Liu, C.-C. et al. (Eds.) (2014). Proceedings of the 22nd International Conference on Computers in Education. Japan: Asia-Pacific Society for Computers in Education

Structured Explanation Generation for Conceptual Understanding in Physics

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Abstract: In science education, usual problem practice hardly helps students reach 'conceptual understanding' with which they can solve various problems by making appropriate models of target systems. Students often superficially read the solution of a problem and apply it wrongly to others without understanding the model. It is difficult to teach how to make appropriate models because model-making expertise includes a lot of implicit knowledge. In this paper, we propose a general framework for systematically describe such knowledge, which makes it possible not only to explain various model and difference between them but also to design/sequence a set of problems appropriate for promoting conceptual understanding. Our framework was proved useful through a preliminary experiment in which the explanations generated based on our framework promoted subjects' conceptual understanding in mechanics.

Keywords: science education, problem practice, conceptual understanding, explanation generation, semantics of constraints

1. Introduction

In science education, one serious drawback of current 'problem practice' is that most students fails to acquire the ability to make an appropriate model for a given task. A domain expert (such as physicist) can model not only the behavior of a system in question, but also she/he can do so in various tasks. Her/his model is always necessary and sufficient for answering the question. Such expertise consists of identifying the structure/state of the system in question and deciding the applicable principles/laws for modeling the behavior of the system. We call such ability 'conceptual understanding' of the domain.

Needless to say, it is very difficult for students to reach such an understanding through problem practice. Instead of considering the model, they often rely on the 'solution' they previously learned (e.g., the procedure of calculation). As a result, they wrongly apply the solution of one problem to another in which the solution is inapplicable. They also can't apply the solution they previously learned to another in which the solution is applicable. Even experience in many problems doesn't help them (Bransford, Brown and Cocking, 2000; VanLehn, 1998; VanLehn and van de Sande, 2009). Without models, the students occasionally succeed (by accident), and fail in many cases.

The major problem is that novice students tend to generate naive representation of a problem focusing on its superficial features (called 'surface structure'). They can't generate the representation based on the structural features (called 'physical structure') (Chi, Feltovich and Glaser, 1981; Larkin, 1983; Larkin, 1985). Therefore, instead of applying principles/laws to make the model, they often apply inappropriate solution based on the superficial similarity between problems (VanLehn, 1998), or use general strategy for operating mathematical equations without considering their physical meanings (Larkin, 1981).

In order to reach conceptual understanding, therefore, students need to learn (1) to infer the structural features of problems from the superficial features, and (2) to apply appropriate principles/laws to structural features to make models necessary for solving problems. For assisting them in problem practice, it is necessary to explain not only how each problem is solved but also why the solution is possible and what physical meaning it has. That is, it must be explicit why the principles/laws are applicable to the given situation (i.e., surface structure) and what physical meaning (physical structure) they imply. Additionally, it is important to explain not only the solution of a problem but also the relation (difference) between problems, that is, how the solution (applicable principles/laws) changes when the situation (problem) is changed. Furthermore, it would promote such learning to provide students with an appropriately designed and sequenced set of problems (Scheiter and Gerjets, 2002; Scheiter and Gerjets, 2003; VanLehn and van de Sande, 2009).

In current problem practice, such instruction has been rarely focused on, at most given by a few (experienced) teachers individually and implicitly. Especially, there have been few intelligent tutoring systems which can explain the relation between arbitrary two problems, and adaptively sequence problems considering the learning effect of order. We think this is because most of the knowledge necessary for such instruction is implicit and difficult to systematize, therefore there have been no general framework for indexing various types of problems.

