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A Model-Based Method for Information Alignment: A Case Study on Educational Standards

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Abstract
We propose a model-based method for information alignment using educational standards as a case study. Discrepancies and inconsistencies in educational standards across different states/cities hinder the retrieval and sharing of educational resources. Unlike existing educational standards alignment systems that only give binary judgments (either "aligned" or "not-aligned"), our proposed system classifies each pair of educational standard statements in one of seven levels of alignments: Strongly Fully-aligned, Weakly Fully-aligned, Partially-aligned***, Partially-aligned**, Partially-aligned*, Poorly-aligned, and Not-aligned. Such a 7-level categorization extends the notion of binary alignment and provides a finer-grained system for comparing educational standards that can broaden categories of resource discovery and retrieval. This study continues our previous use of mathematics education as a domain, because of its generally unambiguous concepts. We adopt a materialization pattern (MP) model developed in our earlier work to represent each standard statement as a verb-phrase graph and a noun-phrase graph; we align a pair of statements using graph matching based on Bloom's Taxonomy, WordNet, and taxonomy of mathematics concepts. Our experiments on data sets of mathematics educational standards show that our proposed system can provide alignment results with a high degree of agreement with domain expert's judgments.

Category: Smart and intelligent computing

Keywords: Information alignment; Model-based method; Educational standards alignment; Materialization pattern (MP) model

I. INTRODUCTION

Information alignment (IA) is the process of determining correspondences between concepts and relationships in different information sources. IA has been extensively studied in such diverse areas as ontology matching [1], business process alignment [2], schema mapping [3, 4], and data fusion [5]. A wide variety of methods has been proposed including linguistic, structural, instance-based, and machine learning techniques. As searching and integrating information from Web-scale sources has become the key to various library services, applying information

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alignment techniques to digital libraries is very important. However, we have found that existing methods for information alignment on structural data including ontologies and database schemas do not work well for the library resources that are annotated by a type of specific information called *textual standards*. In this paper, we propose a model-based method for aligning information contained in such textual standards. In particular, we use US educational standards as our case study.

A *standard* is essentially a textual document with specific structures. A standard defines the common knowledge of a domain, but different standard documents written by different people may vary in many ways. There are three different types of educational standards: content standards, achievement standards, and curriculum standards [6]. In this paper the term educational standards refers to content standards. An *educational standard* consists of a set of statements describing what knowledge and skills students should acquire in a K-12 setting. An example of educational standard statements for mathematics is as follows: estimate the results of computation involving whole numbers, fractions, and decimals.

The need to search for resources according to educational standards has recently become more vital due to the increasing availability of online K-12 curriculum and the standard-based reform movement [7] for educational systems in the United States. Educational resources assigned with one state's standards can be searched or retrieved by teachers in other states through alignment systems, which associate identical or similar concepts across different educational standards [8-10]. Automated or semi-automated alignment systems for educational standards have been proposed recently [8-10]. However, consistent and accurate alignments for educational standards are still missing because of the lack of uniformity in approach and inconsistency in interpreting a correct alignment [10]. These current systems use "aligned or not-aligned" binary judgments or relevant standards suggested for human evaluation [11]. But they do not suggest any clear ranking of alignments. Such methods [11] may also lead to inconsistencies in interpreting a correct alignment because of various possible interpretations of a correct match.

In this paper we introduce a model-based method for mathematics educational standards alignment. Our alignment method produces seven different degrees of alignments: Strongly Fully-aligned (SFA), Weakly Fully-aligned (WFA), Partially-aligned*** (PA***), Partially-aligned** (PA**), Partially-aligned* (PA*), Poorly-aligned (PR), and Not-aligned (NA). These multiple degrees of alignments can provide consistency in interpreting a correct alignment and also broaden categories of search or retrieval for educational resources.

The rest of the paper is organized as follows: we review related work in Section II. In Section III we present terminology used in this paper. In Section IV, we describe our approach for an alignment method. We report on experimental results in Section V. Section VI presents conclusions and future work.

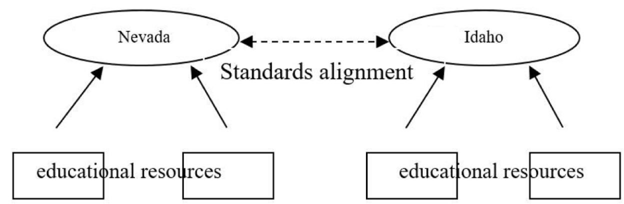


Fig. 1. Educational standards alignment: educational standards between Nevada and Idaho are aligned. A teacher in Nevada can retrieve educational resources tagged with a statement in Idaho that is equivalent or similar to a statement in Nevada.

II. RELATED WORK

Alignment is a term used in a variety of contexts within the standard-based reform movement, which currently dominates decisions and actions in schools. The term "alignment" [12] is summarized as *when two or all three components in a certain education system are consistent* [13], *are in agreement* [14], *are matched* [15], *or work together* [16]. See Fig. 1 for educational standards alignment. In such systems, Yilmazel et al. [10] describe standard alignment as occurring when "standards describing similar concepts are correlated," and Sutton and Golder [9] describe it as "one statement is more-or-less equivalent to another statement."

