a degree of mastery needed can be explicated. *Requisites* indicates the learning goals that should be acquired before attempting to answer the response area of the MLO. It connects to the essential objectives that are supposed to be mastered before attempting the MLO. *Objectives*, differently from *Performance*, does not depend on the type of response area embedded in the MLO. The statement should not simply describe a list of topics, that being too abstract, too narrow, nor being restricted to lower-level cognitive skills. 'Action verbs' are suggested to compose this descriptor. The three descriptors must be expressed in a student-centred manner.

D. Automated formative assessment

The model enables a process of formative assessment consistent with the theoretical framework of Black and Wiliam [16]. They considered Wiliam and Thompson's three fundamental processes for learning and teaching [17]:

- Establishing where the learners are in their learning.
- Establishing where they are going.
- Establishing what needs to be done to get them there.

Crossing the three fundamental processes with different agents (teacher, peer, learner), they conceptualized formative assessment as consisting of five key strategies. This conceptualization is here adapted for a VLC context, five actions are here proposed as an implementation of the key strategies:

1. Definition and use of the reference framework of learning objectives (Instructor and Tutors). Reading and understanding the statements that refer to the framework (Peers, Learners).
2. Development and sharing of MLMs and analysis of results (Instructors). Support for the creation of MLMs (Tutors).
3. Association of materials with descriptors consistent with the framework (Instructor). Support to the definition of descriptors (Tutors).
4. Use and sharing of measurable materials.
5. Use of measurable materials in unsupervised modality (anonymous).

In a VLC, the community agrees upon a framework of learning objectives, each resource is somehow related to one or more intended learning goals. Teachers are asked to associate materials to appropriate descriptors congruently with the framework. During the phases of design and construction of measurable materials, the desired learning results are the guiding principle. Before publishing MLMs to students, external parties (tutors) are involved.

IV. Ontologies for cognitive processes and knowledge

The presented model aims to create a web of interconnecting MLOs. To actively processing this web of resources, that will be progressively augmented with students results, an ontology created upon the Anderson & Krathwohl's taxonomy integrated with the concepts from OntoMath^{PRO}[11] is proposed.

In Anderson & Krathwohl's taxonomy, cognitive processes and knowledge types are hierarchically organized in two levels: a cognitive process can be one of six main processes, in turn split in various basic processes (19 cognitive processes in total). A knowledge can be one of 4 main types, in turn split in various basic types (11 knowledge types in total). The adoption of a taxonomy is an aid to "space" in the definition of learning tasks. Anderson & Krathwohl's ontology is here proposed as a reference for inferring the cognitive processes and the knowledge types implicit in a MLO. Identifying concepts underlying a MLO begins from an analysis of its descriptors: those are composed by using 'action verbs' that ask the student to apply a cognitive process to given disciplinary contents. Since Mathematics is a domain involving "specific" action verbs, those should be retrieved from domain specific ontologies, such as OntoMath^{PRO}.

V. Clustering MLOs by Semantic similarity

Two approaches for clustering digital learning materials for automatic assessment in mathematics are proposed as follows. They differ in the collection of inputs considered: the first approach measures the semantic similarity among what is 'inside' a MLO (content-based similarity), while the second only uses information that define a MLO 'from the outside' (metadata-based similarity) – that are the descriptors. Both approaches involve implementing the 'bag-of-words' model.

Given a collection of input strings, the following phases are executed:

- Tokenization, stop words removal, stemming, bag-of-words representation.
- The 'transformation model', initialized from the corpus of bag-of-words vectors, is used to convert any vector to the tf-idf representation.
- Mini Batch k-Means clustering algorithm [18] is executed on each feature similarity matrices, constructed by calculating cosine similarity for each pair of vectors.

Differently from metadata-based similarity, content-based similarity admits inputs composed of a mixture of texts and formulae. In fact, a MLM can contain words, phrases, and formulae. In natural language, words and phrases themselves imply the semantics. Formulae components are considered as 'words' in the mathematical language, and entire formulae as 'sentences'.

