KNOWLEDGE ORGANIZATION IN CONCEPT MAPS
Teacher Students' Representations of the Relatedness of Physics Concepts

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Abstract: Conceptual understanding of physics is based on understanding what the key concepts are and how they are related. In learning and teaching connections which tie concepts to each other give direction of progress - there is a flux of information. We discuss here how such ordering of concepts can be made visible by using concept maps and how the maps can be used in analysing the students' views and ideas about the inherent logic of the relatedness of concepts. The approach discussed here is informed by the recent cognitively oriented ideas of knowledge organization concentrating on simple knowledge-organization patterns and how they form the basis of more complex concept networks. The results show that even in well connected maps there can be abrupt changes in the information flux in the way knowledge is passed from the initial levels to the final levels. This suggests that handling the information content is very demanding and perhaps a very difficult skill for a teacher student to master.

1 INTRODUCTION

Good conceptual understanding is based on understanding what the key concepts are and how these concepts are connected. This kind of relational structure of knowledge can be presented as a network of concepts or as concept maps(Novak, 2002; Ruiz-Primo and Shavelson, 1996; Liu, 2004; Koponen and Pehkonen, 2010). Moreover, research on the structure of the students' concept maps suggests that a good cocnceptual understanding is reflected as interconnected and web-like structures (Kinchin et al., 2000; Koponen and Pehkonen, 2010).

We concentrate here on the problem of how the relational structure of physics concepts can be represented for purposes of making plans for teaching. The context of making plans to teach is interesting, because it is such a context that the relational structure of concepts must be approached from the viewpoint of how to motivate and justify the introduction of new concepts on the basis of concepts which have already been learned. Consequently, the connections which tie concepts to each other quite naturally provide a comprehensible direction for progress - there is ”flux of information” so that what was learned before is the basis for learning new ideas. In this study we discuss how student teachers (in physics) represent their views about the relatedness of physics concepts by using specially designed concept maps, which pay attention to the experiments and models in linking the concepts (Koponen and Pehkonen, 2010). The maps discussed here have been used in teacher education as tools to represent knowledge and they are simple enough node-link-node representation to express the most evident connections between concepts. There exist richer representational tools, for example the Concept Graphs (Sowa, 2008) but they would be too elaborate for purposes of teachers.

The approach discussed here is informed by the recent cognitively oriented ideas of knowledge organization around basic knowledge-organization patterns and how they form the basis of more complex concept networks (Kemp et al., 2007; Kemp and Tenenbaum, 2008; Duong et al., 2009). The analysis of such concept networks is then very naturally based on the use of network theory through analysis of the concept maps made by the students. Here six cases (five student maps and one “master map”) are studied from a general viewpoint (although the context is specific, namely electricity and magnetism). The analysis reveals the important features of the inherent connectedness, ordering and the flux of information related to the progress in introducing the new concepts in the pre-service teachers' plans made for physics teaching. This information is relevant for pre-service teachers themselves as well as for the instructors.

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2 THEORY

Cognitively oriented studies of knowledge formation suggest that procedures of knowledge construction and processing may be simple ones, reducible to basic patterns, even in those cases where the resulting structures are complex. Of particular importance are different types of hierarchies, cliques, transitive and cyclical patterns (Kemp et al., 2007; Kemp and Tenenbaum, 2008; Duong et al., 2009). Apparently, many aspects of knowledge can then also be represented in terms of such patterns. On this basis, we seek here an understanding of the students' ideas concerning how physics concepts are related and how they can be introduced in teaching.

In teaching physics the experiments and modelling are two basic procedures used to introduce new concepts or to show how they apply in different situations. It is to be expected that the relations between the concepts are then guided by the inherent logic of constructing physics experiments and using models to describe and explain the experimental results (Safayeni et al., 2005; Koponen and Pehkonen, 2010). The operationalising experiment is frequently used in advanced-level physics instruction. In this case the concept is operationalized (i.e. made measurable) through pre-existing concepts. The new concept C is constructed sequentially, starting from the already existing ones A and B which provide the basis for an experiment's design and interpretation. In that process, it often happens that new connection between A and B is also established. Due to this interdependence of concept contained in this procedure, it creates the basic triangular-like pattern $A \rightarrow C \leftarrow B \leftarrow A$ between the concepts (Safayeni et al., 2005; Koponen and Pehkonen, 2010). The modelling procedures may also create similar triangular patterns (Koponen and Pehkonen, 2010).

