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# Towards Objective Evaluation of Students' Data Models

Zoltan Kazi, Branka Radulović

University of Novi Sad, Technical Faculty "Mihajlo Pupin" Zrenjanin, Department of Teaching Methods of Science and Education Technology

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# TOWARDS OBJECTIVE EVALUATION OF STUDENTS' DATA MODELS

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Professional Paper

**Zoltan KAZI, Biljana RADULOVIĆ**

University of Novi Sad, Technical faculty "Mihajlo Pupin", Zrenjanin, Republic of Serbia  
zoltan.kazi@gmail.com

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**Abstract:** Assessment as a way of evaluating the students' knowledge plays a very important role in educational process. This paper presents a system for data model semantic evaluation that is based on comparing ontology with model elements. This approach is based on domain ontology and data model formalization at predicate calculus form that is suitable for reasoning. A set of reasoning rules for ontology to data model mapping was defined. The whole process is empirically verified and confirmed. For this purpose it has been developed a software tool for ontology and data model transformation to predicate logic form and then to a set of Prolog-like clauses. After integration of these sets of clauses and rules, a Prolog-system was used for reasoning in order to quantitatively express the quality of data model with appropriate metric.

**Keywords:** students, assessment, data model, ontology, objective evaluation.

## I. INTRODUCTION

Assessment as a way of evaluating the students' knowledge plays a very important role in educational process. The assessment is a process that may lead to inequities due to the difficulty in applying the same evaluation criteria for students' answers [1]. The modeling competence is one of the core competences that need to be fostered and developed at all educational levels. Assessment of the modeling competence should also be considered as an important domain of research in science teaching and learning and also of science education [2]. Modeling, the process of constructing and deploying scientific models, has received widespread attention as a competence whose development facilitates student learning and knowledge. It is known to be challenging for both students and teachers [2], [3], [4], [5]. Attempts to validate models construction, comparison between models, model revision and modeling-based designs as a student competence in models and modeling are presented in [4], [6], [7].

## II. DATA MODELS EVALUATION

Methodologies and frameworks for data model quality evaluation are generally classified as [8]: data-driven vs. process driven methodologies; measurement vs. improvement methodologies and general vs. specific (related to particular model types or notations) methodologies. Paper [9] presents conceptual modeling errors as human errors at three performance levels: skill-based, rule based and knowledge based. Research [10] shows analysis of proposed solutions to evaluation of conceptual data models. Over than 50 various proposals to conceptual data modeling evaluation are published, but less than 20 percent of them are empirically validated. None of proposed solutions is accepted in practice, outside the research environment. These solutions are at different level of generality, researches ones are more general and difficult to be implemented in practice, while practically motivated are more focused on particular modeling notation. The proposed solutions show lack of agreement of terminology, lack of consistency with related fields and standards, lack of measurements metrics and evaluation procedures, lack of guidelines for improvement (proposed solutions are mostly focus on error detection), lack of attention to process quality (i.e. process of creation of conceptual data models and prevention of errors), but rather to product quality detection (and some of them correction), lack of empirical studies from practice (i.e. studies on how conceptual data model evaluation is made in practice).

Other empirical validation included action research with collaboration of researchers and practitioners in the field and with practical projects and issues in conceptual data modeling evaluation.

Metrics for evaluation of conceptual data models could be classified as:

- Quantitative-based: checking the number of entities, relationships and attributes with certain characteristics [11], complexity of elements and a model [12],
- Qualitative-based: subjective judgment on quality characteristics such as: completeness, integrity, flexibility, comprehensiveness, correctness, simplicity, integration, implement ability [10] and preciseness, completeness, consistency, reliability, timeliness, uniqueness, validity [13],
- Ontology-based [14]: structure-based (suitability, stability, consistency) and content-based (completeness, cohesy, validity),
- Behavioral-based [14]: applicability from user and designer aspect, maintainability, correctness and performances.

Recent researches in the field of automating conceptual data models evaluation consider conceptual data model as a “product”. Certain software tools are developed as prototypes that enable: analysis of conceptual data model elements quality [15], comparison of created conceptual data model with other models [16], and automated reasoning on quality of conceptual data models [17].

