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Exploratory study on cognitive information gain modeling and optimization of personalized recommendations for knowledge reuse

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ABSTRACT

Personalized recommendation for knowledge reuse provides a framework to share product knowledge such as assembly process, environmental impact and energy efficiency in manufacturing, in order to help engineers make their best decisions. It can reduce the search efforts of engineers and mitigate the encumbrance of information overload. However, traditional personalized knowledge recommendation method assumes that engineers differing characteristics—most notably their level of experience for simplify are the same. In this paper, we present a new method for handling personalized knowledge recommendation problem. A measurement model of cognitive information gain to predict the helpfulness of knowledge for engineers based on their level of experience is proposed. Knowledge is analyzed and helpfulness scores of knowledge are calculated by using the cognitive information gain measurement model. Then knowledge recommendations that are optimally helpful relative to engineers' experiences are generated. An example is used to depict the procedure of the proposed method. The example results show that the proposed method is effective and accurate in recommending knowledge that takes into account the level of engineer's experience.

1. Introduction

Digitization of knowledge management in manufacturing industries presents an opportunity for engineers to enhance communication and enable better informed decision making [1]. Personalized recommendation for knowledge reuse uses profiles built from past usage behavior to retrieve information of interest to engineers from a large repository. However, with the increasing complexity of product design and manufacturing, finding the appropriate knowledge is more and more difficult for engineers because (1) multiple knowledge areas are involved according to knowledge needs and engineer does not ascertain the knowledge areas in which his knowledge needs is and (2) the growing amount of knowledge makes engineers confuse and get lost in it [2]. Therefore, in contrast to finding knowledge passively, personalized recommendation for knowledge reuse has been adopted to find the required knowledge and recommend it to engineers.

During the last few decades, numerous papers have been published on knowledge recommending modeling and optimization. Lu and Tseng [3] proposed a novel method that combined the content-based, collaboration-based and emotion-based methods by computing the weights of the methods according to users' interests. Zhang et al. [4] presented an information gain-based model to predict the helpfulness of online product reviews, which suggested the most suitable products and vendors to consumers. Ortega et al. [5] proposed a method using Pareto dominance to perform a pre-filtering process eliminating less representative users from the *k*-neighbors selection process. Salehi et al. [6] proposed a hybrid recommender system for learning materials based on their attributes to improve the accuracy and quality of recommendation. Explicit attribute-based recommender and implicit attribute-based recommender were two main modules in the presented system. Qiu et al. [7] represent an adaptive neighbor recommender scheme for rapid sensor network configuration based on a knowledge model of sensor nodes about the locations of other nodes and the connections between them after deployment. Tejeda-Lorente et al. [8] proposed a new recommender system based on estimating the items' relevance. They developed a recommender system by using a fuzzy linguistic approach, which evaluated the item quality and took into account the evaluated values like a new factor to be considered in the recommendation process. Later, Tejeda-Lorente et al. [9] proposed a fuzzy linguistic approach. They measured the combination of item's relevance for a user with its quality and

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more profitable and accurate recommendations were generated. Tkalcic et al. [10] proposed a methodology for the implicit acquisition of affective labels for images based on an emotion detection technique that took as input the video sequences of the users' facial expressions. They employed a k nearest neighbors' machine learning technique to generate affective labels in the valence-arousal-dominance space.

Although recommendations can be quickly retrieved and listed, personalized preferences such as knowledge backgrounds are rarely considered and the great amount of recommendations makes engineers confuse and get lost in them. Considering such a feature, some researchers have discussed the variabilities between individuals and personalized recommendations are provided by analyzing their preferences. Pujahari et al. [11] proposed an approach to recommender system which learned rules for user preferences using classification based on decision lists. They developed two decision list based classification algorithms like repeated incremental pruning to produce error reduction and predictive rule mining, for learning rules for users past behaviors. Kim et al. [12] proposed a collaborative filtering method to provide an enhanced recommendation quality derived from user-created tags. They employed collaborative tagging as an approach in order to grasp and filter users' preferences for items. Hao et al. [13] proposed a mechanical product self-organized semantic feature evolution technology based designer's preferences. They linked the abstract semantic description, the semantic relative structure and the semantic constraint information axe together with semantic feature relation graph. Later, they [14] used matter-element, event-element and relation-element to characterize the feature information, connection constraint relations and topology variant operations of mechanical conceptual structures and established extensible composite-element model of product part to support personalized knowledge reuse. Wang et al. [15–17] presented a semantic-oriented framework of product knowledge retrieval and multidimensional knowledge integration model. Loepp et al. [18] proposed an approach to interactive recommending that combines the advantages of algorithmic techniques with the benefits of user-controlled, interactive exploration in a novel manner. They extracted latent factors from a matrix of user rating data as commonly used in collaborative filtering. Said et al. [19] presented an inverted neighborhood model to identify less ordinary neighborhoods for the purpose of creating more diverse recommendations. They used a standard k-nearest neighbor recommender as a baseline in both evaluation settings. Luo et al. [20] developed an NMF-based CF model with a single-element-based approach. They proposed the regularized single-element-based NMF model, which integrated the Tikhonov regularizing terms with the non-negative single-element-based update rules. Hernando et al. [21] presented a novel technique for predicting the tastes of users in recommender systems based on collaborative filtering. They factorized the rating matrix into two non-negative matrices whose components lied within the range [0,1] with an understandable probabilistic meaning in order to accurately predict the ratings of users.