In practice, the students use these procedures when they link concepts and represent the relations between the concept in form of concept maps. They draw concept maps representing how they would proceed in introducing new concepts in their teaching and in what order the concepts are introduced.

The concept maps made by the physics teacher students represent not only the relatedness of concepts, but they also represent how concepts are introduced in teaching. This means that, in a sense, networks also represent the "flux of information" which takes place in teaching or, rather, which teacher students have planned to take place in their teaching. In well-planned teaching there should naturally be a regular flux of new information (in order that new knowledge is learned), but no abrupt changes in that flux (otherwise there are fluctuations in demandingness), and no uncontrollable reductions in the flux (which would give a feeling that learned knowledge is not needed in further learning). The information flux is closely related to the possibility of navigating in the network or going from a given node to another node in the network. Therefore, the ordering of nodes, which comes from the ordering of the procedures, has a central role to play in determining the information flux.

3 THE EMPIRICAL DATA

The cases studied here consist of five student maps, all of which are rather rich in their structure. These maps are typical to students, who had completed the task with thought and had taken time to construct the maps (altogether we have 70 maps and this feature characterises about half of them). The number of the concepts was limited to n=34 most central concepts and laws of electromagnetism, but students were free to introduce as many links as they found necessary. One example of the designed maps is shown in Fig. 1. For purposes of comparison and reference, we have also constructed a "master map", where all well-motivated and well-justified connections that are found in the student maps are collated into one map.

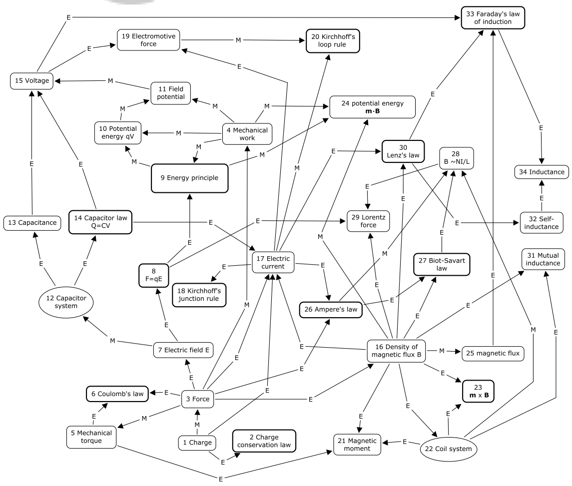

Figure 1: An example of students' concept maps (Gs) for n = 34 concepts in electromagnetism. The map shows concepts (boxes), laws and principles (boxes with thick borders). Links are either operationalising experiments (E) or modelling procedures. The nodes are numbered in the order in which they are introduced through experiments.

In order to visualise the relevant topological features of the maps, it is useful to make the visual appearance of the maps comparable by removing any ambiguity associated with the graphical layout.

This can be done by redrawing the maps so that the same rules for ordering the nodes are used in all cases. In graph theory this is called embedding of the graph (Kolaczyk, 2009). For the embeddings several well-defined methods are available. The embedded maps include the same information as do the originals (i.e. they are isomorphic representations). We use here ”spring-embedding”, which serves the purpose of revealing visually how tightly certain concepts are connected, so it is suitable for visual inspection of the clustering due to triangular patterns. The spring-embedded visualizations expose much about the structure of the concept maps, and more is learned of the structure through the tree embeddings. For example, in Fig. 2 (first row) tree embeddings are shown when one node is chosen as a starting point. Then it is seen just how many hierarchical levels there are in the ordering, and how nodes in these levels can be reached. Then again a node in the hierarchical level is chosen, and yet another ordering is revealed, with a new set of hierarchical levels. When repeated (shown as rows 2 and 3 in Fig. 2), the number of nodes which can be arranged in such a way is reduced as shown in Fig. 2.