MLMs considered in this research were created using and Automatic Assessment System Maple TA. Subsuming the semantics from the formula structure helps to deal with the numerous different modalities for authoring problems enabled by an AAS: for instance, algorithmic variables allow to have potentially 'infinite' versions of the same MLO. Maple, the Advanced Computing Environment on which Maple TA is based, was used for parsing Mathematical problems: a formula is expressed as series of embedded function calls which can be represented as a Directed Acyclic Graph. Formula's components are identified by their names from Maple's syntax and are extracted from the internal data structure representation of the formula.

VI. RESULTS AND DISCUSSION

196 MLOs from 93 MLMs were selected from the collection of questions shared by secondary school teachers among the VLC of PP&S [19]. Two experts in mathematics and physics separately inserted the triples of descriptors to each of the 196 MLOs.

The collections of MLOs can be grouped into 8 'disciplinary' areas: Contextualized problem about Algebra (4), Monomials (68), Polynomials (38), Special products (24), Contextualized problem about Probability (7), Statistics (36), Probability (13), Contextualized problem about Statistics (6).

MLOs of the collection can be grouped in 8 response area types: Maple-graded (23), Matching (1), Mathematical formula (57), Multiple choice (32), Multiple selection (13), List (23), Essay (3), Numeric (44).

Clustering analysis has been conducted by using tools from *Gensim*, [20], *nltk*, [21], and *scipy* [22].

The clustering experiment was repeated 10 times following the previously described phases, for different values of the number *n*, which is the number of clusters that the Mini Batch k-Means algorithm has to generate. Clusterings generated from different collections of input strings are compared as follows.

For each repetition, the collections of input strings are:

- The 6 lists of MLOs' descriptors (**P** stands for the *Performance* descriptor, **O** for *Objectives*, **R** for *Requisites*) for each given author (**1**, **2**): **1P**, **1R**, **1O**, **2P**, **2R**, **2O**.
- The list **ST** of strings defining the surface texts of each MLO.

To estimate the correlation between different clusterings, the *v_measure* homogeneity metric is used, which expresses how successfully *homogeneity* and *completeness* criteria have been satisfied between two clusterings. It returns a score between 0 and 1, where 1 stands for perfectly complete labelling between the two clusterings [23]. The following tables show the mean and standard deviation of the *v_measure* values, for different combinations of clustering generated by the related inputs, in case of $n = 8$ clusters to be generated.

First of all, to guarantee the quality of the clusterings obtained, each clustering is compared to randomly generated clusterings. Each case shows that there is approximately no mutual information with a random clustering, since the *v_measure* mean value is significantly close to zero: the v_measure mean is 0.07 on each case with standard deviation less or equal to 0.02.

TABLE I. shows significant correlation values among the descriptors of the same author. Some dependency among intended outcomes and pre-requisites knowledge is expected, if they are referred to resources from the same discipline, although it is possible to reach the same learning goal starting from different initial situations.

TABLE I. *V_MEASURE* CALCULATED AMONG CLUSTERINGS FROM DIFFERENT AUTHORS' DESCRIPTORS.

Clusterings (n=8)		Mean	Std. dev.
1	***1P | 1O***	0.40	0.03
	1O | 1R	0.39	0.02
	1P | 1R	0.32	0.02
2	***2P | 2O***	0.50	0.04
	2O | 2R	0.40	0.02
	2P | 2R	0.42	0.02

Correlation is less strong comparing clusterings from the descriptors and the surface text, as shown by TABLE II. . This result aligns with the expectation that a question can be composed in potentially infinite modalities. In particular, mathematical problems can be contextualized in "real situation": the descriptors refer to concepts from the mathematical model covered by the problematic situation.

TABLE II. *V_MEASURE* CALCULATED AMONG CLUSTERINGS FROM AUTHORS' DESCRIPTORS AND FROM THE SURFACE TEXTS.