In this paper, we propose a general framework for indexing problems, based on which explanation generation and problem sequencing mentioned above can be automatized. In our framework, making a model in physics is regarded as a process in which various constraints (applied principles/laws and modeling assumptions) are imposed on the target system and its behavior. A model is regarded as the set of constraints. We first formulate the model-making process in physics, then analyze the constraints which compose a model to systematize them based on their physical meanings and roles (functions). After that, we describe the applicable conditions of principles/laws in physics as a set of constraints. The constraints classified/defined in this manner are easily assigned to the situation of a problem. There are also some groups of constraints which are 'exclusive' each other (i.e., can't be valid simultaneously). Therefore, based on such classification and exclusiveness of constraints, it becomes possible to explain what physical meaning (structural features) superficial features of a problem have, what principles/laws are applicable to them and how applicable principles/laws change when the situation is changed. By indexing problems with this framework (we call it 'Semantics of Constraints: SOC'), it becomes possible to automatically extract the 'differences between problems' which is necessary for the comparison and sequencing of problems.

We first discuss the required knowledge and assistance necessary for conceptual understanding based on current research, then introduce the SOC framework. After that, we show the method for generating SOC-based explanations. The results of preliminary experiment are described which proved the usefulness of our framework. Finally, we conclude this paper and mention our future work.

2. Conceptual Understanding and Assistance

Research on problem-solving has revealed the knowledge structure domain experts in science have (Chi, Feltovich and Glaser, 1981; Larkin, 1981; Larkin, 1983; Larkin, 1985; VanLehn, 1998; VanLehn and van de Sande, 2009). Experts can (1) infer the structural features of problems with scientific concepts from the superficial features and generate the representation to which formal operations are applicable. They can also (2) generate an appropriate plan for solving the problem by operating the representation with the knowledge about qualitatively interpreted principles/laws. It is supposed that experts have acquired such knowledge by inducing the essential features through comparison of many problems and by transforming them into (some kinds of) 'schemata' or 'production rules' (VanLehn and van de Sande, 2009). It is, however, difficult for students reach such an understanding through usual problem practice. Even instructional innovations based on recent learning science research have limitedly improved students' understanding (Bransford, Brown and Cocking, 2000).

In order to promote such knowledge acquisition, it is effective to appropriately design a set of problems which includes positive/negative examples and *'near misses'* of various problem categories and to provide them in appropriate order to students (VanLehn and van de Sande, 2009) (in fact, it is reported problem order greatly influences learning (Scheiter and Gerjets, 2002; Scheiter and Gerjets, 2003)). In order to do that, it is necessary to explicitly describe (1) the superficial/structural features of problems and their relations, and (2) qualitative interpretations of principles/laws and their means of application. However, since most of such knowledge is implicit, there have been no general framework for systematically describe such knowledge. We think this is the reason though knowledge structure necessary for expertise was revealed and an effective instructional method was proposed, it haven't been widely practiced. The framework we propose makes it possible to systematically describe such knowledge, based on which the design of a set/sequence of problems and explanation generation for promoting conceptual understanding become possible.

3. Semantics of Constraints

Given a physics problem (which consists of a physical system and query), one makes a model necessary and sufficient for answering the query by embodying an appropriate part of the domain theory. Domain theory consists of a set of propositions each of which describes a principle/law, its applicable condition and resulting constraint(s) on the attribute(s) of the system. Constraints by embodied principles/laws are called the 'physical phenomenon constraints (PPCs).'

In making a model, various modeling assumptions are set for selecting appropriate principles/laws. Modeling assumptions define the structure/behavioral range of a system and physical phenomena to be considered. Since embodied physical phenomenon constraints are valid under some modeling assumptions, applicable conditions of principles/laws can be described with a set of modeling assumptions. That is, a physical phenomenon constraint always has its corresponding modeling assumptions. Constraints by modeling assumptions are called the 'modeling assumption constraints (MACs).'

Boundary condition of a system is given by the 'boundary condition constraints (BCCs).' They define the influence from the outside of the system. Making the influence which cannot be or need not be calculated with a model means defining the boundary of the model (i.e., what physical processes are considered/ignored). That is, a BCC always has its corresponding modeling assumptions.