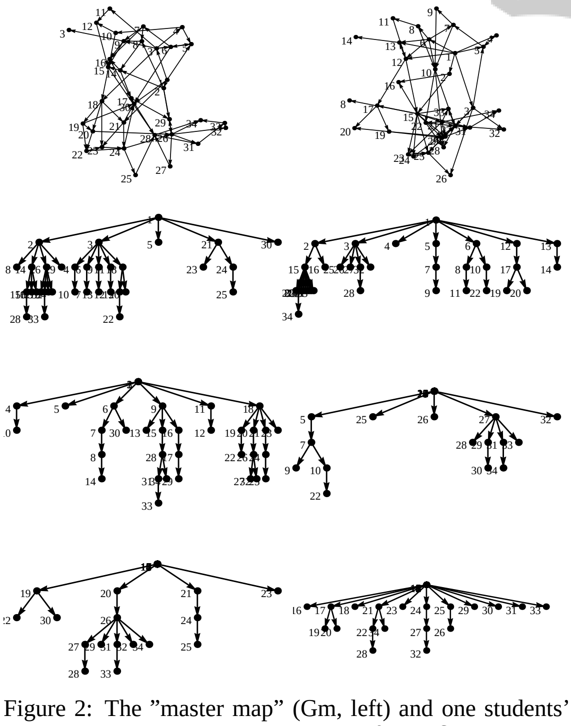

Figure 2: The ”master map” (Gm, left) and one students' map (G1, right) in spring-embedded form (first row). In each case, three examples are given of all 34 possible tree-embedded forms (three rows).

The visualization provides, in principle, all necessary information of the structures. However, on the basis of visualizations alone it is still difficult to get any idea of ordering and relatedness of concepts or how information is passed from the starting level to the final levels. In order to describe such features, we need to develop suitable quantitative measures to describe the structure and information flux.

4 METHOD OF ANALYSIS

The concept maps are basically node-link-node networks or graphs and can be analyzed as such. In a map (network) of n nodes, the variables a_{ij} indicate the connections between nodes i and j so that if nodes are connected, then $a_{ij} = 1$ and if there is no connection, then $a_{ij} = 0$. These elements are the independent variables and they form a nxn dimensional matrix, the so-called adjacency matrix **a**. All quantities (dependent variables) of interest can now be calculated from the matrix **a**, and they are as follows (detailed mathematical definitions are given in Table 1):

1. The degree k_i of the node, which is the number of the incoming and outgoing links k_{in} and k_{out}, respectively. The average degree is denoted by D. The degree describes the connectivity of the map.;
2. The clustering coefficient C_i, which is the ratio of triangles to all the triply connected neighbours around a given concept.The clustering measures the probability that the neighbours of the given concept are also connected i.e. it is a measure for transitive cliques. ;
3. Flux into the nodes (Flux-I) Φ_i, which gives the total number of links terminating at the given node k from all levels $j < k$. This quantity describes how nodes $k < j$ (i.e. concepts introduced earlier) support the introduction of node k. In the present case, it directly describes the ”information” flowing from the previously introduced nodes to ones introduced later;
4. Flux around the nodes (Flux-A) Ψ_k, which gives the total number of links bypassing the given node k from all levels $j < k$. This quantity describes what fraction of nodes $k < j$ (i.e. concepts introduced earlier) *is not* used to support the introduction of node k, but which bypasses the node to higher levels.

The above-defined quantities have a meaning, which is closely connected to the topology of the network. They are also discussed extensively within the literature of network theory, in particular the clustering C as an important measure to characterize the local connectedness of the network (Kolaczyk, 2009). The fluxes Φ and Ψ, on the other hand, directly describes the ”information” flowing from the previously

Table 1: Definitions of the quantities characterizing the topology of the concept networks. In the definitions a_{ij} is the element of the adjacency matrix **a**. The quantities are defined for a given node i. The average number of links per node (average degree) is D.

Quantity	Definition
k_i^{in}	$\sum_j a_{ji}$
k_i^{out}	$\sum_j a_{ij}$
k_i	$\sum_i k_{in}^i + k_{out}^i$
C_i	$\sum_{j'>j} a_{ij}a_{jj'}a_{ij'} / \sum_{j'>j} a_{ij}a_{ij'}$
Φ_i	$\left(\sum_{j=1}^{i-1} k_j^{out} - \sum_{j=1}^{i-1} k_j^{in}\right)/D$
Ψ_i	$\left(\sum_{j=1}^{i-1} k_j^{out} - \sum_{j=1}^{i} k_j^{in}\right)/D$

introduced nodes to ones introduced later (Karrer and Newman, 2009) and they are therefore for our present purposes the most important and interesting quantities.