Based on the above discussions, knowledge is recommended to engineers related to their inputs or design task in these studies. In terms of personalized recommending, researchers mainly focus on developing recommender systems for sales-related purposes. However, there is little extent that recommender systems developed for sales-related purposes can be relevant for design support. Moreover, there are very different knowledge needs between engineers, in terms of their knowledge backgrounds and levels of experience. For example, strength calculation formula is suitable for being recommended to new engineers and inexperience engineers, but its helpfulness to engineers who have high level of experience is limited. Therefore, a personalized knowledge recommendation method based on engineer's level of experience is proposed in this paper. The cognitive information gain of knowledge for engineers is measured. Knowledge is ranked by the method and an ordered list of knowledge with cognitive information gain estimates is generated. Helpful knowledge is recommended to engineer based on his level of experience. A lightweight design of CNC machine tool is used as an example to depict the procedure of the method.

The organization of the paper is as follows. Section 2 describes the measurement model of cognitive information gain of knowledge. In Section 3, the proposed personalized knowledge recommendation method is substantiated by a case study and further discussions on the comparison and applications of the method are provided. Finally conclusions and scope of the further study are given in Section 4.

2. The measurement model of cognitive information gain

For a given product design project, it can be decomposed into several design tasks and each design task is assigned to an engineer by workflow engine. The recommendation process for knowledge is designed to facilitate matching of required knowledge quickly and correctly for a requester of knowledge in activities of product design. In the methodology development, the following definitions are utilized:

- Knowledge: Knowledge is working for supporting product designs, which engineers call upon and use during the design process, such as design manual, design standards and design specifications.
- Knowledge category: Knowledge category is a set of knowledge that can be used to complete a design task.
- Knowledge unit: Knowledge units are provided as basic building blocks for representing and understanding existing knowledge.

In order to reduce the complexity, some assumptions are made as follows:

(1) Engineers are required to use Product Data Manage (PDM) system. Design task is assigned to an engineer by workflow engine of PDM system. PDM system keeps information of design tasks on record and stores it.
(2) Knowledge and knowledge units are stored in PDM system. Latest knowledge is regularly updated and knowledge units which knowledge contains are flagged at the same time.
(3) Knowledge requirements of design task can be flagged by selecting key words or knowledge units in PDM system when the design task is assigned.

2.1. Knowledge recommendation process model

For knowledge recommendation, let $C=\{c_1, c_2,\ldots,c_i,\ldots,c_m\}$ be the set of categories in knowledge space. Let $K=\{k_1, k_2,\ldots,k_l,\ldots,k_N\}$ be the set of knowledge and $U=\{u_1,u_2,\ldots,u_j,\ldots,u_n\}$ be the set of knowledge unit. Ontology is employed to establish profiles of design task, knowledge and knowledge unit [22]. Ontology supplies clear and complete knowledge and also facilitates designer intervention and customization during the design activities. A resource library is developed as a means for modeling and defining design task, knowledge and knowledge unit. Fig. 1 shows an example of knowledge "gear static strength check" based on ontology. Knowledge and knowledge units are stored in the meta database of PDM system and data structure is shown in Fig. 2.

The recommendation process for knowledge can be illustrated with an example shown in Fig. 3. As shown in Fig. 3, the knowledge requirement "*Angular_Velocity*" combines four knowledge units: