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The fuzzy cognitive pairwise comparisons for ranking and grade clustering to build a recommender system: An application of smartphone recommendation

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ABSTRACT

In a competitive high-end product market, many enterprises offer a variety of products to compete the market shares in different segments. Due to rich information of plenty of competitive product alternatives, consumers face the challenges to compare and choose the most suitable products. Whilst a product comprises different tangible and intangible features, consumers tend to buy the features rather than a product itself. A successful product has most features meeting the consumer needs. Perception values of product features from consumers are complex to be measured and predicted. To reduce information overload for searching their preferred products, this paper proposes the Fuzzy Cognitive Pairwise Comparison for Ranking and Grading Clustering (FCPC-RGC) to build a recommender system. The fuzzy number enables rating flexibility for the users to handle rating uncertainty. The Fuzzy Cognitive Pairwise Comparison (FCPC) is used to evaluate consumer preferences for multiple features of a product by pairwise comparison ratings. The Fuzzy Grade Clustering (FGC) is used to group the product alternatives into different consumer preference grades. To verify the validity and applicability of FCPC-RGC, a smartphone recommender system using the proposal approach is demonstrated how the system is able to help the consumers to recommend the suitable products according to the customers' individual preference.

1. Introduction

With rapid product launches from many enterprises to compete the shares in different market segments, consumers may face the challenges to explore and compare to find the most suitable products from the rich products information without sufficient market knowledge. The recommender systems perform the essential information retrieval tasks to recommend the appropriate items to the consumers. Review of recommender systems can be found in (Adomavicius and Tuzhilin, 2005; Bobadilla et al., 2013; Manouselis and Costopoulou, 2007; Burke, 2002).

There are three major categories of recommender systems: collaborative filtering (Goldberg et al., 1992; Herlocker et al., 2004; Shi et al., 2014), content-based filtering (Lops et al., 2011; Pazzani and Billsus, 2007), and hybrid approaches (de Campos et al., 2010; Salter and Antonopoulos, 2006; Pazzani, 1999). Collaborative filtering relies on the ratings from the other users to form patterns to predict a user's rating preference, whilst content-based filtering relies on items information with user ratings to make prediction, and hybrid filtering is the combination among these two methods and/or the other methods in different ways. Both collaborative filtering and content-based filtering have the drawbacks for the 'ramp-up' problems of new users and new items (Burke, 2002). In this paper, the proposed hybrid approach does not rely on the other users' rating history but the individual users' rating preferences to make recommendation results.

Since the high-end products are with short product life cycles, the classical approaches exploring historical data such as obsolete rating scores and products content may not be suitable to adaptively recommend the latest products. For the trending products, the recommender system should mainly consider the most recent data. Since a high-end product has many attributes (or features) perceived differently by diverse users, evaluating users' preferences with respect to multiple attributes is a complicated process. Multi-criteria decision making approaches have been used to evaluate users' preferences with respect to multiple attributes, for example, (Manouselis and Costopoulou, 2007; Adomavicius and YoungOk, 2007; Lakiotaki and Matsatsinis, 2011) . In this study, the Fuzzy Cognitive Pairwise Comparison (FCPC) (Yuen, 2009, 2014a) is used to evaluate the users' preferences for multi-criteria ranking and grade clustering in a product recommendation system. FCPC is the extension of the CPC (Yuen, 2009, 2012a, 2014b) with fuzzy sets.

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The FCPC (Yuen, 2009, 2014a, 2012a, 2014b) is used to elicit the users' preferences by comparing a series of the preferences of paired objects with fuzzy rating variables. An example of FCPC interface is shown in Fig. 2 in Section 2.4. With a reference object for paired comparisons, users' preference should be captured with better granularity. Conventionally, the direct rating with Likert scales and without the reference objects is the popular method for evaluation. Likert scales can be represented in fuzzy numbers. For example, (Cao and Li, 2007) demonstrated a direct rating method using fuzzy numbers to evaluate the consumer electronic products. The direct rating may not work better than the pairwise comparisons, as preference in nominal scale represented by direct rating scores may be relatively too subjective to be defined. Regarding a pairwise comparison approach, (Rokach and Kisilevich, 2012) demonstrated an approach using AHP's paired ratio scale (Saaty, 1977, 1980, 2005) for a recommender system; (Liu and Shih, 2005) integrated AHP, K-means clustering, and association rule mining in terms of recency, frequency, monetary (RFM) features for the product recommendations; (Işıklar and Büyüközkan, 2007) applied AHP and TOPSIS to evaluate mobile phones. However, there are a lot of debates for the inappropriateness of the AHP (Belton and Gear, 1983; Dyer, 1990; Forman, 1993; Belton and Goodwin, 1996; Forman and Gass, 2001; Gass, 2005; Whitaker, 2007; Bernasconi et al., 2010, 2011; Koczkodaj, 1993; Koczkodaj and Szwarc, 2014; Koczkodaj et al., 2016).

The FCPC is the core component of the Cognitive Network Process (CNP) (Yuen, 2009, 2014a, 2012a, 2014b) which is the ideal alternative of the Analytic Hierarchy Process (AHP) (Saaty, 1977, 1980, 2005) potentially producing wrong applications. The core idea of AHP relies on the paired ratio scale. The basic numerical definition of the paired ratio scale does not always appropriately represent the human intuitive judgement of paired difference, and thus CNP uses paired interval scale to replace paired ratio scale. The inappropriate definition of paired ratio scale for AHP follows the inappropriate Fuzzy AHP (FAHP), as the FAHP applies fuzzy number to the paired ratio scale. Extent Analysis Method (EAM) (Chang, 1996), the most popular approach for the FAHP, has been progressively applied in various areas, but relatively recent research (Wang et al., 2008; Wang and Chin, 2008; Yuen, 2012b) has showed the fallacy of the EAM.

The proposed Fuzzy Grade Clustering (FGC) method is used to efficiently cluster the data into ordinal grades such as low, medium, and high. The *k*-means clustering method (MacQueen, 1967) is widely used to cluster the data into different nominal groups. The *k*-means method, however, produces the local optimal clusters due to random initial centers. Inappropriate choices of initial centers lead to poor results by k-means. To address this issue, the k-mean process can be repeated many times to achieve the best cluster results, but a lot of computational workloads are required. In addition, the k-means method cannot adopt the fuzzy data and the factor weights are not considered. Fuzzy c-means (Dunn and Fuzzy, 1973)cannot deal with fuzzy input data, although it has the name "fuzzy", and in fact it is still a probabilistic method in the calculation process. The proposed FGC offsets the above shortages to grade the fuzzy weighted data in ordinal level to provide the better recommendation results.

The rest of this article is organized as follows. Section 2 proposes the novel Fuzzy Cognitive Pairwise Comparison for Ranking and Grade Clustering (FCPC-RGC) for recommender systems. Section 3 presents the validity and applicability of the proposed hybrid method. Section 4 concludes the notion of the FCPC-RGC.

2. Fuzzy cognitive pairwise comparison for ranking and grade clustering

The framework of the proposed Fuzzy Cognitive Pairwise Comparison for Ranking and Grade Clustering (FCPC-RGC) is illustrated in Fig. 1. A product of mixed features can be organized as a feature specification. According to the feature specification served as data schema, the items data are fetched from various sources such as mobile retailers, company engineers and customers. As some feature values are with uncertainty,

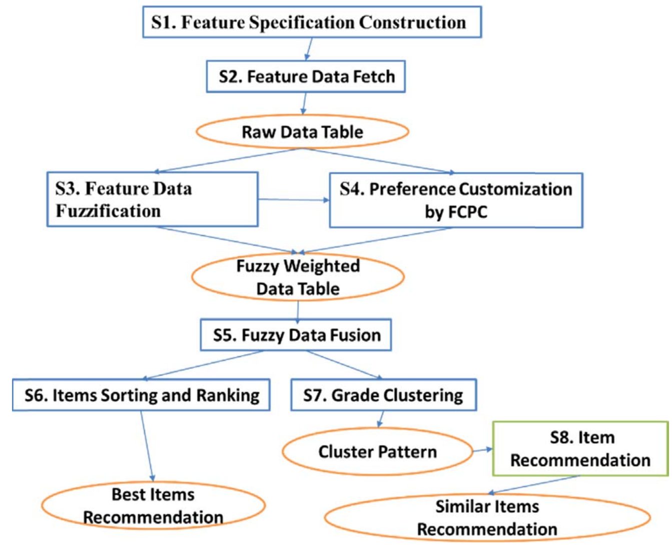

Fig. 1. Framework of FCPC-RGC.

their crisp values could be converted to fuzzy numbers by some fuzzification functions. Since different consumers perceive the feature values differently, the customer preference customization by Fuzzy Cognitive Pairwise Comparison (FCPC) is to elicit the current consumer preference on the feature weights and nominal feature values.

From steps 1–4 in Fig. 1, the multidimensional raw feature data table is produced and fuzzified as the fuzzy weighted data table, which is further aggregated into the single dimension data, a vector of Fuzzy Item Values (FIVs). To sort and rank items with FIVs, the best items are recommended in descending order. With taking FIVs to calculate the similarity by Grade Clustering algorithm, grade patterns are derived and can be used for recommendation. The details of each step of the FCPC-RGC are presented as follows.

2.1. Feature specification construction

When a new high-end product launches with new features introduced, customers may have no or little knowledge to the new features. The feature specification of the new product is designed and evaluated by enterprise domain experts. A product item comprises a set of features $\hat{\beta} = (\hat{\beta}_1, \ldots, \hat{\beta}_i, \ldots, \hat{\beta}_N)$. Subject to the complexity of the item features structure, the item features can be organized as a hierarchical tree structure. Features in different levels are represented by nodes. A feature $\hat{\beta}_i$ has a set of $\hat{\beta}_i$'s sub-level features $\left(\hat{\beta}_{i,1}, \ldots, \hat{\beta}_{i,j}, \ldots, \hat{\beta}_{i,N_i}\right)$, and an sub-level feature $\hat{\beta}_{i,j}$ has a set of $\hat{\beta}_{i,j}$'s sub-level features $\left(\hat{\beta}_{i,j,1}, \ldots, \hat{\beta}_{i,j,k}, \ldots, \hat{\beta}_{i,j,N_{i,j}}\right)$. An example of the feature specification of smartphone is illustrated in Fig. 3 in Section 3.

2.2. Feature data fetch

The features organized as a hierarchical tree with several levels of nodes are regarded as a data scheme to fetch data. The internal nodes have the subordinate nodes whilst the external nodes are the leaf nodes without subordinate nodes. For each item, data for the measurable feature indicators$(c_1, \ldots, c_j, \ldots, c_N)$ located in the external nodes are fetched. Feature values in internal nodes are computed by using the measurable feature data. A raw data table of M item sets of N measureable features $\{r_{kj}: k = 1, \ldots, M; j = 1, \ldots, N;\}$ is created to structure the item data.

2.3. Feature data fuzzification

The raw data table $\{r_{kj}\}$ may contain crisp, nominal, ordinal and/or

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