In our framework, a model is the union of physical phenomenon constraints, boundary condition constraints and modeling assumption constraints. Usually, only the first two constraints are written as a model while the last constraints are remained implicit. However, MACs gives the validity to PPCs and BCCs. When modeling assumptions are changed, physical phenomena and boundary conditions also qualitatively change. In order to make a model correctly, therefore, it is necessary to under-stand the physical meaning of the constraints based on modeling assumptions (i.e., why an assumption is set and what role it plays). In most cases, such knowledge is acquired by a few students. In this research, we develop a framework for describing such knowledge explicitly, based on which the function for promoting conceptual understanding is designed. In the following two subsections, we elaborate on each class of constraints (BCC is omitted owing to limited space) to systematize their physical meanings and relations.

3.1 Modeling Assumption Constraints (MACs)

Modeling assumption constraints define the physical processes considered/ignored in a model. They are classified in two ways from different viewpoints: structural and functional.

The structural viewpoint focuses on defining the structure and its state of a model. The 'physical structure constraint' specifies what kind of objects, relations and their attributes in a system are considered. It corresponds to selecting a viewpoint, granularity or coordinate system of a system. An example is the specification about whether their mechanical relations/attributes (e.g., mass, applied forces) or their electrical ones (e.g., current, resistance) are considered. On the other hand, the 'operating range constraint' specifies the range within which a model is valid since physical phenomena occur assuming a system is in a specific state. For example, a model of a resistance assuming its value is constant needs the specification that its current and voltage are within the proportional range.

The functional viewpoint focuses on defining the boundary of a model to specify what kind of physical processes are considered/ignored. The 'process consideration constraint' makes such selection about physical processes of the same granularity (where, the 'out-sourcing/black-boxing constraint' ignores a physical process by put-ting it out of the system or into a black box regarding its effect as a boundary condition, and the 'process selection constraint' simply ignores a physical process and its effect). For example, assuming constant voltage supplied from outside is an out-sourcing constraint. Considering two parallel-connected resistors as a compound re-sister is a black-boxing constraint. Considering/ignoring the friction between two objects is a process selection constraint. The 'physical world constraint' maintains the fundamental laws of the physical world, such as 'rigid objects never overlap.' More microscopic physics is necessary to explain why this constraint is valid, that is, it specifies the physical processes of smaller granularity are ignored. The 'process simplifying constraint' substitutes the simplified process for an original complicated process in order to make the (mainly mathematical) calculation with a model easier. An example is to consider the behavior of a pendulum with small amplitude as simple harmonic oscillation (not as circular motion).

Constraint classes from the structural viewpoint are useful for enumerating modeling assumptions because they rather suggest the components and their relations of a system. For example, when a variable in an equation stands for a physical quantity, it is easy to infer an object and its attribute corresponding to the quantity is considered (which are physical structure constraints). Constraint classes from the functional viewpoint are useful for considering the meaning of modeling assumptions because they rather suggest the process structure (processes considered and their relations). For example, considering/ignoring a physical attribute (which is a physical structure constraint) suggests a physical process concerning the attribute is considered/ignored (which is a process selection constraint). That is, the classes from the structural view-point rather concern the surface structure of a problem, while the classes from the functional viewpoint rather concern its physical structure. Furthermore, as shown above, the classes from both viewpoints are related to each other based on their physical meanings. Therefore, with these classifications, it becomes possible to systematically describe the knowledge about the relation between superficial and structural features of problems.

Additionally, there are often sets of modeling assumption constraints which are mutually exclusive (can't be assumed simultaneously). For example, in the same time interval, 'transient state' and 'steady state' (which are operating range constraints) can't be assumed simultaneously. In the same (part of a) system, 'consider friction' and 'not consider friction' (which are process consideration constraints) can't be assumed simultaneously. Such exclusiveness between modeling assumptions gives important clues to identify the differences between models/problems (see section 4.2).

3.2 Physical Phenomenon Constraints (PPCs)

Relatively simpler physical phenomenon constraint is the 'physical device constraint' which arises within a component of a system. That is, it is a 'local constraint.' Since it indicates the physical property of the component, each domain has its specific physical device constraints (for example, Ohm's law constrains the values of current and voltage in an electric device). In contrast, there are 'global constraints' which indicates the behavior of multiple components or the whole system. Global constraints are classified as follows.