Clusterings (n=8)		Mean	Std. dev.
1	***1P | ST***	0.30	0.02
	1R | ST	0.27	0.03
	1O | ST	0.26	0.02
2	***2P | ST***	0.26	0.03
	2R | ST	0.20	0.02
	2O | ST	0.24	0.03

To investigate how the generated clusterings reflect the disciplinary area of the collection of MLOs, they were compared to the 'ground truth' labelling composed by the 8 'disciplinary' areas previously mentioned (indicated as **aGT**). The values of TABLE III. validate the assumption that semantically related words tend to co-occur, thence strength of the semantic relationship which links MLOs can be inferred from observations regarding the distribution of words. At the same time, the descriptors enable to express concepts slightly different from the disciplinary area involved in mathematical problems.

TABLE III. *V_MEASURE* CALCULATED AMONG CLUSTERINGS AND THE GROUND TRUTH CLUSTERING BY 'DISCIPLINARY' AREAS.

Clusterings (n=8)		Mean	Std. dev.
1	***1P | aGT***	0.52	0.01
	1R | aGT	0.54	0.01
	1O | aGT	0.53	0.01
2	***2P | aGT***	0.57	0.01
	2R | aGT	0.54	0.01
	2O | aGT	0.52	0.01

	ST **|** ***aGT***	0.44	0.02

Similar values are obtained by using the 'ground truth' labelling composed by the 8 response areas types (**rGT**). Surprisingly these values are reached despite there is no evidence of high inter-annotation agreement between the two authors (TABLE IV.). Differences between authors can occur if they use distinct words for expressing semantically related concepts, such as "polynomial" and "algebraic expression", or "write the value of the expression" and "write the results". Furthermore, inconsistencies might occur if authors do not use 'action verbs'. Adopting ontologies as semantic-proxies would enable to capture those semantic related concepts.

TABLE IV. *V_MEASURE* CALCULATED AMONG CLUSTERINGS FROM DIFFERENT AUTHORS.

Clusterings (n=8)		Mean	Std. dev.
1 2	***1P*** **|** ***2P***	0.326	0.014
	1R **|** ***2R***	0.316	0.027
	1O **|** ***2O***	0.318	0.020
	1P **|** ***2O***	0.291	0.031
	1O **|** ***2R***	0.263	0.023
	1P **|** ***2R***	0.268	0.013

To evaluate whether clusterings correlation depends on the number of clusters generated, the same process was repeated for values of *n* higher and lower than 8. It has been noted that correlation values slightly increase/decrease with the increase/decrease of *n* – and this is true also for the correlation between the randomly generated clusterings – confirming that a 8 is approximately the number of clusters to be expected.

A. Concept-tuned clustering

The experiment was repeated attempting 'noise reduction' by the following rules for tokens' filtering:

1. Words that appear in less than 2 input strings are filtered out.
2. Words that appear in more than the half of the input strings are filtered out.
3. Words are kept regardless the previous rules, if they belong to the set of concepts of the ontologies mentioned in section IV.
4. After the previous rules, only the first *k* most frequent words are kept.

These rules are proposed to enhance the influence of relevant concepts to the semantic measures.

The following graphs show the mean of the *v_measure* values, for different combinations of clustering generated by the related inputs, in case of $n = 8$ clusters to be generated, with the value *k* between 10 and 30 in steps of 2. As the value of k decreases, some correlation values remain around the ones shown in the previous tables. This stability suggests the candidates with respect to which to confirm a certain degree of correlation.

Fig. 1 suggests significant correlation values among *Performance* and *Objectives* of the same author.

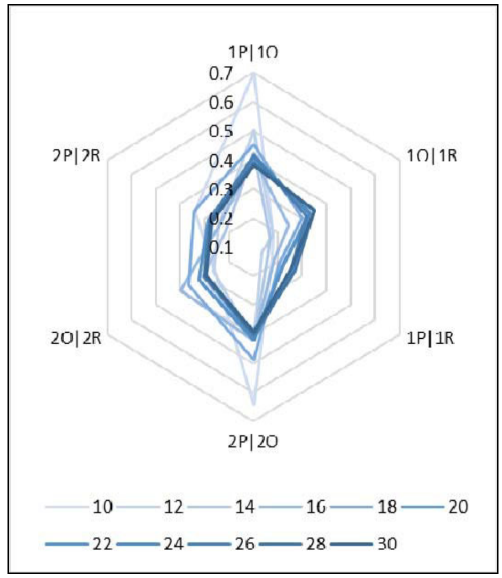

Fig. 1. *v_measure* means calculated among clusterings from different authors' descriptors ($n = 8$, k from 10 to 30).