Existing tools for aligning educational standard mainly employ natural language processing (NLP) techniques for the task. The Standard Alignment Tool (SAT) [10] and AlignPro [8] are examples of automatic alignment systems for educational standards using NLP. AlignPro makes its judgments based on descriptions of content and instructional objectives. The SAT uses text categorization for standards alignment. For text categorization, the SAT uses A2A + McREL Compendix [17, 18], which has manual alignments made by experts in educational standards for training a multi-label classifier. It uses three types of text content: benchmark text (McREL), the text of all the levels from the path to the root, and relevant vocabulary assigned by McREL [18]. It also uses the Machine Learning Toolkit for supporting text categorization. It takes a resource and produces all the equivalent educational standards statements. The label classifier is only trained against A2A + McREL benchmarks for text categorization. McREL vocabulary terms heavily influence the text categorization ability of the system. The SAT may not work correctly against new standards that do not have McREL vocabulary terms. These alignment systems do not offer a clear definition of ranking a correct alignment; they may therefore lead to inconsistencies in interpreting a correct alignment because of various possible interpretations of correct standard match for alignment of human evaluation. This is our primary motivation for proposing a system that produces multiple degrees of alignments. The Achievement Standards Network (ASN) is currently building an alignment system which uses intermediary statements in order to align different state educational standards statements [9].

III. PRELIMINARIES

This section summarizes the conceptual model and terminology used in our method (see details in [19]).

Educational standards alignment: This matches educational standards that describe identical or similar concepts.

Cognitive process: This is an operation that affects mental contents. In our context it refers to the verbs in educational standards [20].

Materialization pattern (MP) model: This represents an MP class and its verb materialization hierarchy that realizes the class' behaviors. An MP class represents a concept represented by a noun. A materialization hierarchy is a verb hierarchy that models the behaviors of the MP class. The relationship between the MP class and the materialization hierarchy is represented as a realization relationship of UML. See Fig. 2 as an MP diagram for the sentence "Recognize, compare, and classify whole numbers." From the sentence we extract an MP class "Whole number" as a math concept, and three verb stereotype classes "Recognize", "Compare, and "Classify" as the cognitive process of the MP class "Whole number." These three verb stereotype classes are subclasses of a class "Realize," which is an abstract class with no instance. A verb materialization hierarchy has verb stereotype classes "Realize", "Recognize", "Compare", and "Classify." A realization relationship exists between the classes "Whole number" and these verb stereotype classes.

Generalization set [21]: In UML a taxonomic classification creates a generalization hierarchy. UML 2.0 uses the generalization set concept, an inheritance arrowhead with a label representing the name of the set. It is used for different taxonomic classification about the same class.

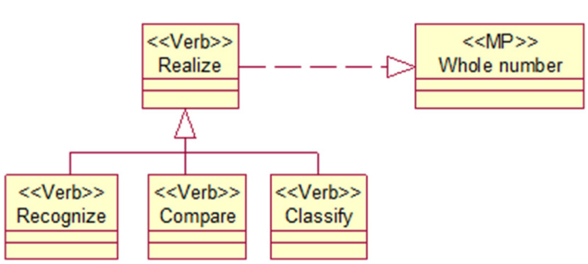


Fig. 2. An MP model for the math standard statement: "Recognize, compare, and classify whole numbers." The class "Whole number" is an MP class. "Realize", "Recognize", "Compare", and "Classify" are verb stereotype classes.

Graph [22]: This is a pair $G = (V, E)$, where V is a finite set of vertices and E is a binary relation on V. The ordered pairs in E are called the edges of the graph. A path is defined in the obvious way.

Rooted tree [22]: This is an acyclic graph G with a vertex (the root), from which there is a unique path to every other vertex of G.

Bloom's Taxonomy [23]: This has three domains of educational learning: cognitive domain, affective domain, and psychomotor domain. Bloom identifies six categories within the cognitive domain: knowledge, comprehension, application, analysis, synthesis, and evaluation.

IV. OUR MODEL-BASED METHOD FOR EDUCATIONAL STANDARDS ALIGNMENT

We present our method in this section. We begin with an overview of the method, and then we describe individual components.

A. Overall Design

This section presents an overview of a model-based method for mathematics educational standards alignment in Fig. 3. Choi et al. [19] classify mathematics educational standards statements based on the Reed-Kellogg system [24] into different types of MP statements. These MP statements have been classified by analyzing over 1,000 mathematics educational standard statements from different states. We developed a visualization tool called MPViz to create MP models for educational standards in UML notation [25]. MPViz utilizes a graph editing tool named Graphviz Dotty (http://www.graphviz.org/). MP statements are represented as graphs in MPViz.

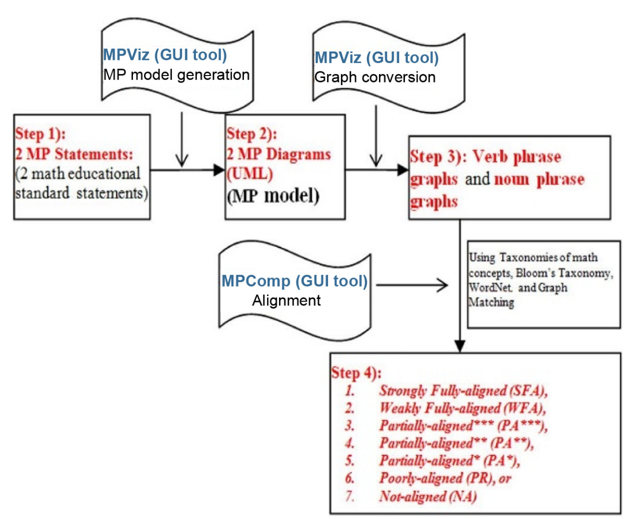


Fig. 3. Overview of our alignment method.

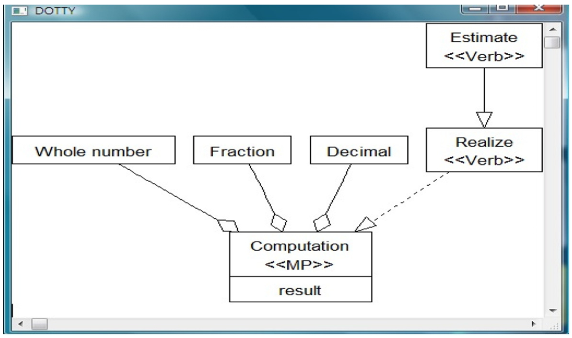


Fig. 4. MP model of the input statement above in MPViz.

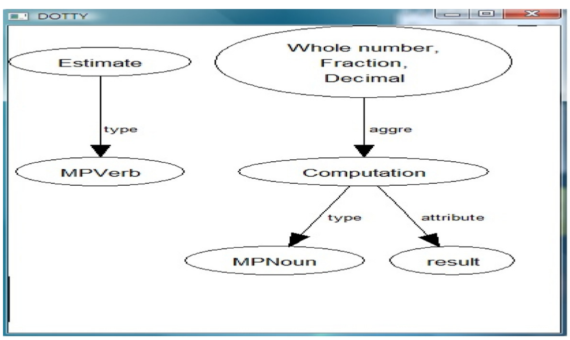


Fig. 5. Verb & noun phrase graphs of Fig. 4 in MPViz.

From step 1) to step 3) we outline the process of converting input statements into internal representation in a graph form for alignments. For example, we enter an input statement, "Estimate the results of computation involving whole numbers, fractions, and decimals" into a GUI screen of the MPViz. Next, MPViz automatically creates the MP model of this input statement and convert it to graphs as shown in Figs. 4 and 5, respectively.

B. Graph Matching based on Bloom's Taxonomy, WordNet, and Taxonomy of Mathematics Concepts

Graph matching is used for aligning two mathematics educational standards statements on the sentence level. Matching uses the Bloom's Taxonomy [23] for cognitive verb [20] categorization, WordNet [26] for word similarity, and taxonomies of mathematics concepts for related concepts. Two problems for sentence alignment are: 1) sentences have the same information but little similarity on the surface [27]; and 2) sentences do not convey the same information but have overlapping vocabularies [10]. These two problems can be mostly ignored for mathematics educational standards alignment because these statements are very well defined.

1) Bloom's Cognitive Taxonomy

The *cognitive process* [19] refers to the verbs used in the educational standards statements [20]. Such verbs are termed cognitive verbs [19]. For this alignment, they are categorized based on six categories of Bloom's Cognitive Taxonomy [23]. We define the same *cognitive process* occurring when two cognitive verbs belong to the same category of that taxonomy. See Table 1 for the classification of cognitive verbs based on Bloom's Cognitive Taxonomy.

Table 1. Classification of cognitive verbs based on Bloom's Cognitive Taxonomy

Knowledge	Count, Count on, Display, Define, Describe, Draw, Identify, Labels, List, Match*, Memorize, Name, Outlines, Point, Quote, Read, Recall, Recite, Recognize, Record, Repeat, Replicate, Reproduce, Specify, State, Tell, Write
Comprehension	Answer, Associate, Classify*, Compare*, Convert, Defend, Discuss, Distinguish, Estimate, Exemplify, Explain, Extend*, Extrapolate, Find, Generalize, Give examples, Illustrate*, Interpret, Infer, Locate, Match*, Order, Read, Represent, Paraphrase, Predict, Provide examples, Rewrite, Sort, Summarize
Application	Add, Apply, Build, Calculate, Change, Classify*, Copy, Complete, Compute, Collect, Conduct, Convert, Demonstrate, Determine, Discover, Divide, Draw, Establish, Examine, Extend, Graph, Gather, Interpolate, Manipulate, Make, Measure, Modify, Model, Operate, Perform, Prepare, Produce, Round, Show, Simplify, Sketch, Solve*, Subtract, Translate, Use
Analysis	Analyze, Arrange, Breakdown, Categorize*, Choose, Classify*, Combine, Compare*, Compose, Construct, Decompose, Design, Detect, Develop, Diagram, Differentiate, Discriminate, Distinguish, Illustrate*, Infer, Outline, Partition, Point out, Relate, Select, Separate, Solve*, Subdivide, Utilize
Synthesis	Categorize*, Combine, Compile, Compose, Create, Develop, Drive, Design, Devise, Explain*, Express, Formulate, Generate, Group, Integrate, Modify, Order, Organize, Plan, Prescribe, Propose, Rearrange, Reconstruct, Reorganize, Revise, Rewrite, Summarize*, Transform, Specify
Evaluation	Appraise, Approximate, Assess, Check, Conclude, Consider, Contrast, Criticize, Critique, Determine, Estimate, Evaluate, Grade, Judge, Justify, Measure, Prove, Rank, Rate, Recommend

2) Taxonomy of Mathematics Concepts

We create taxonomy of K-12 mathematics concepts based on McREL's (Mid-continent Research for Education and Learning) standards [18]. This on-going process is used for discovering related mathematics concepts for alignment purposes. Such concepts are defined as those in sibling, parent, or children relationships in a tree corresponding to a common generalization set [21].

3) A Threshold Value for Word Similarity

We used a predefined function [28, 29] for word similarities between nouns, verbs, mathematics concepts, or attributes of mathematics educational standard statements. It computes the similarity between two words based on the WordNet dictionary. We use a revised version of Wu & Palmer's method [30] for word similarity and define $Sim_{sd}(w1, w2) = 2 * \text{depth (LCS)} / (\text{depth}(w1) + \text{depth}(w2))$. Here $w1$ and $w2$ are two words for comparison, depth($w1$) & depth($w2$) are depth of their respective nodes in WordNet taxonomy, and LCS is their Least Common Subsumer in that taxonomy. In order to define two words as having equivalent meanings, we set up our own threshold at the similarity value of 0.95. We arrived at this value after testing data with Sim_{sd}, and comparing our results with existing data [20]. We concluded that a pair of words is equivalent when the similarity value given by Sim_{sd} is over 0.95.

4) An Example of Alignment Using Graph Matching

The following illustrates two examples of math educational standards statements: 1) Add and subtract whole numbers with and without regrouping (Ohio State); and 2) Add and subtract decimals using money model (Nevada State). Math concepts (e.g., whole number, decimal in 1) and 2), respectively) and the cognitive verbs (e.g., add, subtract in 1) and 2)) are well-defined terms. Graph matching in Figs. 6 and 7 for alignments is as follows:

- Compare two nodes ("Whole number" & "Decimal") of math concepts from noun phrase graphs: "Whole number" and "Decimal" are *related math concepts*;
- Compare two nodes ("Add, Subtract") of cognitive verbs from verb phrase graphs: They belong to the *same cognitive process*. We conclude that the statements are "Poorly-aligned" (see Table 2);
- The two nodes of modifiers of math concepts ("Regrouping" & "Money model") do not need to be compared;
- The two edges of prepositional relationships ("with

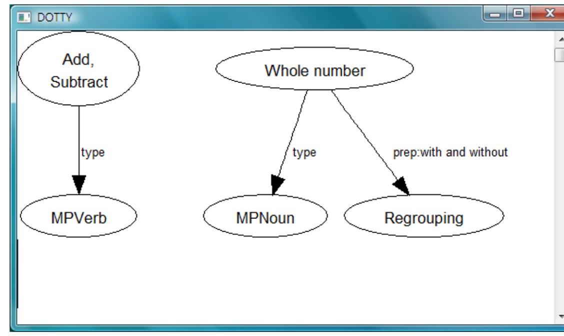


Fig. 6. Verb & noun phrase graphs of a statement 1 in MPViz.

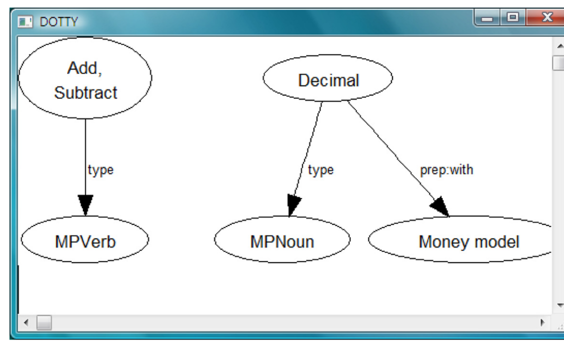


Fig. 7. Verb & noun phrase graphs of a statement 2 in MPViz.

Table 2. Summary of the 7-level alignment system

Different degrees	Meaning/usage	Math concepts	Cognitive verbs	Attributes or modifier of math concepts
Strongly Fully-aligned	Identical statements	Same	Same	Same
Weakly Fully-aligned	More-or-less equivalent statements	Same	Same	Only one statement has modifiers
Partially-aligned***	Similar statements that state the same math concepts through different methods	Same	Same	Different
Partially-aligned**	More-or-less similar statements that state the same math concepts through different methods	Same	Different verbs but the same cognitive process	N/A
Partially-aligned*	Statements have the same math concept	Same	Different cognitive process	N/A
Poorly-aligned	Different but related math concepts	Related	The same cognitive process	N/A
Not-aligned	Totally different	Different	N/A	N/A

N/A: not applicable.

and without" & "with") do not need to be compared.

Mathematics concepts and cognitive verbs in MP model [19] are converted to verb phrase graphs and noun phrase graphs for alignment by MPVitz, as shown in Fig. 5. Alignment is performed by the alignment tool MPComp; it compares each node of mathematics concepts, each node of cognitive verbs (cognitive process of math concepts), and each node of modifiers of mathematics concepts in each verb phrase graph and each noun phrase graph.

C. Different Degrees of Alignments

Upon the conversion of an MP model to graphs, each standard statement is represented as a cognitive verb phrase graph (e.g., add and subtract) and a noun phrase graph of mathematics concepts (e.g., decimal). Thus, matching two statements is now a problem of comparing their corresponding mathematics concepts, cognitive verbs, and related attributes or modifiers. Considering all types of comparisons, we arrive at our seven levels of alignment between two standard statements. Strongly Fully-aligned (SFA) is for identical statements. Weakly Fully-aligned (WFA) is for more-or-less equivalent statements, but one statement includes the meaning of the other one. Partially-aligned*** (PA***), Partially-aligned** (PA**), and Partially-aligned* (PA*) are for mathematics educational standards statements that have the same mathematics concepts, but with differing degrees of alignments, in the order PA***, PA**, and PA*. Poorly-aligned (PR) is for mathematics educational standards statements that have related math concepts and the same cognitive process. Not-aligned (NA) is for two mathematics educational standards statements that have totally different meanings.

D. The 7-level Educational Standards Alignment System

In this section, we first present an overall sketch in Fig. 8 of a matching algorithm for our alignment method; this is followed by examples of the seven levels of alignment; finally, we summarize the levels in Table 2. The formal definitions and algorithms of the processes outlined in Fig. 8 can be found in [31]. In our algorithm when we match two statements, their corresponding mathematics concepts, cognitive verbs, and related attributes or modifiers are compared. The comparison between terms from two statements can be either *single-term matching* or *multi-term matching*. Single-term matching means comparing a pair of terms, e.g., "add" and "subtract." We regard a pair of terms to have equivalent meaning if their similarity score given by Sim_{sd} is over 0.95. See Section IV-A3. Multi-term matching means comparing two lists of terms, e.g., (read, write, compare) and (read, compare). Given two lists A and B, $|A|<=|B|$ if either A is contained in B, or each term in A can be matched to one with equivalent meaning in B. The order of terms in the list has no significance in multi-term matching.

1) Strongly Fully-aligned

The mathematics standard statements have the exact same meaning, the same mathematics concepts, the same cognitive verbs, and the same properties (attributes or modifiers) of mathematics concepts or cognitive verbs (Fig. 9).

2) Weakly Fully-aligned

The meaning of one mathematics standard statement is included in the other statement. They have the same mathematics concepts and the same cognitive verbs with

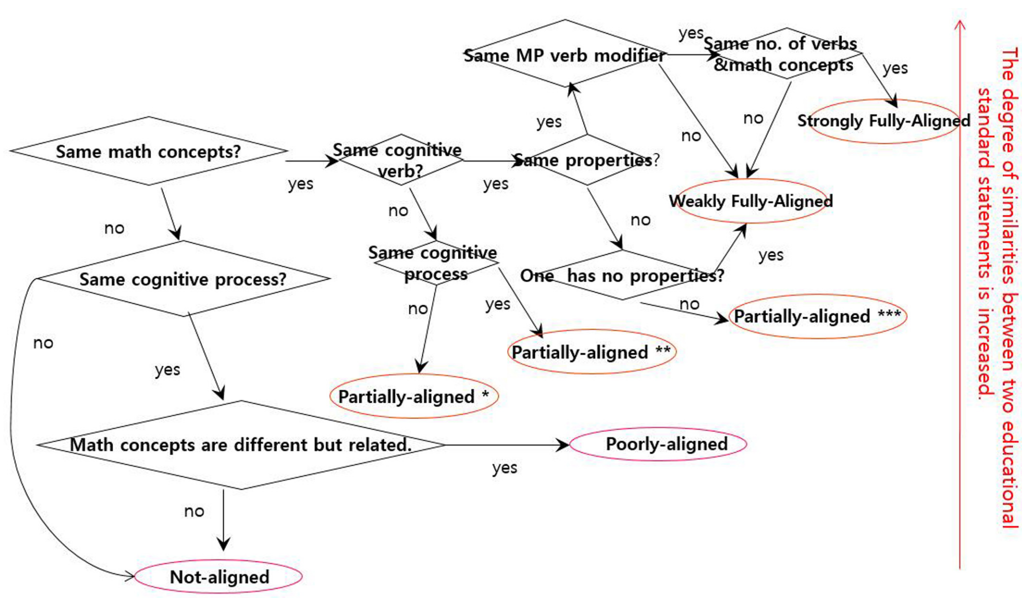


Fig. 8. A flowchart for a graph matching algorithm.

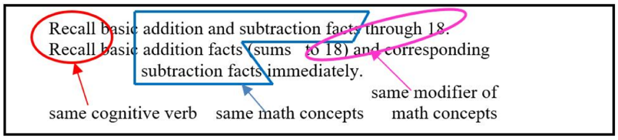


Fig. 9. An example of "Strongly Fully-aligned."

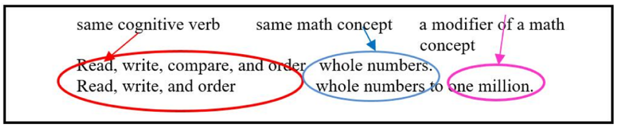


Fig. 10. An example of "Weakly Fully-aligned."

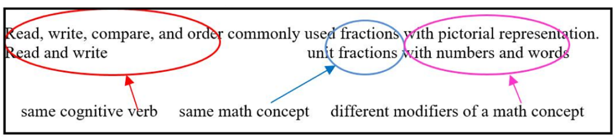


Fig. 11. An example of "Partially-aligned***."

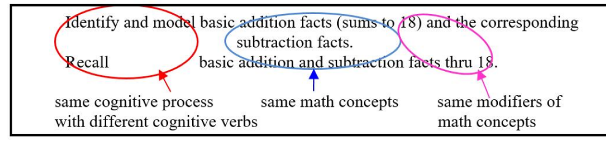


Fig. 12. An example of "Partially-aligned**."

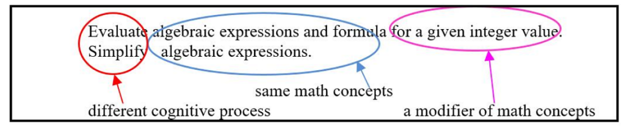


Fig. 13. An example of "Partially-aligned*,"

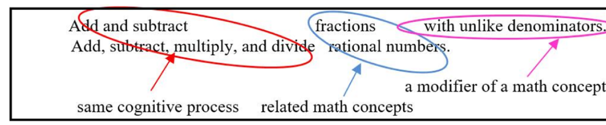


Fig. 14. An example of "Poorly-aligned."

different numbers of mathematics concepts or cognitive verbs. Only one statement has modifiers of math concepts or cognitive verbs (Fig. 10).

3) Partially-aligned*

Two mathematics standard statements have the same mathematics concepts and the same cognitive verbs but different modifiers of mathematics concepts (Fig. 11).

4) Partially-aligned

Two standard statements have the same math concepts and the same cognitive process with different cognitive verbs (Fig. 12).

5) Partially-aligned*

Two standard statements have the same math concepts and the different cognitive process (Fig. 13).

6) Poorly-aligned

Two standard statements have different but related math concepts and the same cognitive process (Fig. 14).

7) Not-aligned

Two math standard statements have different math concepts and different cognitive process.

V. EXPERIMENTAL EVALUATION

We have conducted experiments on evaluating the model-based method proposed in this paper, by measuring its performance relative to some "gold standard." One candidate for this standard is the results of existing alignment methods. However, as we have indicated above, techniques for ontology and schema mapping are not applicable to educational standards. Moreover, linguistics-based alignment solutions produce results with low accuracy. Instead, we therefore take the alignment results by a human expert as the "gold standard." Specifically, we compare the results of our method with human expert's judgment. The evaluation of our alignment method can be assessed by comparing the computational measures of our alignment method with the judgment of a human expert. For this experiment, we extract 80 pairs of mathematics educational standards statements from the states of Ohio and Texas, and 122 pairs of standards statements from Nevada and Idaho. Each state has its own content of statements, but in general their mathematics educational standards have five subcategories: 1) Numbers, Number Sense, and Computation, 2) Patterns, Functions, and Algebra, 3) Measurement, 4) Geometry, and 5) Data Analysis. Each pair in our study was extracted from the same subcategory for alignment. For example, approximately 20 pairs of statements from the same subcategory from Nevada and Idaho have been extracted.

A. Evaluation Metrics

We use Cohen's kappa [32] to compare the results of our alignment method with the "gold standard" generated by a human expert, since it measures the agreement between two raters. Fleiss's guidelines [33] characterize kappa as follows:

- Excellent agreement if kappa is over 0.75;
- Fair to good agreement if it ranges from 0.40 to 0.75; and

Table 3. Our alignment results * gold standard cross-tabulation frequency

Our alignment method	Gold standard							
	SFA	WFA	PA***	PA**	PA*	PR	NA	Total
SFA	6	0	0	0	0	0	0	6
WFA	1	16	0	1	0	1	0	19
PA***	2	5	11	0	0	0	2	20
PA**	1	1	0	14	0	1	1	18
PA*	0	0	1	2	11	0	1	15
PR	0	0	0	1	1	21	2	25
NA	1	4	0	0	2	3	9	19
Total	11	26	12	18	14	26	15	122

SFA: Strongly Fully-aligned, WFA: Weakly Fully-aligned, PA***: Partially-aligned***, PA**: Partially-aligned**, PA*: Partially-aligned*, PR: Poorly-aligned, NA: Not-aligned.

- Poor agreement if it is below 0.40.

Precision, recall, and F-measure have also used as evaluation metrics for measuring correctness of different degrees of alignment. They are defined as follows:

- Precision: number of answers that are correctly labeled in each category by our alignment method / number of answers labeled in each category by our alignment method.
- Recall: number of answers that are correctly labeled in each category by our alignment method / number of answers that should be labeled in each category
- F-measure: 2*Precision*Recall / (Precision + Recall)

B. Evaluation Results and Discussion

Table 3 shows the cross-tabulation of the comparison between our alignment results and the gold standard for Nevada and Idaho.

1) Cohen's kappa

For the 80 pairs of math educational standards from Ohio and Texas, the results are kappa = 0.711 with p-value < 0.001, which means that there is a substantial agreement between our proposed method and expert judgment with statistical significance [33].

For the 122 pairs of math educational standards from Nevada and Idaho, the results are kappa = 0.671 with p-value < 0.001, which also indicates a substantial agreement between our method and expert judgment with statistical significance [33].

2) Precision, Recall, and F-measure

Table 4 shows the precision, recall, and F-measure scores for the 122 pairs of math educational standards from Nevada and Idaho. The figures for the other data set (80 pairs of standard statements from Ohio and Texas) are similar. We choose only to discuss the results for Nevada and Idaho in this section.

As shown in Table 4, for the seven alignment levels, precision scores range from 47.37% (NA) to 100.00% (SFA); recall scores range from 54.55% (SFA) to 91.67% (PA***); and F-measure scores range from 52.94% (NA) to 82.35% (PR). As compared to a human expert, our method tends to be more conservative when determining a pair of statements as aligned than as not aligned, as strongly aligned than as weakly aligned. For example, for alignment levels with subtle difference, e.g., among SFA, WFA, and PA***, our method tends to assign statement pairs to a lower level, PA***, which results in the relatively low precision and high recall of this category. Although our alignment method performs well for comparing well-defined terms such as mathematical concepts, it still needs further improvement in capturing semantic similarity/relatedness between words for both math concepts and cognitive verbs.

In our experiments we evaluate our alignment methods on matching educational standards for mathematics. It can certainly be modified, extended and applied to educational standards in other subjects such as science. In order to do so, we also need to replace the corresponding modules of our current method with a collection of well-

Table 4. Precision, recall, and F-measure from Nevada and Idaho standards

	Precision (%)	Recall (%)	F-measure (%)
SFA	100	54.55	70.59
WFA	84.21	61.54	71.53
PA***	55.00	91.67	68.75
PA**	77.78	77.78	77.78
PA*	73.33	78.57	75.86
PR	84.00	80.77	82.35
NA	47.37	60.00	52.94

SFA: Strongly Fully-aligned, WFA: Weakly Fully-aligned, PA***: Partially-aligned***, PA**: Partially-aligned**, PA*: Partially-aligned*, PR: Poorly-aligned, NA: Not-aligned.

defined concepts in science, taxonomy of these concepts, and a categorization of cognitive terms used in educational standards. Furthermore, the model-based method can be generalized to a wide variety of information alignment tasks for digital library resources involving textual standard statements.

VI. CONCLUSIONS AND FUTURE WORK

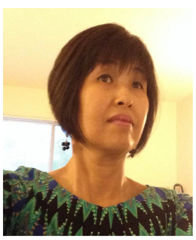
We have presented a novel model-based method for information alignment. Our method targets on a specific type of information that is often found in various digital libraries. Such information is described as standard statements developed for a certain domain. We took the US mathematics educational standards as the subject for study and proposed a conceptual model and related graph matching algorithms. For education standards alignment, we are motivated by the lack of uniformity in existing approaches and inconsistency in interpreting a correct alignment. We proposed a novel method that produces multiple degrees of alignment instead of simple Boolean decision in existing systems. Our contributions are: 1) we have proposed a novel semi-automatic model-based method for information alignment by using a conceptual model and graph matching; 2) multiple degrees of alignment improve consistency in interpreting correct alignments and also empower education professional by broadening categories of search and retrieval for educational resources; and 3) our experiments show substantial agreement between our alignment method and the "gold standard" generated by a human expert.

In the future, we plan to enhance our method by incorporating a semantic module so as to improve the alignment performance for educational standards. Furthermore, we also plan to extend and validate our alignment method for aligning other standard annotated information sources.

