

Understanding the Role of Structure in Concept Maps

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Abstract

Concept mapping is widely used in educational settings to aid knowledge construction, sharing, and comparison, as well as to assess students' understanding. However, despite this rich range of uses, there have been few controlled studies of the relationship between concept maps and people's internal conceptualizations. Because concept maps represent information as a network of concepts, an interesting question is how structural factors relate to concept importance. This paper presents results on modeling map-builders' assessments of concept importance in terms of structural factors. Twenty subjects were asked to construct a concept map on a topic of interest and subsequently to rank labels of concepts extracted from their maps, based on the concepts' importance in describing the map's topic. Analysis of the results supports that subjects rank concepts higher if they are closer to the map's root concept and if they have more outgoing connections or incoming connections relative to the other concepts. Agreement between the model's predictions and subjects' rankings was high, with Spearman's rank correlation coefficients in some cases 1.0 or close to 1.0. These results suggest that topology alone is a sufficient indicator to extract topic-relevant information from concept maps. This has ramifications for developing tools to assess student concept maps and concept map authoring support systems. The results have been applied in the design of "suggester" systems that aid domain experts in building concept maps, by using structural information to identify important concepts and search for topic-relevant information in previously built concept map libraries and on the Web.

Keywords: concept mapping; cognitive modeling; intelligent suggesters; Web search

Introduction

Concept maps represent knowledge in a two-dimensional, graphical representation capturing concepts—described by labeled nodes—and their relationships, described by the links between concepts. Each concept–link–concept triple corresponds to a simplified natural language sentence expressing a proposition (e.g., "glaciers cause land erosion"). Concept mapping (Novak & Gowin, 1984) has been widely used for knowledge elicitation, for encouraging knowledge construction by students and others, and for making internal conceptualizations explicit to facilitate knowledge sharing, comparison, and assessment. However, despite this extensive use, there has been little study of how well concept maps actually reflect people's internal conceptualizations. As described in the following section, this is of particular interest because of the relationship of concept maps to the long tradition of modeling concepts and relationships using schemes based on graphs and networks, in both psychology and artificial intelligence (e.g., (Ausubel, 1963; Collins & Quillian, 1969; Quillian, 1968; Sowa, 1984; Tulving, 1972)). In addition, models enabling prediction of concept importance from concept maps would be useful for interpreting the knowledge elicited via concept mapping, for using concept maps in assessment of students, and for developing context-sensitive systems to

provide information to aid students or others in the concept mapping process (e.g., (Leake et al., 2003)).

Because concept maps represent information as a network of concepts, an interesting question concerns the sufficiency of models based solely on structural information to predict concept importance. This paper presents new studies of models of the relationship of structural factors to the appropriateness of concepts as topic descriptors, in the context of a concept map. Previously, we presented these models and examined their applicability to concept map *understanding*, to model how concept map viewers' judgments of concept importance are influenced by structure (Leake, Maguitman, & Reichherzer, 2004). This paper presents results from a new, complementary study, focusing on concept map *generation*. This study examines how the naturally emerging structure in constructed concept maps aids in predicting the map-builders' assessments of concept importance.

Our previous study showed that assessment of concept importance during understanding of concept maps may depend not only on the content of the concepts and links included in the map, but also on the map's topology. The study considered topological and layout factors that might influence the decisions on which concepts are most topic-relevant, such as changes in a concept map's number of outgoing and incoming connections, distance to the root concept, and layout differences. When provided with only the structural information from a concept map (labels were replaced with artificial words to exclude domain knowledge about concept importance), structure influenced human assessment of concept importance, but layout did not. An important remaining question is whether topological factors can be predictive of the concept map author's assessment of concept importance. Addressing this question is important for assessing knowledge captured in concept maps, as well as for our long-term goal to build intelligent suggesters and document navigation tools, because information about concept importance can be critical for such systems. Consequently, to address this question, we conducted a new study, complementary to the first, whose design and results are addressed by this paper.

The paper begins with a synopsis of concept mapping and a brief survey of its relationship to the study of human knowledge. It then reviews the models used in the previous study and presents our experimental design and new results. It concludes with a sketch of potential applications of the models to build artificial intelligence tools to support the concept mapping process.

Modeling Concepts and their Relationships¹

Concept mapping was developed by Joseph Novak (Novak & Gowin, 1984), to support the process of "meaningful learn-

¹This and the following section are condensed and adapted from (Leake et al., 2004).

ing” of Ausubel’s cognitive learning theory (Ausubel, 1963), which requires deliberate effort by learners to connect new concepts to relevant preexisting concepts and propositions in their own cognitive structures. The concept mapping process is designed to externalize students’ concepts and propositions, facilitating their connection with newly acquired concepts. Concept maps have been used by teachers to assess students’ understanding, by students to compare their knowledge and collaboratively refine their understanding, and by experts for modeling and sharing knowledge.

Concept maps are part of the tradition in cognitive psychology and artificial intelligence of modeling concepts and their relationships using graphs or networks. Examples include the hierarchical network model (Collins & Quillian, 1969), semantic memory (Tulving, 1972) and conceptual structures (Ausubel, 1963), as well as more formal approaches such as conceptual graphs (Sowa, 1984) or semantic networks (Quillian, 1968). Because theories of knowledge organization commonly assume that knowledge can be modeled in terms of a set of components and their relationships, the externalization of these structures by concept mapping is appealing to examine subjects’ knowledge (West, Park, Pomeroy, & Sandoval, 2002), and empirical studies provide support for this approach (Aidman & Egan, 1998; Michael, 1994).

However, the role of concept map structure in revealing subjects’ conceptualizations is still poorly understood. Some previous work studies knowledge organization by using topological information about graphs to define measures of graph similarity (Goldsmith & Davenport, 1990) and for concept clustering (Esposito, 1990), under the premise that more closely-related concepts in cognitive structure will also be closer in the graph representation. This has been used in turn to induce concept proximity or relatedness. Our previous and current studies investigate complementary questions on the influence of other structural factors.

Models for Analyzing Concept Maps

Previously, we developed four candidate models of the influence of structural factors on the importance of particular concepts to the topic of concept maps (Leake et al., 2004). Each model represents concepts as nodes in the concept map graph. The first three models consider the map’s topology, while the fourth model, a baseline, disregards the topology and considers each concept to be equally important. For this study, we exclude the baseline model because the study examines concept rankings, which the baseline model cannot produce because it does not distinguish between concepts.

Our design of the models started from the structural factors identified as important in the concept mapping literature. Novak proposes that concept maps are best constructed with a focus question in mind that drives the concept mapping process and the organization of the concept map. Generally, a root concept serves as a starting point to explore the topic discussed by a concept map. Concepts directly linked to the root concept explain the root concept and its role with respect to the focus question. The directly linked concepts are further explained with additional concepts, resulting in a hierarchical organization with cross-relationships, providing a rich topological structure. The models reflect this structure by weighting concept importance based on factors such as close-

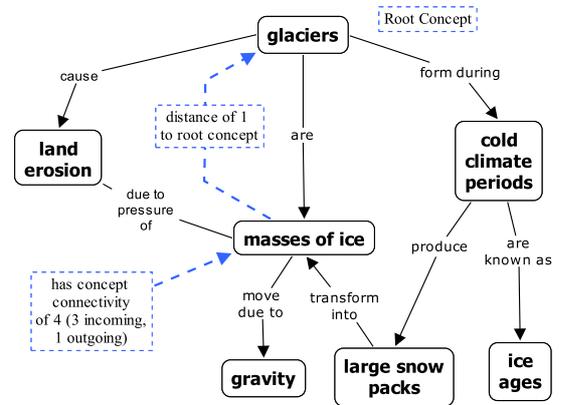


Figure 1: A simple concept map about glaciers, annotated with sample structural properties.

ness to the root concept and connectivity. The models are parameterized, to enable the actual contributions of hierarchical structure and connectivity to be determined empirically.

Connectivity Root-Distance Model (CRD)

The Connectivity Root-Distance model reflects two influences on concept importance, the connectivity of the concept to other concepts, and the distance of the concept to the root concept. Because concepts with high connectivity participate in many propositions, they might be expected to be important; because the root concept (typically located at the top of a map) tends to serve as a starting point for exploration, concepts located closer might be expected to be more important than those farther away. For a concept k with o outgoing and i incoming connections to other concepts, d steps away from the map’s root concept, CRD assigns the weight:

$$W(k) = (\alpha \cdot o(k) + \beta \cdot i(k)) \cdot (1/(d(k) + 1))^\delta$$

The model parameters α , β , and δ determine influence of the outgoing connections, incoming connections, and distance to the root concept. Figure 1 illustrates factors affecting the model’s assignment of weight for the concept “masses of ice.”