In general, a physical system evolves through time, starting from an initial state. It is either (1) changing dynamically, (2) in a steady state or (3) changes discontinuously. Therefore, we call the constraints in these states, the 'dynamic change constraint,' the 'steady state constraint' and the 'discontinuous change constraint,' respectively. Additionally, when a quantity is conserved through time, the constraint which indicates its amount is the same at arbitrary two time points is called 'conservation law constraint.'

Dynamic change constraint constrains the behavior of a system in a time interval during which it is changing dynamically. It often indicates the relation between the driving power of dynamic change and the influences on it. For example, Newton's second law (equation of motion) relates an object's acceleration with the forces applied to it. Steady state constraint constrains the behavior of a system in a time interval during which it is in a steady state. It indicates the balance/cancellation between influences on the driving power of dynamic change. An example is the equation of balance of forces about an object at rest. Discontinuous change constraint constrains the behavior of a system at a time point on which it changes discontinuously. It indicates the relation between the amounts of a quantity before and after the change. An example is the formula of coefficient of restitution. A quantity is called a 'conserved quantity' when its amount is constant during the temporal evolution of a system. Conservation law constraint indicates the amounts of a conserved quantity at arbitrary two time points are the same. An equation of heat exchange between two objects and an equation of conservation of energy/momentum are the examples.

A global physical phenomenon constraint aggregates a set of local physical phenomenon constraints. For example, Newton's second law (equation of motion), which is a dynamic change constraint in mechanics, includes a set of local constraints each of which indicates a force applied to the target object (physical device constraints such as elastic force, friction). Such inclusion relation between PPCs gives important clues to identify the dominant principle(s)/law(s) in solving a problem.

Additionally, there are often sets of physical phenomenon constraints of which modeling assumptions (preconditions) are mutually exclusive. These PPCs are never simultaneously valid in the same state of the same system. For example, since 'static friction' and 'kinetic friction' have exclusive preconditions (operating range constraints) about a contact surface of two objects, they are never valid simultaneously at the same surface. The first three global PPCs (i.e., dynamic change, steady state and discontinuous change constraints) are exclusive for the same reason. They often entirely change each other when preconditions are changed. For example, suppose a mechanical system is in a steady state by assuming 'friction' which cancels other forces. When the assumption is changed to 'frictionless,' the system can dynamically change. Such exclusiveness between PPCs gives important clues to identify the differences between models/problems (see section 4.2).

4. Explanation Generation

4.1 Framework of model-making process description

In our framework, each principle/law is described as a 'model fragment' (Falkenhainer and Forbus, 1991) which consists of its applicable condition and its consequence(s). Applicable condition is described as a set of modeling assumption constraints, while a consequence is described as a physical phenomenon constraint. A model consists of the union of PPCs given by instantiated model fragments, MACs giving applicable conditions for them, and boundary condition constraints given in a problem. (Note that an instantiated 'model fragment' is distinguished from 'model fragment class' which describes a principle/law itself.) A model-making process (i.e., solution) is described as the procedure in which model fragments are applied (instantiated) in turn to the situations (represented with MACs and BCCs) to yield new consequences (represented with PPCs). (Note that a consequence of a model fragment can be the condition for others.)

Figure 1a and 1b show examples, in which it is explicitly described why/how each principle/law is applied to the given situation. In contrast, usual description of solution focuses on the calculation of the required physical amount from the given ones, while the principles/laws and conditions which justify the calculation are attached in the ad hoc way. SOC enables implicit assumptions and physical meanings of calculation to be systematically described.

Additionally, a pair/set of model fragment classes which have similar conditions (situations) but have exclusive MAC(s)/PPC(s) as applicable condition(s)/consequence(s) is called 'exclusive model fragment classes.' Grouping such model fragment classes helps the comparison of models.