Combining action research with practitioners and laboratory research with both experts and novices in conceptual data modeling, progress is made toward generality and applicability of proposed conceptual data model evaluation framework in practice [16]. Still, empirical verification of the proposed framework is subjective in quality criteria metrics ranking, i.e. ranking of created conceptual data models is performed by qualified persons and it is not automated. Recent research results are related to automation in evaluation of conceptual data model [14], [18], [19]. Other prototypes consider process of conceptual data model creation and improve it by enabling assistance or complete automation in: consulting support to novice designers related to conceptual data model elements quality [9], and automated creation of conceptual data model design [20].

### III. SYSTEM FOR DATA MODEL EVALUATION

Motivated by previously presented problems and researches we started a project related to Entity Relationship (ER) data model semantic evaluation. The main idea was integration of automated reasoning system, ontology, data model and reasoning rules in aim to evaluate the ER data model semantic quality. The ontology is proved to be the adequate technique for dealing with semantic of data. The approach is formulated in the context of data model quality measurement and formal theories [10], [11], [13], [14], [16], [21]. Our research goal was to develop and empirically verify an automated system for reasoning that will have features such as:

- Rule-based system,
- Enable automated reasoning on ER data model quality,
- Provide answers related to particular element of a created conceptual data model and an overall data model quality evaluation,
- Enable evaluation of semantic aspect of the created ER model and therefore should be based on comparison with “semantically rich” models that enables presenting semantic variations,
- Scalable, i.e. should be applicable to any size of the conceptual model.

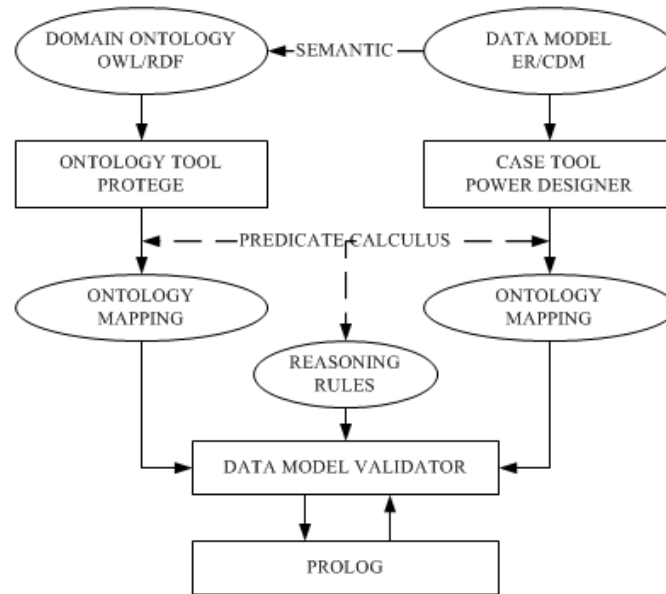


Figure 1. Proposed system for data model evaluation

The developed reasoning system consists of several modules, i.e. software tools integrated to a complex system. These modules are: ontology editor/tool for creating ontology, CASE tool for creating ER data model, Data Model Valuator (DMV) tool for transformation and integration of ontology and ER data model into formal language sentences, and Prolog as a core reasoning system that computes answers to queries. This system was introduced in [22] and fully described in paper [23].

Data model is a formal abstraction through which the real world is mapped in the database [24]. It enables representation of a real world concepts and elements through a set of data entities and their connections. They can be represented in various ways: graphical representation with schemas, data dictionary representation and formal languages representation, such as predicate logic calculus. Formal presentation of ER data model is extension of formalization presented in [25] where data model is represented as  $S = (E, A, R, C, P)$ , where:

- E is a finite set of entities,
- A is a finite set of attributes,
- R is a finite set of relationships,
- C is a finite set of constraints concerning domain, definition, relationships and semantics associated to the elements and attributes,
- P is a finite set of association rules among entities, attributes, relationships and constraints.

Formalization of an ER model includes creating sets of elements that are written as Prolog-like clauses.

