Venn Lattice: An exploratory conceptual space implementing the state concept property formalism

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Abstract. We describe domain exploration as a complex search process in which learning occurs and cognitive representational models change continuously. The state concept property-formalism is presented as a suitable approach to describe domain exploration formally. We propose to extend this formalism to include the unity of concept lattice and Venn diagram.

Keywords: domain exploration · conceptual space · Venn diagram · concept lattice.

The idea of domain exploration reflects the notion that cognitive representation models are constantly evolving over time. Towards a document-based domain exploration, search can be described as an evolving search process [1]. The evolving search model is not limited to a simple match between search query and document result set. According to this model, the user starts at a reference point or, more concretely, a reference document, and from here starts a kind of endless search through a variety of document sources. With each new retrieved document the user can create a new idea of area under concern. This means that the user performs a series of queries to find a suitable solution to a given problem [10]. In each search step, the user's cognitive representational model can change as the user "learns to see the invisible" [8]. This happens when the user is able to discriminate something in a new way while reading a particular document as an element of their search path. Such situations also known as sense-making [13] are important because the user has to learn and unlearn a new cognitive representation model. The model of cognitive representation itself and its implications are fundamentally transforming. Thus, when the user

enters a new search query, he not only modifies the existing search query, but often also updates the content of the search query with respect to his new mind set. More recently, domain exploration has evolved according to the concept of search-as-learning, where the user's search goal is primarily to achieve a clear learning outcome [9, 12]. Based on these process characteristics, the question remains how we can represent concepts in cases of learning where the cognitive representational model is in progress.

In the case of domain exploration, we propose to implement dynamically emerging cognitive representation models based on the tate-Context-Property (SCOP) formalism [4, 5]. SCOP assumes that concepts and their application are intertwined, with the elements of a concept existing only within a concrete complex situation reflected on the basis of a specific context. "In this contextualized theory, not only does a concept give meaning to a stimulus or situation, but the situation evokes meaning in the concept, and when more than one is active they evoke meaning in each other." [4] When concepts are restructured into more complex concepts, new features emerge or existing features are lost. The SCOP-formalism allows the context that gives rise to a concept, and the change in state of the concept that it gives rise to, to be explicitly included in the formal description of a concept. A concept description includes a set of concept states, a set of relevant contexts, a set of relevant features, a function describing the applicability or weight of a particular feature given a particular state and context, and a function describing the transition probability from one state to another under the influence of a particular context.

In SCOP, the relevant features are represented as a lattice of features. This is based on the assumption that only a change in feature structure can change the nature of a concept. We propose to use an concept lattice [7] instead of a pure feature lattice because a concept is not only described by its features but also requires other concepts. From our point of view, we can separate functional and perfunctional terms - similar to the already observed heuristics of citation patterns [14] or a separation into seed term and other terms [3]. Within a concept lattice, we use perfunctional concepts in addition to features to describe a functional concept. From a formal point of view, the use of term grids has the advantage that the complete logic of formal concept analysis can be applied and it is possible to calculate with different types of conceptual scaling [2]. Using concept lattices based on Hasse Diagrams can become quite difficult from the user's point of view [11], since a geometric concept specification (as implemented in the Gärdenfors' conceptual space framework [6], for example) is not possible. Therefore, we propose to extend concept lattices as data layer by a Venn diagram as user interface layer. Both together form a unit that we call VennLattice. The integration of concept lattice and Venn and Euler diagram has already been described [11]. Users specify a concept using a Venn diagram, which is formalized into a valid concept lattice. Moreover, Venn diagrams can also be used to implicitly indicate features between concepts. This feature is important for domain exploration where features cannot normally be explicitly specified. The Venn

diagram as the user interface and the concept lattice as the data layer together form a single entity that extends the already proposed SCOP formalism.

In document search, there are several approaches to build a document ranking based on the SCOP formalism (e.g. [15]). Nevertheless, none of these approaches attempts to implement an emergent cognitive representation model. In this paper, we present a first architectural design of how Venn Lattice SCOP implementation can be realized in a case study of domain exploration.

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