4.2 Procedure

4.2.1 Explanation of the model-making process (solution)

The description of model-making process mentioned above makes it possible to explain why/how each principle/law is applied explicitly referring to its modeling assumptions. In figure 1b, for example, the formula '$v^2 - v_0^2 = 2ax$' (dynamic change constraint) is used which relates an object's displacement, velocity and acceleration in a time interval. Note that the constraint *'acceleration is constant in the interval'* (operating range constraint) is explicitly described which is an important precondition for this model fragment to be applied. Many students wrongly use this formula when an object's acceleration temporally varies. The explanation explicitly referring to modeling assumptions would be helpful in avoiding such mistakes.

Additionally, in solving problems, it is important to recognize not only each local principle/law and its consequence, but also the global principle/law which dominates the behavior of the whole system. The solution of domain experts is often 'dominant-principle/law-driven,' that is, they first recognize the dominant principle/law of a problem, then apply local principles/laws to 'fill in the slots' of the global principle/law (Chi, Feltovich and Glaser, 1981; Larkin, 1983; VanLehn and van de Sande, 2009). In our framework, a model fragment of global physical phenomenon constraint (PPC) are defined as the aggregation of the model fragments of local PPC which compose the global one (the applicable condition of a global model fragment is the union of its component model fragments). Global model fragments make it possible to explain the model-making process (solution) focusing on the dominant principle/law. For example, in figure 1a, the model fragment 'balance-of-forces' gives a steady state constraint (global PPC) and its applicable condition includes some physical device constraints (local constraints) given by other model fragments. Based on such inclusion relation, the sequence of explanation can be controlled as follows: first, to indicate the given condition 'a block is at rest' (which means its velocity doesn't temporally vary) suggests 'balance of forces' should be used, then to refer to the laws 'gravity' and 'static friction' which influence the *driving power* of the block's velocity. The generated explanation is shown in figure 2a.

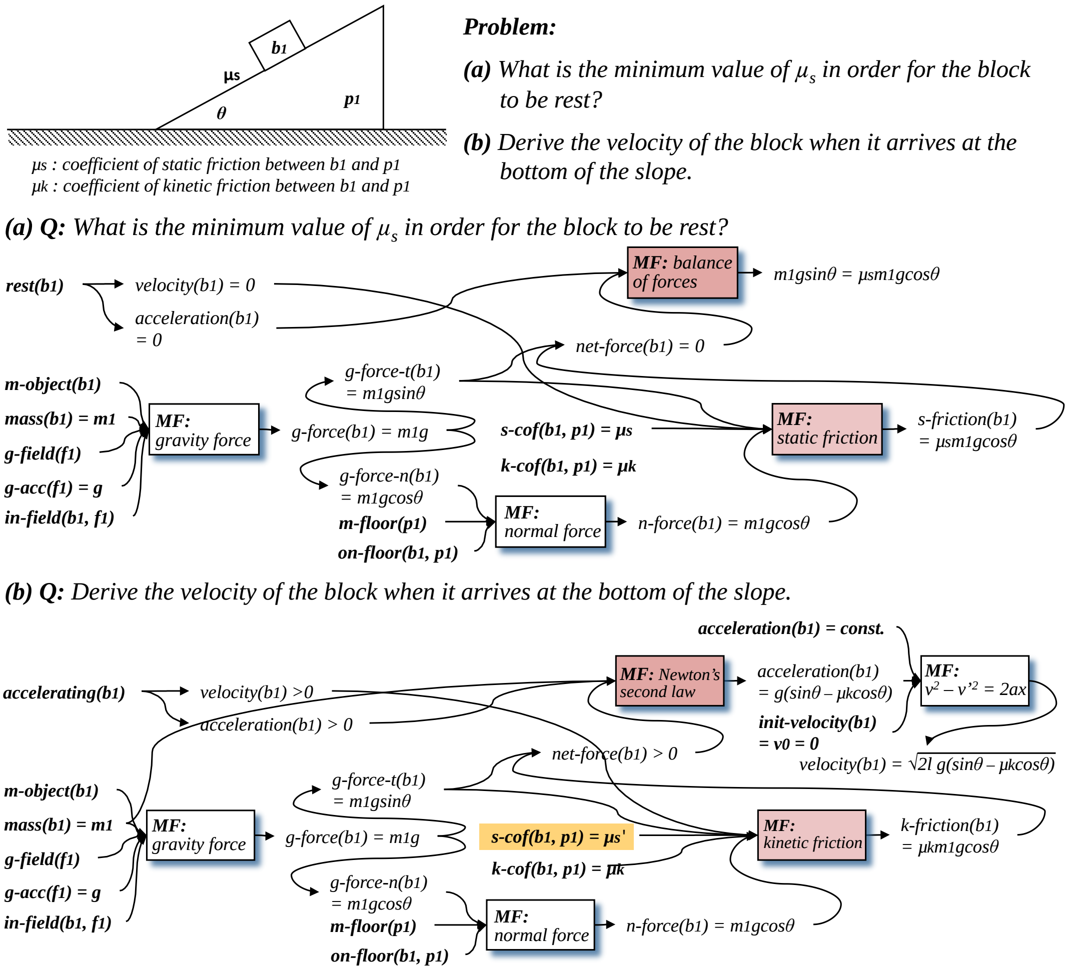

Figure 1. Examples of model-making process.

(a) Since an object keeps at rest, the principle 'balance of forces' is used. So, all the forces applied to the object are required (in the parallel direction to the include plane). Gravity mg is applied downwards and its component parallel to the plane is *mgsinθ*. Since the plane's surface is rough, static friction *μsmgcosθ* is applied. These forces balances with each other, that is, *mgsinθ = μsmgcosθ*. From this equation, *μs* must be greater than or equal to *tanθ*. (partly omitted)

(b) Since an object moves at uniform acceleration, the principle 'Newton's second law' is used. So, all the forces applied to the object are required (in the parallel direction to the include plane). Gravity mg is applied downwards and its component parallel to the plane is *mgsinθ*. Since the plane's surface is rough, kinetic friction *μkmgcosθ* is applied. These forces influences the acceleration of the object, that is, *ma = mgsinθ - μkmgcosθ*. From this equation, *a = g(sinθ - μkcosθ)*. Since the acceleration is constant, the formula '$v^2 - v'^2 = 2ax$' is applicable. Consequently, the velocity of the object at the bottom of the slope is $\sqrt{2lg(\sin\theta - \mu k\cos\theta)}$. (partly omitted)

Figure 2. Examples of generated explanation.

4.2.2 Explanation of the difference between models (problems)

The difference between models (problems) can be inferred by comparing their model fragments. There are two types of relations between problems: (1) the problems which have the same/similar surface structures (situations) but have different physical structures (instantiated model fragments belong to different classes) and (2) those which have different surface structures (situations) but have the same/similar physical structures (instantiated model fragments belong to the same classes). Both relations play an important role for promoting conceptual understanding (Scheiter and Gerjets, 2002; Scheiter and Gerjets, 2003). As for the latter, the difference is easily inferred by identifying the corresponding pair of model fragments (each of which belongs to each model) both of which give the (global) PPCs of the same class. The difference can be explained by showing their preconditions (situations) are different.

As for the former, the difference is inferred by identifying the corresponding pair of model fragments (each of which belongs to each model) which belong to exclusive model fragment classes. Since their situations are similar but their modeling assumption constraint(s) and physical phenomenon constraint(s) are exclusively different, they indicate the difference of two models before/after the change of the situation. The type of the difference can be explained by referring to their modeling assumption classes. For example, when two corresponding model fragments have the same physical structure constraints and exclusively different operating range constraints, it is inferred that the difference of two models is change of the operating range about the partial system they match. The model fragments 'static-friction' in figure 1a and 'kinetic-friction' in 1b are in such relation. It can be inferred that the local constraint between a block and slope is changed from 'static-friction' to 'kinetic-friction' by changing the operating range, by which the global constraint 'balance of forces' (steady state constraint) is changed to 'Newton's second law' (dynamic change constraint) (the generated explanation is shown in figure 2b).

Additionally, when comparing models (problems), it is important to recognize not only the change of each local principle/law and its consequence, but also the change of the global principle/law which dominates the behavior of the whole system. Global model fragments which aggregate the model fragments of local PPCs, make it possible to explain the behavioral change of the whole system focusing on the dominant principle/law.