5 RESULTS

Five cases of students' concept maps are discussed in terms of the structural measures and the information fluxes. The selected cases are typical, in the sense that the features found in them can be found also in all similar, richly connected maps. About half of the cases appear to be these types of maps (the total sample of maps collected consists of about 70 in number). The quantitative analysis of the maps is carried out by using the quantities defined in Table 1. These quantities were constructed so that they correspond to the properties of interest: connectivity, relative amount of transitive triangular cliques and information fluxes.

The average values of the clustering and fluxes are given in Table 2 for the maps Gm and G1 shown in Fig. 2 and for other four maps G2-G5. These values are representative for larger class of maps (about one half). In general, the student maps, which have high clustering and connectedness, are all very similar in the level of averaged values, detailed differences becoming apparent only in node-by-node analysis. On average the clustering attains values around 0.15-0.30, which is common to networks designed for purposes of passage of information (Kolaczyk, 2009). Large values of clustering indicate that there are appreciable connections also between concepts connected to a given concept, i.e. an abundance of the nearest neighbour connections. In a more traditional view of concepts maps, this means an appreciable number of cross-links and thus shortcuts within a given level of hierarchy (Ruiz-Primo and Shavelson,

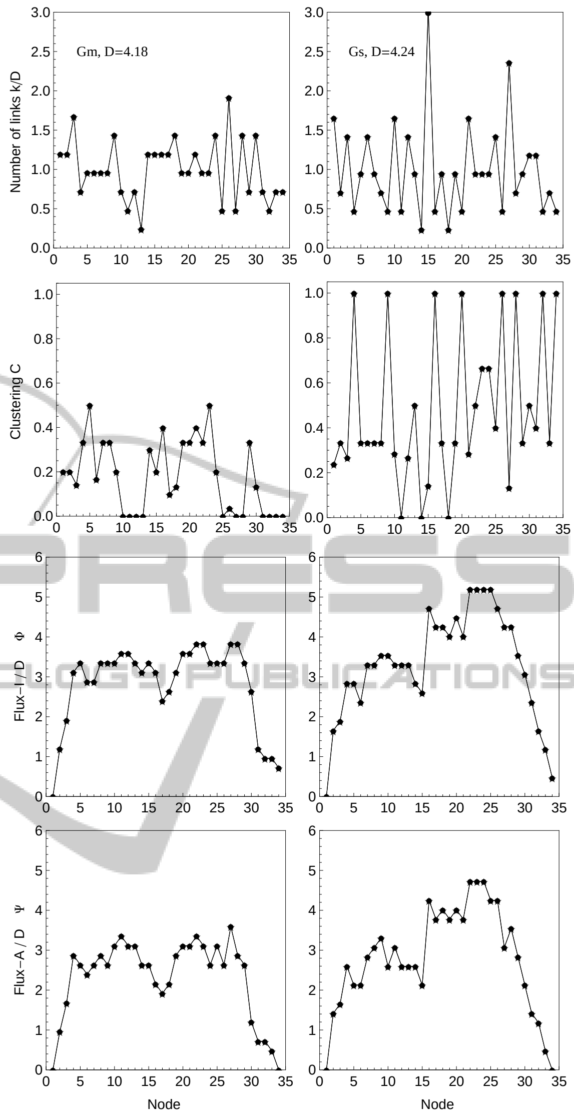

Figure 3: Node-by-node (nodes 1-34) values of degree D, clustering C, and fluxes Φ and Ψ. The first column shows the values for master map Gm and the second column for the student map Gs=G1.

1996; McClure et al., 1999). However, the clustering must not be too large, because otherwise the navigability and the passing of information in the maps is difficult.