Performance and *Objectives* appear to be stably aligned both with disciplinary areas (Fig. 2) and response areas.

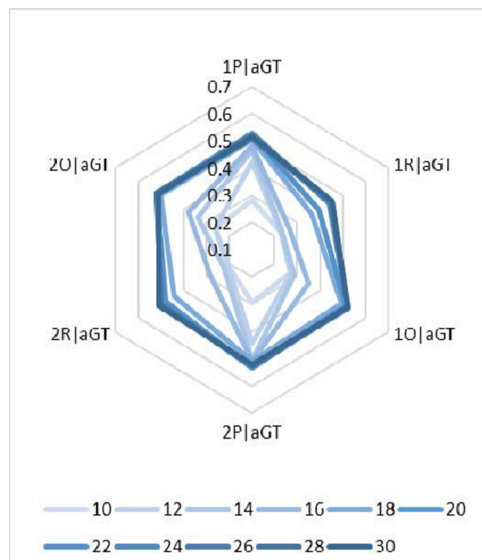

Fig. 2. *v_measure* calculated among clusterings and the ground truth clustering by 'disciplinary' areas ($n = 8$, k from 10 to 30).

There is still no evidence of high inter-annotation agreement between the two authors, with exception of low values of the number of words considered for the similarity measurement. Lastly, the clustering from surface texts tends to confirm independence from 'metadata' clustering. On the contrary, it maintains high correlation with the 'ground truth' clusterings (Fig. 3).

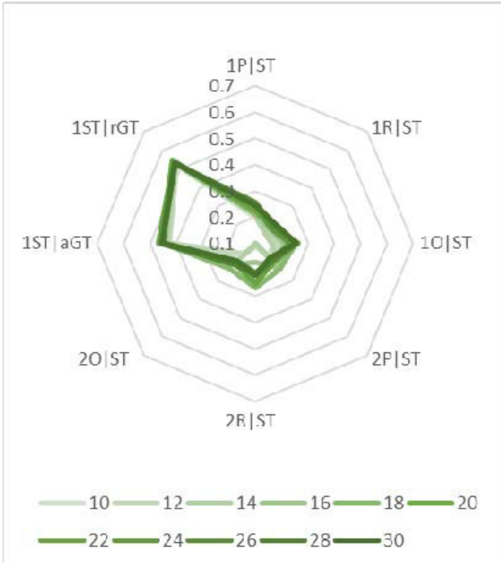

Fig. 3. *v_measure* means calculated among the clustering from the surface texts and clusterings from authors' descriptors or the 'ground truth' labellings ($n = 8$, k from 10 to 30).

VII. Conclusions

This investigation is a first step towards the implementation of a system for adaptively providing learning resources. Results suggest the adoption of ontologies as semantic-proxies: as a next step, a mix between corpus-based and knowledge based semantic clustering will be experimented, exploiting the ontological model presented in section IV.

The implementation of this research will guide future improvements of Automatic Assessment Tools. This analysis will grow by activating projects at national and European scale [24], involving instructors and students to further investigate MLM authoring and automatic dispatching.

References

[1] S. Harispe, S. Ranwez, S. Janaqi and J. Montmain, "Semantic Similarity from Natural Language and Ontology Analysis", 2015.

[2] A.M. Elizarov, A.B. Zhizhchenko, N.G. Zhil'tsov, A.V. Kirillovich and E.K. Lipachev, "Mathematical knowledge ontologies and recommender systems for collections of documents in physics and mathematics", Doklady Mathematics, 93, 231-233, 2016.

[3] V. Tam, E.Y. Lam and S.T. Fung, "A new framework of concept clustering and learning path optimization to develop the next-generation e-learning systems", Journal of Computers in Education, Volume 1, Number 4, Page 335, 2014.

[4] P. Ion, M. Trott, E. Weisstein and F. Wiedijk, "White Paper of the Semantic Representation of Mathematical Knowledge Workshop", 2016.