Ontology is often used to capture and share knowledge in a specific domain of interest [15]. Ontology describes the concepts in the domain and also the relationships that hold between those concepts [24]. The basic characteristics of ontology are hierarchy of concepts/objects, which is established by using different semantic links [26]. Ontology elements like type, class, subclass, property, sub-property, domain and range could be mapped to predicate logic form according to [27]. Predicate logic form of ontology could be written in Prolog-like form like ER model elements. Structure of ontology is a collection of OWL/RDF elements that re transformed into RDF expression as a collection of triplets, each consisting of subject, predicate and objects [28]. Facts that are described with RDF triplets represent a relation between things denoted by subject and object of the triplet, or even their properties: RDF (Subject, Predicate, Object).

Mapping RDF/OWL ontology elements into Prolog-like clauses considered an RDF name for predicate name in Prolog system.

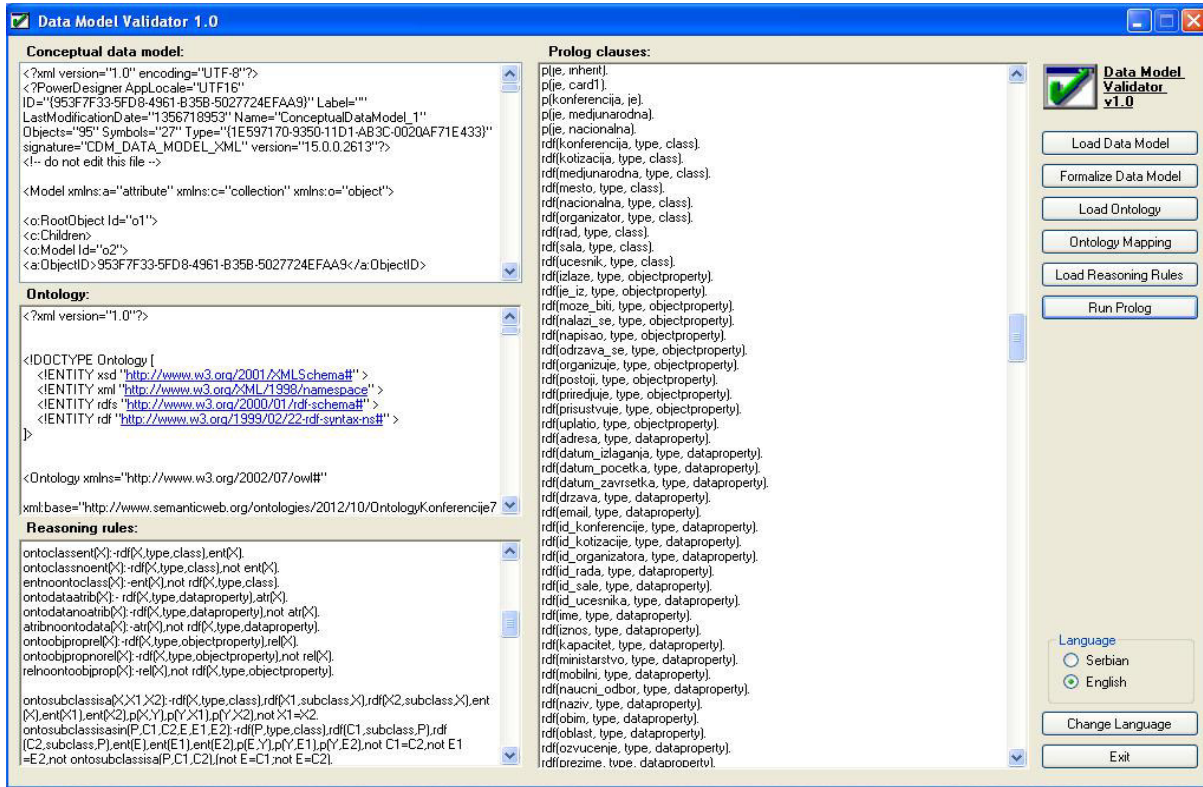


Figure 2. Data Model Validator software tool

Model evaluation in this system is performed by applying a set of reasoning rules to formalized representation of ER data model and ontology in aim to compare them. Mapping ontology to data model elements are based on research [27], were:

- Ontology class is mapped to entity type,
- Ontology data property is mapped to attribute,
- Ontology data property range is mapped to attribute data type/domain,
- Ontology object property is mapped to relationship,
- Ontology property constraint is mapped to relationship property (cardinality, dependency).