Hub Authority and Root-Distance Model (HARD)

CRD performs a local analysis, only taking immediate neighbors into account. The Hub Authority and Root-Distance (HARD) model reflects a global analysis, centering on three different types of concepts, based on Kleinberg’s (1999) algorithm for topological analysis of graphs, used to identify important nodes in a hyperlinked environment. Weights for *authorities* (concepts with multiple incoming connections from hub nodes), *hubs* (concepts with multiple outgoing connections to authority nodes), and *upper concepts* (concepts with short distance to the root concept), are calculated following (A. Cañas, Leake, & Maguitman, 2001). In Figure 1, “glaciers” is primarily a hub concept, due to the number of outgoing connections relative to other concepts in the map, and “masses of ice” is primarily an authority, due to its mostly incoming connections relative to other concepts. The HARD model assigns weights by:

$$W(k) = (\phi \cdot h(k) + \psi \cdot a(k) + \gamma \cdot u(k))$$

In this formula, h , a , and u are the corresponding hub, authority, and upper node weights of a concept in a map and ϕ , ψ , and γ are the model parameters, which reflect the influences of the different roles that a concept may play.

Path Counter Model (PC)

Like the CRD model, the Path Counter model reflects connectivity, but instead of considering only immediate connectivity, it considers indirect relationships as well. PC counts all possible paths that start from the concept in question and either (1) end on a concept with no outgoing connections, or (2) end on a concept that has already been visited in a path. High connectivity concepts, which participate in many paths, also contribute to the number of paths crossing concepts indirectly linked to them. For example, in Figure 1, the PC value for the concept “gravity” is three, because there are three paths extending from the root concept to “gravity,” due to “masses of ice” being well connected in the map. If n is the number of paths crossing a concept k , its weight is computed as $W(k) = n$. Unlike the previous two models, this model considers only a single influence on concept weight, and consequently requires no parameters.

All three candidate models can be used to rank concepts in a concept map according to their weight $W(k)$ with higher weights corresponding to more important concepts. In the following experiment, the participants’ concept rankings are compared to the models’, using parameter settings chosen to maximize the ranking correlations.

Experiments and Results

We conducted a human-subjects experiment to study how two topological factors, root distance and connectivity, predict the map-builder’s assessment of the concept’s role as a topic descriptor. In contrast to our previous study, which examined how subjects’ assessments of concept importance are influenced by structural factors when they see new concept maps, this study examines how the structure of the maps they author reflects their internal concept judgments. The study required participants to construct their own concept maps on a topic of their choice and then to rank concepts extracted from the map. The experiment also studied the best fitting model parameters for the CRD and HARD model, to assess the different roles of the topological influences.

Method

Twenty paid subjects, including students and staff from Indiana University and others, were recruited for a one-hour experiment. The experiment was divided into (1) a training session to familiarize participants with concept maps and their applications, (2) a concept mapping session during which participants construct a concept map on a topic of their choice, and (3) an assessment session, which required participants to rank concepts extracted from their maps and to answer general questions about the study and themselves. For the training session, participants are shown five concept maps on different topics and with different topological structures to ensure that participants (1) regard concept mapping as a general-purpose knowledge capturing tool and (2) are not biased by a particular structure that a training concept map may exhibit. Participants do not receive any instructions on how

to build a concept map or organize the concepts in their map; they are only informed about concept mapping’s application as a tool for learning, teaching, and knowledge capture. Participants must infer any knowledge on how to build a map from the five concept maps shown during the training session. Thus, influence on their maps’ structural organization from conventions of the concept mapping literature is minimized. Following the training session, participants are asked to construct a single concept map on a familiar topic (e.g. glaciers) and to specify the topic and their focus (e.g. how they form and glacial erosion) for the discussion in the map.

We expect the ability of the models to predict topic importance to depend on the quality of the concept map drawn, in the following sense. If the subject’s concept map describes an insufficient part of his or her knowledge of the selected topic, this is likely to affect the outcome, by reducing the structure available for analysis. Consequently, to ensure that the concept map captures the participants’ knowledge on the topic, after the participant prepared an initial map, five general questions were asked to stimulate further development of the concept map. The questions were designed to encourage participants to include additional concepts and relations in their maps, and their general nature ensured that participants had the same chance to improve their maps before the start of the assessment task. For example, we asked participants to (1) draw additional relations between two randomly selected concepts, (2) include additional propositions involving a randomly selected concept, (3) think of additional statements not yet included in their map, and (4) think of one or more additional concepts related to the topic but not yet included in their map.

For the assessment task, participants ranked a total of five different sets of concept labels extracted from their concept maps, according to their importance to the selected topic and focus. Each set was presented separately along with the topic and the focus as a frame of reference to remind them about the concept mapping session and the concepts and the propositions they included in their map. For each ranking task, between four and five concept labels were extracted; each concept differed from the others in either connectivity or distance to the root concept or both. The ranking task forced participants to reflect on the topic and make a decision with respect to the concept’s role. To relax the constraints on the task, participants were allowed to generate multiple rankings for the same list, in order to provide some flexibility if two concepts were considered equally important.

As discussed previously, it is accepted that concept maps are best constructed with a focus and goal in mind to drive the mapping process and constrain the map content. If the goal and focus are unknown, participants may have difficulties deciding which concepts and propositions to include in their maps. Similarly, the ranking of concepts’ importance to the map’s topic will depend on the map’s goal and focus. Consequently, we asked all participants to construct their maps for the purpose of *teaching the selected topic*, to ensure that (1) the rankings are based on what participants elucidated in their maps and (2) results from participants are comparable. We anticipated that when the focus for constructing a map is teaching the selected topic to an audience unfamiliar with the subject, the map will become more focused in terms

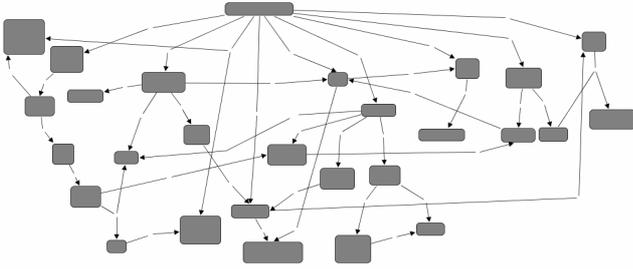


Figure 2: Sample illustrating the structure of concept map constructed by a participant.

of the selection of concepts and relations necessary to explain the topic. This is important for the subsequent ranking task, when participants have to decide on a concept’s relevance to describe the map’s topic.

Results

The ranking task performed by the participants involved, on average, 46% of the concepts in their concept maps. Rankings among concepts involved either concepts selected with different distances to the root concept or with different connectivities to cover the variations in topological factors being studied. On average, the concept maps included 30 concepts and 69 connections (or a ratio of 2.31 connections per concept) resulting in a rich structure. The structure of one subject’s concept map is illustrated in Figure 2.

Model predictions and human judgments on the importance of concepts were compared using Spearman’s ranking correlations. Each participant’s ranking results were compared separately against the three candidate models and the average ranking correlation was computed across participants. For each participant, additional rankings were generated, when possible, by combining one or more concept rankings into a single, longer ranking list. This increased the number of rankings per participant by one or two rankings and the size of the longest ranking list to five or six concepts.

Before computing the ranking correlation between model and human concept rankings, the parameterized CRD and HARD models were fitted against human-judged rankings to produce the highest ranking correlations. Data fitting was performed on the original ranking lists recorded by a participant as well as on the ranking lists that included the combined, longer concept rankings. The model parameters resulting in the best fit were determined using a hill-climbing search algorithm applied to each participants’ rankings separately.

Table 1 summarizes the results of the average Spearman’s ranking correlation (r_S) and presents representative parameters determined from the data set. The r_S values in parenthesis are the average ranking correlations between best-fitting model predictions and the set of rankings containing combined rankings in addition to the original rankings of a participant. Assuming that the rankings are performed independently across the different participants (an assumption that holds easily because topics and the structure of maps are different), the results are statistically significant. The probability that Spearman’s ranking correlations above 0.8 (or even 0.6, the smallest correlation measured for the HARD model)

occur by chance for the rankings submitted by all 20 participants is small ($p < 0.01$).

The results indicate that model and human judgment on the importance of concepts are similar, suggesting the sufficiency of topology alone to make such predictions. They also show that topological factors influencing human judgment varies across the participants. For example, for some participants, outgoing connections or hub concepts seem to be more important than incoming connections or authority concepts as indicated by the parameters $\alpha > \beta$ and $\phi > \psi$. For others, the opposite is true. Also, some treat concepts near the root concept as relevant while concepts more distant from the root concept are not treated as very relevant, as indicated by $\delta > 1$. If the parameters are preset to a fixed value for all participants, the average Spearman’s ranking correlation drops to 0.71 for the CRD and 0.73 for the HARD model. The larger drop in average ranking correlation for the CRD model shows that the CRD model tends to be more dependent on best-fitting parameters than the HARD model. This may not be surprising, because the CRD model considers local topological influences while HARD considers the global structure, which is less affected by small local changes and relies more upon global interdependence between concepts.

Model	Parameters for Best Fit			average r_S
	α / ϕ	β / ψ	δ / γ	
CRD	6.0	1.0	1.0	0.813 (0.808)
	1.0	10.0	5.0	
	0.88	0.0	0.25	
	1.0	1.0	1.0	
HARD	1.0	1.0	1.0	0.825 (0.820)
	1.0	-1.0	3.0	
	-1.0	1.0	2.0	
	1.0	2.5	1.0	
PC	N/A	N/A	N/A	0.667 (0.677)

Table 1: Summary of model parameters and the average Spearman’s ranking correlation for 20 participants.

Discussion

For the study, participants were drawn from a subject pool that included male and female students and staff from Indiana University, as well as individuals from elsewhere, whose age ranged from 25 to 38. The participants’ professional backgrounds and interests led to choices of a range of different topics including sports, regional geography, education, law, mathematics, environmental science, computer science, mechanical engineering, and aircraft landing. Participants expressed confidence on the subjects they discussed in their maps. When asked to rate themselves on a 7-point Likert scale, with 1 representing novice and 7 expert, the average rating was 5.7. All participants reported that they had few problems building the concept map, even though only two out of twenty participants had prior concept mapping experience. The structure of the resulting concept maps also underscores participants’ ability to express their ideas on a domain via concept maps: That participants made on average 2.31 connections between each concept pair suggests that even with

very little training and no prior experience (except in 2 cases), subjects could build maps with a rich structure.

Two factors which could negatively affect the results of the experiment are focus shifts during map construction and whether the concept map adequately represents the participant's knowledge on the subject with respect to the chosen topic and the focus for the topic. If critical concepts and connections are missing, incomplete structure could affect the model's predictions. We tried to guard against this problem by asking general questions involving the concepts in the concept maps and the topic to stimulate participants to reflect on missing information in their concept map. In all cases, these questions prompted participants to include several new concepts and connections. If focus shifts, but subsequent rankings are based on the original focus, the map structure which reflects the changes would not be expected to be as useful in identifying topic-describing concepts. Participants were frequently reminded to remain faithful to the focus they set out to discuss at the beginning of the concept mapping session, but in one case, a shift in focus was discovered after the participant submitted the answers in the questionnaire. However, the results recorded in this incident did not decrease the average ranking correlations for any of the three models.

A research question not pursued in this study is how the best-fitting parameter values may change if subjects are asked to construct more than a single concept map on different topics. One possibility would be that concept map authors adopt a certain structural "style", indicated by the hierarchical organization and the occurrence of certain high connectivity nodes, that repeats itself across different concept maps. If so, such a structural "style" might facilitate predictions of how specific individuals will assess the importance of concepts in concept maps. Another possibility would be that the best-fitting parameter values would vary even within individuals. We expect to pursue this question in subsequent research.

Potential Applications to Education

A variety of tools have been developed to assist students in studying subjects via concept mapping. The tools analyze the students' concept maps to provide general suggestions on how to improve the map or to question the student about the information represented in the map. For example, the Reasonable Fallible Analyser (RFA) (Conlon, 2004) scores students' concept maps to provide feedback on the quality of their concept maps and hints on how to improve them. RFA compares a student's concept map with an expert concept map to count correct concepts and propositions in addition to missing concepts, links, and "dubious" connections as part of the quality assessment. The tool generates a report intended to enable students to reflect upon their maps and make necessary adjustments (or to argue for a higher score than the tool assigned, if they feel that their propositions reflect the meaning of the propositions in the expert map). Another tool, discussed in (Leelawong et al., 2003), employs qualitative reasoning techniques applied to concept maps to draw conclusions and to present these conclusions via an interface agent known as Betty. The tool supports concept map construction but requires students to use link relations from a predefined set to enable Betty to reason about the subject without domain knowledge on the subject. When queried, Betty gives an ex-

planation of her reasoning using the information provided in the student's concept map. The query itself is expressed in terms of the effects a concept may have on another concept in the map. Betty uses forward propagation in the concept map graph and information about the type of the link between two concepts to derive an answer in terms of the concepts and relations used in the map.

Tools such as RFA and Betty could benefit from the topological models presented in this paper to further improve recommendations and interactions with students. For example, the RFA tool could apply the models in its quality assessment, by giving topic concepts a higher weight in the overall score of the comparison between student and expert concept map. Likewise, the interface agent Betty could select topic describing concepts in the map when generating explanations in response to student queries.

The use of structural methods, as studied in this paper, contrasts with the prevailing approach of comparing maps based on the labels of the concepts and relationships. In the absence of sophisticated natural language processing—which is beyond the scope of these systems—such an approach largely ignores the structural information, which, as our experiment shows, carries useful information about how the map's author views the concepts' roles with respect to the map's topic.

The models presented in this paper could be applied to other graph-based structures representing human knowledge or design decisions. For example, graph structures generated from Unified Modeling Language (UML) class diagrams might be analyzed to determine classes that play an important role in the model. Similarly, graph structures generated from OWL (Web Ontology Language) ontologies might be analyzed for classes that play an important role in the ontology. The application of our models to a wider range of representations is a subject for future research.

Application to Systems for Aiding Concept Map Construction and to Document Access Tools

We have applied the models ourselves, in the design of automatic "suggester" systems integrated into the CmapTools concept mapping software and also in the design of a document access and navigation tool on the basis of concept maps.² The CmapTools software is a suite of electronic tools for constructing and sharing concept maps and was developed at the Institute for Human and Machine Cognition (A. J. Cañas et al., 2004). One of the suggesters uses the calculated importance values to weight keywords from concept labels in a concept map, in order to retrieve similar prior concept maps for comparison and to suggest propositions from those maps. The other suggester uses the similarity weighting to weight keywords for Web search, to derive topics for the user to consider when starting a new concept map to broaden the knowledge model. Similarly to the suggester, the document navigation and access tool uses the model to select topic describing concepts to search for related documents in libraries. For the implementation of the suggesters, we experimented with different model parameters. The results from this experiment suggests that model parameter that take each of the

²We are grateful to Alberto Cañas and the IHMC CmapTools development team for giving us access to the software and for their valuable contributions to this project.

structural factor equally into consideration are sufficient to return good results. The project is summarized in (Leake et al., 2003), and research continues on the document navigation and access tool.

Conclusion

This paper reports on a study of how concept map structure reflects the map author's concept importance judgments. This is complementary to our previous study of structural influences on interpretations of concept maps built by others. In this study, two structural factors were explored, concept connectivity and distance from the root concept.

Among the three models, the HARD model, which considers the global structure of the map, achieved a slightly higher correlation with human rankings than the CRD model. While the previous study highlighted the importance of the concept map's local structure to assess concept importance, this study shows that the global structure is equally important for predicting concept importance. In addition, the results suggest that the HARD model is more robust as determined by the tighter range of model parameters that achieved the best fit between model and human prediction.

Modeling judgments of concept importance helps elucidate the knowledge captured in concept maps. This can be useful to teachers and experts constructing concept maps and to novices reviewing expert concept maps to learn a subject. The predictiveness of concept map structure also has important ramifications for developing support systems, because it enables identifying important topics based on automated structural analysis, without sophisticated natural language processing. We have applied the models presented in this paper to the design of "suggester" systems which aid domain experts in building concept maps, by using structural information to identify important concepts and search for topic-relevant information in previously built concept map libraries and on the Web. We expect these to lead to a new set of tools for assisting concept map construction, as well as information access and management.

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