[5] R. Navigli, "Ontologies". The Oxford Handbook of Computational Linguistics (2nd edition, R. Mitkov, Ed.), Oxford University Press, 2016.

[6] S. Lerman (Ed.), "Encyclopedia of Mathematics Education, Springer Netherlands", 63-68, 2014.

[7] B. Bloom. (Ed.), "Taxonomy of Education al Objectives", Handbook I: Cognitive Domain, David McKay Company, Inc, New York, 1956.

[8] I.V.S. Mullis, M.O. Martin, T.A. Smith, R.A. Garden, K.D. Gregory, E.J. Gonzalez, S.J. Chrostowski and K.M. O'Connor. "TIMSS assessment frameworks and specifications", 2nd edn. International Association for the Evaluation of Educational Achievement, Chestnut Hill, 2003.

[9] L.W. Anderson, D.R. Krathwohl et al., "A taxonomy for learning, teaching, and assessing. A revision of Bloom's taxonomy of educational objectives", New York, Addison Wesley Longman, 2001.

[10] E. Beevers and C.S. Paterson, "Automatic Assessment Of Problem-Solving Skills In Mathematics", Active Learning In Higher Education, 2003.

[11] O. Nevzorova, N. Zhiltsov, Nikita, A. Kirillovich and E. Lipachev, "OntoMathPRO ontology: A linked data hub for mathematics. Communications in Computer and Information Science", 468. 2014.

[12] F. Ellerani and M. Parricchi, "Ambienti per lo sviluppo professionale degli insegnanti", Web 2.0, gruppo, comunità di apprendimento, 2010.

[13] C. Pardini, C. Demartini, M. Marchisio, "PP&S100 - una comunità di comunità di collaborative learning attraverso le nuove tecnologie, 2013.

[14] A. Barana and M. Marchisio, "Ten good reasons to adopt an automated formative assessment model for learning and teaching Mathematics and scientific disciplines", Procedia - Social and Behavioral Sciences, 228, pp. 608-613, 2016.

[15] I. Petri, "Automated Assessment of Programming Assignments: Visual Feedback, Assignment Mobility, and Assessment of Students' Testing Skill", 2011.

[16] P. Black and D. Wiliam, "Developing theory of formative assessment", Evaluation and Accountability 21(1), pp. 5-31, 2009.

[17] D. Wiliam and M. Thompson, "Integrating assessment with instruction: What will it take to make it work?", The future of assessment: Shaping teaching and learning, Mahwah, NJ, pp. 53-82, 2007.

[18] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot and E. Duchesnay, "Scikit-learn: Machine Learning in Python". JMLR 12. 2825-2830, 2011.

[19] A. Brancaccio, C. Demartini, M. Marchisio, C. Palumbo, C. Pardini, A. Patrucco, R. Zich, "Problem Posing and Solving: Strategic Italian Key Action to Enhance Teaching and Learning of Mathematics and Informatics in High School", in Proceedings of 2015 IEEE 39th Annual Computer Software and Applications Conference, 2015, pp. 845-850, doi: 10.1109/COMPSAC.2015.126.

[20] R. Řehůřek and P. Sojka, "Software Framework for Topic Modelling with Large Corpora", Proceedings of LREC 2010 workshop New Challenges for NLP Frameworks, Valletta, Malta: University of Malta, pp. 46-50, 2010.

[21] S. Bird, L. Edward and K. Ewan, "Natural Language Processing with Python", O'Reilly Media Inc, 2009.

[22] Jones E., Oliphant E., Peterson P., et al. SciPy: Open Source Scientific Tools for Python, 2001-, http://www.scipy.org/ [Online; accessed 2018-01-29].

[23] A. Rosenberg and J. Hirschberg, "V-Measure: A conditional entropy-based external cluster evaluation measure", Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning(EMNLP-CoNLL), pp. 410-420, 2007.

[24] A. Brancaccio, M. Esposito, M. Marchisio and C. Pardini. "L'efficacia dell'apprendimento in rete degli immigrati digitali. L'esperienza SMART per le discipline scientifiche", Mondo Digitale, 15, ISSN: 1720-898X, pp. 803-821, 2016.

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