REFERENCES

1. N. Choi, I. Y. Song, and H. Han, "A survey on ontology mapping," *ACM SIGMOD Record*, vol. 35, no. 3, pp. 34-41, 2006.
2. W. M. P. van der Aalst, "Business alignment: using process mining as a tool for Delta analysis and conformance testing," *Requirement Engineering*, vol. 10, no. 3, pp. 198-211, 2005.
3. E. Rahm and P. A. Bernstein, "A survey of approaches to automatic schema matching," *The VLDB Journal*, vol. 10, no. 4, pp. 334-350, 2001.
4. S. Melnik, H. Garcia-Molina, and E. Rahm, "Similarity flooding: a versatile graph matching algorithm and its application to schema matching," in *Proceedings of the 18th International Conference on Data Engineering*, San Jose, CA, 2002, pp. 117-128.
5. H. B. Mitchell, *Multi-Sensor Data Fusion: An Introduction*, Berlin: Springer, 2007.
6. North Dakota Department of Public Instruction, *North Dakota Standards and Assessments Development Protocols*, Bismarck, ND: North Dakota Department of Public Instruction, 2002.
7. L, Hamilton, B. Stecher, and K. Yuan, "Standards-based reform in the United States: History, research, and future directions," Rand Education, Santa Monica, CA, 2008.
8. Instron, http://www.instron.com.
9. S. A. Sutton and D. Golder, "Achievement Standards Network (ASN): an application profile for mapping K-12 educational resources to achievement standards," in *Proceedings of the International Conference on Dublin Core and Metadata Applications*, Berlin, Germany, 2008, pp. 69-79.
10. O. Yilmazel, N. Balasubramanian, S. C. Harwell, J. Bailey, A. R. Diekema, and E. D. Liddy, "Text categorization for aligning educational standards," in *Proceedings of the Hawaii International Conference on System Sciences*, Waikoloa, HI, 2007.
11. A. R. Diekema and E. D. Liddy, "Computer-assisted content standard assignment & alignment," presented at the National Science Digital Library Annual Meeting, Chicago, IL, 2004.
12. G. Nasstrom and W. Henriksson, "Alignment of standards and assessment: a theoretical and empirical study of methods for alignment," *Electronic Journal of Research in Educational Psychology*, vol. 6, no. 3, pp. 667-690, 2008.
13. J. B. Biggs, *Teaching for Quality Learning at University*, New York, NY: Open University Press, 1999.
14. N. L. Webb, "Alignment of science and mathematics standards and assessments in four states (Research Monograph No. 18)," National Institute for Science Education, Madison, WI, 1999.
15. P. M. La Marca, "Alignment of standards and assessments as an accountability criterion," *Practical Assessment, Research & Evaluation*, vol. 7, article no. 21, 2001.
16. S. Ananda, "Achieving alignment," *Leadership*, vol. 33, no. 1, pp. 18-21, 2003.
17. Align to Achieve, http://www.aligntoachieve.com.
18. McREL International, http://www.mcrel.org.
19. N. Choi, I. Y. Song, and Y. An, "Developing and analyzing the MP (Materialization Pattern) model for math educational standards," *Journal of Universal Computer Science*, vol. 16, no. 17, pp. 2394-2414, 2010.
20. North Carolina Standards, "ACRE: Accountability and Curriculum Reform Effort," http://www.ncpublicschools.org/acre/standards/.
21. S. W. Ambler, "UML 2 class diagrams: an agile introduction," http://www.agilemodeling.com/artifacts/classDiagram.htm.
22. R. Skvarcius and W. B. Robinson, *Discrete Mathematics with Computer Science Applications*, Menlo Park, CA: Benjamin-Cummings Publishing, 1986.
23. B. S. Bloom, *Taxonomy of Educational Objectives: The Classification of Educational Goals*, New York: Longmans, 1956.
24. A. Reed, and B. Kellogg, *Graded Lessons in English: An Elementary English Grammar, Consisting of One Hundred Practical Lessons, Carefully Graded and Adapted to the Class-Room*, New York: Maynard, Merrill & Company, 1897.
25. G. Booch, J. Rumbaugh, and I. Jacobson, *The Unified Modeling Language User Guide*, 2nd ed., Upper Saddle River, NJ: Addison-Wesley, 2005.
26. C. Fellbaum, *WordNet: An Electronic Lexical Database*, Cambridge, MA: The MIT Press, 1998.
27. R. Barzilay and N. Elhadad, "Sentence alignment for mono-

lingual comparable corpora," in *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, Sapporo, Japan, 2003, pp. 25-32.
28. P. Resnik, "Semantic similarity in a taxonomy: an information-based measure and its application to problems of ambiguity in natural language," *Journal of Artificial Intelligence Research*, vol. 11, pp. 95-130, 1999.
29. T. Simpson and T. Dao, "WordNet-based semantic similarity measurement," 2016; http://www.codeproject.com/Articles/11835/WordNet-based-semantic-similarity-measurement.
30. Z. Wu, and M. Palmer, "Verb semantics and lexical selection," in *Proceedings of the Annual Meeting on Associations for Computational Linguistics*, Las Cruces, New Mexico, 1994, pp. 133-138.
31. N. Choi, "A semi-automatic alignment method for math educational standards using the MP (Materialization Pattern) model," Ph.D. dissertation, Drexel University, PA, 2011.
32. J. Cohen, "Weighted kappa: nominal scale agreement provision for scaled disagreement or partial credit," *Psychological Bulletin*, vol. 70, no. 4, pp. 213-220, 1968.
33. J. L. Fleiss, *Statistical Methods for Rates and Proportions*, 2nd ed., New York: John Wiley & Sons, 1981, pp. 38-46.



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