5. Preliminary Experiment

5.1 Design

We conducted an experiment to evaluate the usefulness of our framework. A SOC-based explanation generator was implemented. The purpose was to examine whether the SOC-based explanation promotes students' conceptual understanding, that is, whether their representation of problems was improved and they became able to solve various types of problems by using correct models.

Subjects: Fifteen graduates and under graduates whose majors are engineering participated in.

Instruments: (1) *Two sets of problems in elementary mechanics*: They were called 'problem set 1 (PS-1)' and 'problem set 2 (PS-2).' Each set included fifteen problems of various surface/physical structures. Problems might have similar situations but different solutions, or have different situations but similar solutions. The sets had no common problem. (2) *Usual explanation about the solutions of eleven problems in PS-1*: The calculation of the required physical amount from the given ones was mainly explained. (3) *SOC-based explanation about the solutions of the same problems as usual explanation*: In addition to the solution of each problem, the differences between problems were explained about eight pairs of problems which had similar surface/physical structures. (4) *Explanation generator used for generating SOC-based explanation*: Model-making processes described by the experimenter (first author) were input and their explanations were output, which were rewritten into readable natural language by the experimenter (without changing the point).

Procedure: First, subjects were given PS-1 and asked to group the problems into some categories based on some kind of 'similarity' they suppose (any number/size of categories were allowed), then asked to label each category they made (called 'categorization task 1'). After that, they were asked to solve eight problems in PS-1 (called 'pre-test'). After a week, the subjects were divided into two groups: one was the 'control group' (seven subjects) and another was the 'experimental group' (eight subjects). The average scores of both groups in pre-test were made equivalent. The subjects in control group were given the usual explanation and asked to learn it. The subjects in experimental group were given the SOC-based explanation and asked to learn it. After that, by using PS-2, 'categorization task 2' was conducted in the same way as above. Finally, subjects were asked to solve eight problems in PS-2 (called 'post-test').

Measure: The quality of the representation of problems was measured with the categories, their 'frequencies' (number of problems accounted for) and the time required in each categorization task. The ability to solve various types of problems was measured with the scores in each test. The effect of learning with usual/SOC-based explanation on the quality of representation and the ability of problem-solving was measured with the comparison of the results of two categorization tasks and pre-/post-tests. The superiority of SOC-based explanation to usual explanation was measured with the differences of improvement of categorization and problem-solving between experimental and control groups.

5.2 Results

The categories made by subjects and their frequencies in categorization task 1 are shown in table 1. Most of the subjects categorized the problems based on the similarity of their superficial features, such as the components of the system (e.g., inclined plane, springs), the figures of motion (e.g., circular motion, free fall). Additionally, all subjects finished the task within ten minutes. The results of categorization task 2 are shown in table 2 (for control group) and table 3 (for experimental group). Many subjects of control group still categorized the problems based on the similarity of their superficial features, while many subjects of experimental group became to categorize the problems based on the similarity of their structural features, that is, the dominant principles/laws of problems (e.g., Newton's second law, balance of forces, conservation of energy). Additionally, all subjects of control group finished the task within ten minutes again, while the subjects of experimental group required from twenty-five to thirty-five minutes. These results suggest that the learning with SOC-based explanation promoted representing problems based on their structural features rather than their superficial features (the increase of the time required suggests the subjects of experimental group inferred the physical structure from surface structure).

The average scores in pre- and post-tests are shown in figure 3 (in both tests, full marks were 52). In pre-test, there was no significant difference of average scores between groups (control group: 36.0 and experimental group: 33.6, t-test $p >.10$). In post-test, though there was also no significant difference of average scores between groups (control group: 42.7 and experimental group: 47.6, t-test: $p >.10$), the increase of average score of experimental group was larger than that of control group. This result suggests that the learning with SOC-based explanation promoted the ability to solve various types of problems, that is, to make appropriate models regardless of their superficial features.

These results suggest that SOC-based explanation about the solution of problems and their differences can assist students in reaching conceptual understanding.