The information fluxes are rather large in all studied cases. The fluxes are given as a total flux per expected number of links (total flux divided by average value D of links per node, see Table 1 for definition. The results reveal that typically, per one link connected to a given node, there are from three to four links coming from the lower levels. This means that each node is rather well supported by the many previous nodes - the meaning content of the concept (node) is supported or backed up by knowledge contained on the network existing before the introduction of the new node. This, quite evidently, is one characteristic of well-planned teaching. In the sample of 70 maps there are, however, several cases which are nearly chain-like and very poorly connected with $D < 2$ and fluxes of order $\Psi \approx 1$ and $\Phi \approx 1$. It should be noted that not only in poorly connected maps information flux is low. In a well-connected network, though one which is poorly ordered or directed, the fluxes would be also very small and the passage of information would be nearly hindered. In terms of the inherent logic of how concepts are introduced, this type of situation would indicate either: 1) circular reasoning, or 2) constant reference backwards.

In clustering and the fluxes there are large node-by-node variations. The large variability from node to node indicates that there is a tendency for certain concepts to gather more links than other concept would do. A suitable quantity characterizing the relative variation is the dispersion of the variable defined as $\delta X = \sigma_X / X$, where X is the variable's average value and σ_X is the standard deviation. Interestingly, the dispersions for D, C and fluxes Φ and Ψ given in Table 2 show that in student maps there is more variation than in the "master map", which means that student maps are not equally regular and balanced as the master map. This of course is related to the fact that in student maps there are abrupt changes in the information fluxes; some concepts become very central and much effort goes into their introduction. This, on the other hand, is somewhat awkward for teaching, because it means that demandingness of learning may increase in an uncontrollable way. The master map does not have such abrupt changes; instead, it displays a rather steady flux of information throughout the whole concept network. The results suggest that rich concept maps not only have large values of clustering and fluxes but, in addition, the node-by-node values do not vary much. This means that all concepts are roughly similar in the degree of importance for the whole structure. This, of course, is required from well-planned teaching, where most of the topics discussed should appear to be of importance for a student. Maintaining small node-by-node variability is relatively demanding, perhaps owing to the fact that it apparently requires evaluating the functionality of the structure as a whole instead only of locally.

6 CONCLUSIONS

We have explored physics teacher-student plans for the teaching of physics (electricity and magnetism), carried out in a physics-teacher preparation course. The plans were represented in the form of concept maps. The concept maps were made such that each link between concepts needed to be justified either through an experimental or modelling procedure, and they were explained in a written report coming with the map. The aspects of interest in these plans are the relatedness of concepts, and how the ordering of the concept allows the introduction of new concepts in the maps. We have introduced here a new method, which can be used to analyse the students' plans so that their inherent logic, ordering and the way to use the information in the plans is revealed. These aspects, we believe, are of importance for understanding and evaluating students' view of how concepts are related and how they can be introduced in teaching physics.

The structural analysis of the concept maps is based on the identification of the basic knowledge-ordering patterns. The pattern of most importance is a triangular pattern, connected to the procedures of experiments and modelling. However, the analysis of the plans for teaching show that even in cases where the maps have a rich set of connections, and when concepts are well connected, the inherent logic and the way knowledge is passed from the initial levels to the final levels may be awkward and that there are often abrupt changes in the information flux. Interestingly, when all valid connections found in the students' maps are combined and reorganized, the resulting map shows a very regular and steady information flux. This suggests that handling the information content is very demanding and perhaps one of the most difficult skills for a teacher student to master. This notion has direct implications for teacher education and it also calls for methods to monitor this kind of development. The method of analysis introduced here is a step in this relatively unexplored direction.

Table 2: Average degree D, clustering C and fluxes Ψ and Φ for master map Gm and student maps G1-G5. The dispersions δX of the variables X (see text) are also given.

	Gm	G1	G2	G3	G4	G5
D	4.18	4.24	3.47	3.06	3.18	3.18
δD	0.38	0.60	0.62	0.54	0.66	0.59
C	0.18	0.48	0.25	0.15	0.25	0.16
δC	0.90	0.69	1.28	1.94	1.39	1.91
Φ	2.82	3.31	3.00	2.76	2.97	3.12
$\delta \Phi$	0.37	0.40	0.48	0.47	0.60	0.46
Ψ	2.32	2.81	2.51	2.26	2.47	2.62
$\delta \Psi$	0.43	0.46	0.56	0.53	0.70	0.48

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