The reasoning rules for evaluation of ontology-to-conceptual data model mapping are presented in [23]:

- Rule 1 - Ontology classes that are covered by entities in ER model. For each class from ontology must be defined named entity set in data model.
- Rule 2 - Ontology classes that are not covered by entities in ER data model.
- Rule 3 - Data properties from ontology that are covered by attributes in ER data model. For each data property in ontology must be defined named attribute in data model.
- Rule 4 - Ontology data properties that are not covered by attributes in ER data model:
- Rule 5 - Data properties and data properties ranges from ontology that are covered by attributes with defined data types in conceptual data model. For each attribute in data model from set of attributes there is a restriction with data type name.
- Rule 6 - Object properties from ontology that is covered by relationships in conceptual data model. For each object property from ontology must be declared named relationship in ER data model.
- Rule 7 - Ontology object properties that are not covered by relationships in conceptual data model.
- Rule 8 - Ontology object properties that are covered by relationships in conceptual data model that are defined between entities that match to appropriate ontology classes.
- Rule 9 - Ontology object property ranges that are covered by relationship cardinality in conceptual data model that are defined between entities that match to appropriate ontology classes.
- Rule 10 – Ontology classes and subclasses that are covered by IS\_A hierarchy entities in conceptual data model. According to [27] for each class from ontology must be defined a named entity super-class

type in data model, and each ontology subclass is presented with entity subtype, with restriction that subtypes in data model must be different objects.

- Rule 11 – Ontology classes and subclasses that are not covered by IS\_A hierarchy entities in conceptual data model. For each ontology class must is not defined named entity super-class type in data model, and each ontology subclass is not presented with entity subtype.

For each ER data model final rank evaluation from the aspect of ontology mapping (OM) is quantitatively represented as a sum of ontology mapping evaluation points for each element of the data model. These particular marks for elements are measured by handling the Prolog answers on goals. For each data element is given a “weight factor”  $K_x$ , where  $x$  represents an ER element type. Weight factor, according to [16], represents a quantitative expressed significance of an element in the analysis of the whole conceptual data model.

An ontology point for entities is calculated as [23]:

$$OM_E = \frac{\sum_{i_E=1}^{i_E=1} E(Rule1)_{i_E} \cdot 100}{\sum_{i_E=1}^{i_E=1} E(Rule1)_{i_E} + \sum_{i_E=1}^{i_E=1} E(Rule2)_{i_E}}, \quad (1)$$

An ontology point for attributes is calculated as:

$$OM_A = \frac{\sum_{i_A=1}^{i_A=1} A(Rule3)_{i_A} + \sum_{i_A=1}^{i_A=1} A(Rule5)_{i_A}}{2} \cdot 100, \quad (2)$$

$$OM_A = \frac{\sum_{i_A=1}^{i_A=1} A(Rule3)_{i_A} + \sum_{i_A=1}^{i_A=1} A(Rule4)_{i_A}}{2}, \quad (2)$$

An ontology point for relationships is calculated as:

$$OM_R = \frac{\sum_{i_R=1}^{i_R=1} R(Rule6)_{i_R} + \sum_{i_R=1}^{i_R=1} R(Rule8)_{i_R} + \sum_{i_R=1}^{i_R=1} R(Rule9)_{i_R}}{3} \cdot 100, \quad (3)$$

$$OM_R = \frac{\sum_{i_R=1}^{i_R=1} R(Rule6)_{i_R} + \sum_{i_R=1}^{i_R=1} R(Rule7)_{i_R}}{3}, \quad (3)$$

An ontology point for classes and subclasses is calculated as:

$$OM_{SC} = \frac{\sum_{i_{SC}=1}^{i_{SC}=1} SC(Rule10)_{i_{SC}} \cdot 100}{\sum_{i_{SC}=1}^{i_{SC}=1} SC(Rule10)_{i_{SC}} + \sum_{i_{SC}=1}^{i_{SC}=1} SC(Rule11)_{i_{SC}}}, \quad (4)$$

Total ontology mark for entire ER data model is calculated as:

$$OM = \frac{K_E \cdot OM_E + K_A \cdot OM_A + K_R \cdot OM_R + K_{SC} \cdot OM_{SC}}{4}, \quad (5)$$

Explanation for equation (1)-(5) elements:

- $OM$  is ontology points for each data model,
- $OM_E$  is ontology points for entities,
- $OM_A$  is ontology points for attributes,
- $OM_R$  is ontology points for relationships,
- $OM_{SC}$  is ontology points for super-classes entities and sub-classes entities,
- $K_E, K_A, K_R, K_{SC}$  are weight factors.

Minimum values for  $OM, OM_E, OM_A, OM_R$  and  $OM_{SC}$  particular marks are 0, while maximum value could be 100 for particular and also for total ontology mark for a whole data model [23].

#### IV. PROCESS OF USING THE SYSTEM

The proposed system is implemented by using following software tools [22], [23]:

- Ontology editor Protégé developed at Stanford University for creating ontology.
- CASE tool Sybase Power Designer for projecting ER/conceptual data model.
- Amzi!Prolog as a reasoning system that computes answers to queries.

For the purpose of files transformation and integration to appropriate Prolog program needed for Amzi!Prolog, special Data Model Valuator (DMV) tool was created by using Microsoft Visual Studio.NET development environment. The process of using this tool starts with creating ontology by using an ontology editor. The ER model is created in a CASE tool. DMV tool could be started. A user could start an option for loading ER model and an option for formalization of data model that will parse elements of data model to a set of Prolog-like clauses and present them in user interface. Another option is loading ontology for its transformation to a set of Prolog-like clauses that are also presented. Third step is loading a set of defined reasoning rules. After all clauses are created and ready in integrated list (i.e. conceptual model's clauses, ontology's clauses and reasoning rules), we used Prolog as a core reasoning system for computation of answers to queries related to particular data model and ontology. Answers from reasoning system must be included in previously defined metrics (1), (2), (3), (4) and (5) for ER data model semantic evaluation. On this mode must be calculated ontology marks for all elements of ER model by metrics (1), (2), (3), (4) and then the final ontology mark for entire ER model by (5).

#### V. EMPIRICAL STUDY AND RESULTS

The empirical testing of the system has been made with a case study in application of initial set of reasoning rules to a single ER data model. Empirical research is conducted as a laboratory experiment with students' data models collected from the practical exam. Participants of this research are students from University of Novi Sad, Technical faculty "Mihajlo Pupin" in Zrenjanin, Serbia. They are all students of the second year of undergraduate (bachelor) studies of information technology engineering. These 44 participants were given the same exam, i.e. a textual specification of a case study for organizing international conferences. A single ontology is created to represent the specified case study and domain of problem area.

Each of students' data model was loaded in DMV tool to be integrated with ontology and set of reasoning rules. Integrated programs were individually loaded in the Amzi!Prolog listener environment for executing queries according to 11 rules. After mapping ontology in empirical study with DMV tool into the Prolog-like clauses we create over 330 facts in RDF triplets. Students' data models results with minimally 160 to more than 250 facts in Prolog sentences. Integrated program for reasoning with rules has from 500 to almost 600 clauses that were all individually loaded into the Amzi!Prolog to be processed. Prolog listener has shown results of each query answer computation.

Statistics is performed upon all results data used for overall evaluation of each ER data model by using equation (5) and  $K_x=1$ , which means that each "weight factor" is 1 for any of evaluated model, i.e. all considered as are equally significant.

Table 1: Empirical results for data model semantic evaluation

Data model code	Ontological mark for entities	Ontological mark for attributes	Ontological mark for relationships	Ontological mark for classes and subclasses	Total ontological mark for data model
K01	78	32	34	0	<b>36</b>
K02	89	44	59	25	<b>54</b>
K03	100	57	81	100	<b>85</b>
K04	78	67	50	0	<b>49</b>
K05	100	57	63	100	<b>80</b>
K06	100	64	69	100	<b>83</b>
K07	78	47	41	0	<b>41</b>
K08	100	57	63	100	<b>80</b>
K09	100	68	75	100	<b>86</b>

K10	100	60	78	100	<b>85</b>
K11	89	50	31	0	<b>43</b>
K12	89	53	50	100	<b>73</b>
K13	100	49	44	0	<b>48</b>
K14	100	57	41	100	<b>74</b>
K15	100	37	63	50	<b>62</b>
K16	100	34	47	100	<b>70</b>
K17	100	62	56	100	<b>80</b>
K18	100	67	22	100	<b>72</b>
K19	100	66	44	100	<b>77</b>
K20	100	34	28	0	<b>41</b>
K21	67	42	22	100	<b>58</b>
K22	100	56	53	0	<b>52</b>
K23	100	43	59	100	<b>76</b>
K24	100	40	56	100	<b>74</b>
K25	100	39	56	100	<b>74</b>
K26	78	52	44	0	<b>43</b>
K27	100	34	59	100	<b>74</b>
K28	100	37	56	100	<b>73</b>
K29	100	59	63	100	<b>80</b>
K30	78	44	50	0	<b>43</b>
K31	100	56	66	100	<b>80</b>
K32	78	36	50	0	<b>41</b>
K33	78	43	41	0	<b>40</b>
K34	89	54	19	0	<b>41</b>
K35	89	56	19	0	<b>41</b>
K36	78	44	50	0	<b>43</b>
K37	67	42	41	0	<b>37</b>
K38	100	62	66	100	<b>82</b>
K39	100	44	34	0	<b>45</b>
K40	100	36	56	100	<b>73</b>
K41	100	27	56	100	<b>71</b>
K42	100	62	56	100	<b>80</b>
K43	78	51	19	0	<b>37</b>
K44	100	47	16	0	<b>41</b>

Analysis of statistics on empirical results shows that ontology classes are covered by entities in ER data model with more than 92%, ontology data properties are covered with 54% appropriate attributes, while object properties are covered by relationships in ER model with 41%. Ontology classes are covered by only 30% of appropriate super-class type entities. At the end it can be seen that ontology sub-classes are covered by 30% subtype entities. Ontology data properties and data property ranges are covered by 41% of attributes and data types in data model. A result of computation of each model's ontology mapping evaluation mark is presented in Table 1. Analysis of empirical results for each ER data model ontology mapping evaluation shows that the best models do not have better than 86% evaluation points, while the worst done models are at 36%. Average result of all tested and evaluated data models is almost 64% of semantically correctness, i.e. completeness and suitability to domain ontology.



Table 2: Number of students' marks when weight factors are:  $K_E=1.0$ ,  $K_A=1.0$ ,  $K_R=1.0$   $K_{SC}=1.0$

Score (points)	Mark	Number of students
<55	5	19
55-64	6	2
65-74	7	10
75-84	8	12
85-94	9	1
>94	10	0

Table 2 shows the distribution of students' assessment to the exam evaluation criteria that is currently used at universities in Serbia. Number of students' marks is determinate with following weight factors values are equally significant:  $K_E=1.0$ ,  $K_A=1.0$ ,  $K_R=1.0$   $K_{SC}=1.0$ . The same data is shown on Figure 3. It can be seen that 19 students would not have passed the exam, while 25 would have a positive assessment.

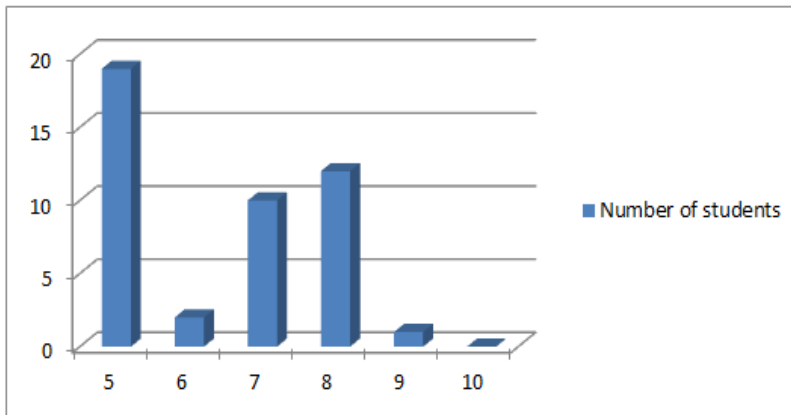


Figure 3. Students' assessment with weight factors values:  $K_E=1.0$ ,  $K_A=1.0$ ,  $K_R=1.0$   $K_{SC}=1.0$

Table 3 shows the distribution of students' assessment with weight factors values that are set different:  $K_E=1.8$ ,  $K_A=1.0$ ,  $K_R=0.6$   $K_{SC}=0.6$ . The same data is shown on Figure 3. It can be seen that only 9 students would not have passed the exam, while even 35 would have a positive assessment. Determination of these weight factors that are not equally significant should be done and defined by a professor of the course which is taken.

Table 3: Number of students' marks when weight factors are:  $K_E=1.8$ ,  $K_A=1.0$ ,  $K_R=0.6$   $K_{SC}=0.6$

Score (points)	Mark	Number of students
<55	5	9
55-64	6	10
65-74	7	2
75-84	8	18
85-94	9	5
>94	10	0

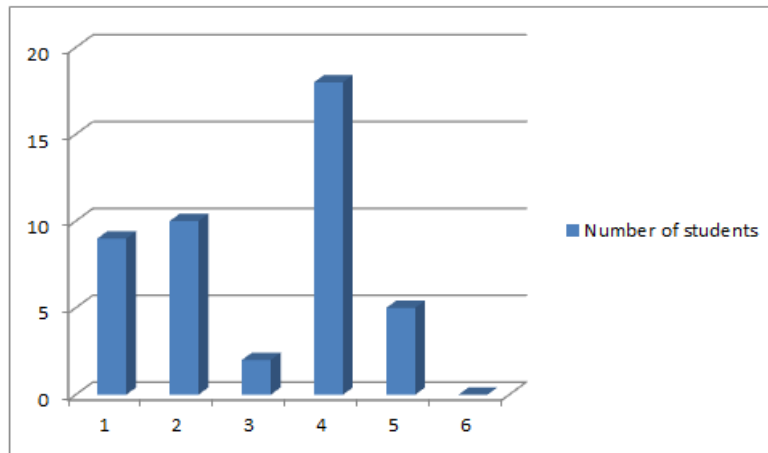


Figure 4. Students' assessment with weight factors values:  $K_E=1.8$ ,  $K_A=1.0$ ,  $K_R=0.6$ ,  $K_{SC}=0.6$

## VI. CONCLUSION

The objective evaluation the students' knowledge in courses which deals with databases or information systems theory and practice could be done with a software system for data model semantic evaluation. This system is based on comparing ontology with data model elements. This approach is based on domain ontology and data model formalization at a form that is suitable for reasoning with a set of reasoning rules for ontology to data model mapping. A specific software tool was developed and implemented for ontology and data model transformation to predicate logic form and then to a set of Prolog-like clauses. This system integrates results of using CASE tool for data model creation, ontology editor for ontology creation, reasoning rules for data model evaluation based on mapping with ontology within an automated reasoning system that computes answers needed for metric. After integration of these sets of clauses and rules, a Prolog-system was used for making queries and reasoning in order to quantitatively express the quality of data model with appropriate metric. Final marks are calculated with a spreadsheet program.

Results of empirical testing and verification of the developed system was done with the students of Technical faculty "Mihajlo Pupin". Students' assignments were not evaluated with this system. The evaluation was done according to a certain system in the traditional way. This system is currently not used at the Technical faculty "Mihajlo Pupin", but it could be used with a future work that may include better automatization of whole system for quick answers, adapting DMV software to process other types of data models, extension of reasoning rules to enable both syntax and semantic verification, in aim to enable more complete data model verification. This system must be empirically tested with large data models that are not laboratory cases. One further step could be development of consultation expert module that would provide presentation of data modeling errors and suggestions to improvements.

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