Table 1: Categories in task-1

	Number of subjects using category labels (N_1=15)	Average size of category (N_2=15)	Number of problems accounted for ($N=N_1\times N_2$ =225)	Number of problems wrongly accounted for (N^*=225)	Number of problems correctly accounted for (N^C=N-N^*)
Springs	**12**	**3.1**	**37**	**2**	**35**
Free fall etc.	**9**	**4.1**	**37**	**2**	**35**
Collision	**12**	**2.0**	**24**	**0**	**24**
Circular motion	**12**	**1.9**	**23**	**1**	**22**
Acceleration	**3**	**5.7**	**17**	**1**	**16**
Strings	**7**	**2.0**	**14**	**0**	**14**
Inclined planes	**5**	**2.2**	**11**	**0**	**11**
Balance	5	2.4	12	4	8
Object only	1	5.0	5	0	5
Friction	3	1.7	5	0	5
Second law	2	2.5	5	2	3
Pulleys	1	2.0	2	0	2
Balance of energies	1	4.0	4	2	2
Motion of weight	1	2.0	2	0	2

Table 2: Categories in task-2 (usual)

	Number of subjects using category labels (N_1=7)	Average size of category (N_2=15)	Number of problems accounted for ($N=N_1 \times N_2$ =105)	Number of problems wrongly accounted for (N^*=105)	Number of problems correctly accounted for ($N^C=N-N^*$)
Springs	**4**	**4.5**	**18**	**0**	**18**
Inclined planes	**4**	**3.3**	**13**	**0**	**13**
Balance of forces	**3**	**3.7**	**11**	**0**	**11**
Conservation of energy	3	6.0	18	9	9
Second law	3	3.7	11	2	9
Pulley and string	2	3.5	7	0	7
Circular motion	4	1.5	6	0	6
Pendulum	3	1.7	5	0	5
Simple harmonic motion	2	2.0	4	1	3
Collision	2	1.0	2	0	2

Table 3: Categories in task-2 (SOC)

	Number of subjects using category labels (N_1=8)	Average size of category (N_2=15)	Number of problems accounted for ($N=N_1 \times N_2$ =120)	Number of problems wrongly accounted for (N^*=120)	Number of problems correctly accounted for ($N^C=N-N^*$)
Balance of forces	**7**	**4.4**	**31**	**5**	**26**
Second law	**7**	**3.6**	**25**	**1**	**24**
Conservation of energy	**8**	**4.1**	**33**	**12**	**21**
Linear accelerated motion	3	3.3	10	2	8
Conservation of momentum	3	1.3	4	1	3
Acceleration	1	3	3	0	3
Springs	1	3	3	0	3
Pulleys	1	3	3	0	3
Simple harmonic motion and period	2	1	2	0	2
String and tension	1	2	2	0	2
Time	1	2	2	0	2

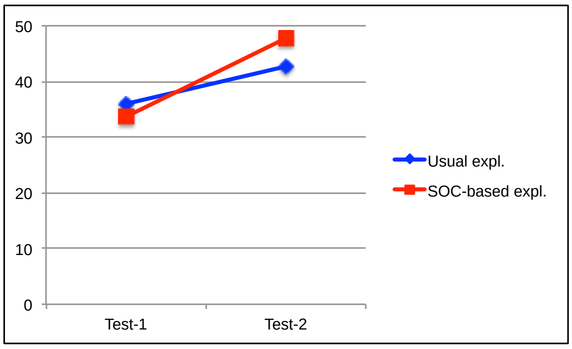

Figure 3. Average scores of tests.

6. Conclusion

Aiming at promoting conceptual understanding through problem practice, we proposed the SOC framework based on which the knowledge necessary for designing a set of problems, sequencing them and generating explanations can be described. We showed the explanations generated with our framework could promote conceptual understanding through a preliminary experiment. SOC-based explanation generator can provide a basic function for designing various instructional methods (e.g., a detailed explanation is gradually simplified (scaffolding-fading), a sequence of problems is given which promotes spontaneous induction). Design of such instructional methods and verification of their effectiveness are our future work.

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