Dynamic Generation of Personalized Product Bundles in Enterprise Networks

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Abstract. Product bundling is a marketing strategy that concerns offering several products for sale as one combined product. Current technology mainly focuses on the creation of static bundles, which involves pre-computing product bundles and associated discounts. However, due to the inherent dynamism and constant change of current and potential customer information, as is particularly the case in enterprise networks, static product bundles prove to be inefficient. In this paper an approach for dynamic generation of personalized product bundles using agents is proposed. Our approach involves creating bundles based on substitution and complementarity associations between product items, and subsequently ranking the produced bundles according to individual preferences and history of each customer. The proposed approach has been implemented in e-Furniture, an agent-based system supporting networking of furniture and wood product manufacturing enterprises.

Keywords: Product Bundling, Personalization, Agent-Based Systems, Enterprise Networks.

1 Introduction

Retailers often encounter situations where a customer has expressed interest in a product or service but wants to negotiate a lower price, for example, a price that is more "market competitive". Such negotiations require sellers to quickly decide on how to lower the price for the product without taking a loss and offer attractive alternatives to the customer [1]. Moreover, the Internet has emerged as a new channel for distribution of information concerning actual and digital products reaching a vast customer base. However, providers of online product information have difficulties as to how to price, package and market them and struggle with a variety of revenue models [2]. Finally, it is quite common to combine products from different suppliers whose availability and price varies dynamically as is often the case in enterprise networks [3]. For example, it is common for shippers in logistics networks to collaborate and combine their shipment requests in order to negotiate better rates and in the food

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industry for businesses to combine products, such as organic cold meat and wines, in order to increase their sales.

A common approach to address the above issues is *"bundling"*, which involves combining additional products or services that may be of interest to a customer in lieu of lowering the price for the initial item of interest [1]. For instance, sporting and cultural organizations offer season tickets, restaurants provide complete dinners, and retail stores offer discounts to a customer buying more than one product [4]. Generally, a bundle represents a package that contains at least two elements and presents a value-add on to potential consumers. The creation of such bundles with superior characteristics over individual item offers has long been recognized as an opportunity for companies to increase their competitive advantages in the market [5].

The objective of this paper is to introduce an approach for dynamic generation of personalized product bundles in enterprise networks. The proposed bundles include a primary product item determined from user preferences and additional complementary items that are estimated to offer more utility to the user [6]. Personalization is achieved by ranking the proposed bundles according to user preferences and usage history. The remainder of this paper is structured as follows. In section 2 we provide an overview of the e-Furniture project, while in Section 3 we describe our dynamic product bundling approach. A discussion about preliminary evaluation results is provided in Section 4. Finally, we discuss conclusions and further work in Section 5.

2 The e-Furniture Project

Aiming to support 'smart' collaboration in furniture and wood product enterprise networks the e-Furniture system [7] involves an agent-based infrastructure capable of bundling products and services taking into account individual requirements of both manufacturers and customers. e-Furniture covers both B2B transactions and B2C transactions, targeting economies of scale and profit increase for providers, and increased satisfaction for customers.

A main objective of e-Furniture is to provide assistance in typical purchasing decisions involving product bundles. Bundling products of different providers is a key technique for SME's to increase their range of offered products and hence increase customer satisfaction. In the case of smart business networks in particular, product bundles can be created dynamically according to customer requirements and the solutions offered by the partners in the business network.

The e-Furniture infrastructure is an open system viewed as a grid of distributed interconnecting partner nodes, as shown in Fig. 1. A designated node acts as main coordinator for all other nodes by storing network wide customer and product information, by intermediating to establish communication for new partner nodes joining the network, and by resolving conflicts that may arise.

We have adopted an agent-oriented view in designing the e-Furniture software architecture and all main operations and interfaces are driven by software agents. Upon registration and joining the network, participating companies provide product catalog

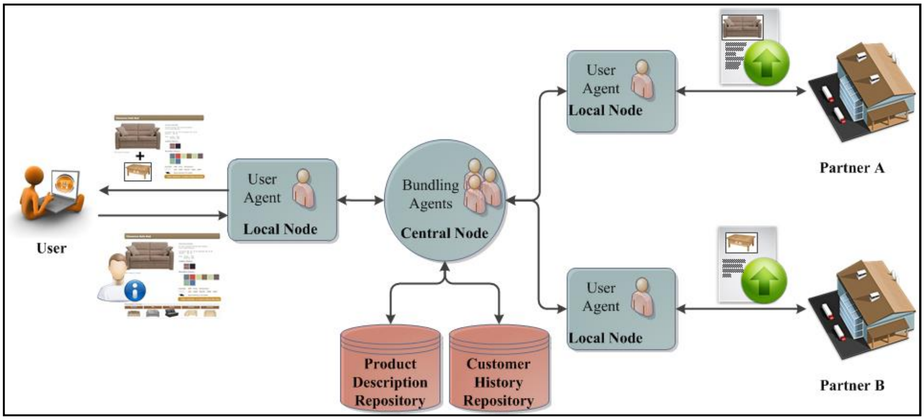


Fig. 1. High-level architecture of the e-Furniture system

descriptions which are uploaded automatically to the main e-Furniture node server. Both business and retail customers connect to the server storing their profile and preferences and navigate searching for products of their interest. In response, a number of e-Furniture agents interact dynamically and the system finally returns a number of product bundle recommendations targeting the particular user characteristics.

3 Dynamic Product Bundling

3.1 Overview

The research area of networked enterprises represents a complex, large scale and multidisciplinary domain, involving distributed, heterogeneous, and autonomous entities [8, 9]. Agent technology provides a natural way to design and implement such enterprise-wide manufacturing environments for distributed manufacturing enterprises. In particular, the multi-agent system (MAS) approach is ideally suited to represent problems that have multiple problem-solving methods, multiple perspectives and/or multiple problem-solving entities [10]. Therefore, we propose an agent-based architecture for integrating information in this highly distributed environment in order to dynamically generate personalized product bundles.

The main features of our approach include extraction of substitution and complementarity associations between products and use them to generate bundles, and ranking the produced bundles based on individual customer historical data. Substitution associations reflect the degree to which two products are similar and can substitute each other. Complementarity associations reflect the degree to which an item enhances the purchasing possibility of another when offered together in a bundle. A more detailed description of the proposed approach is provided in the following sections.

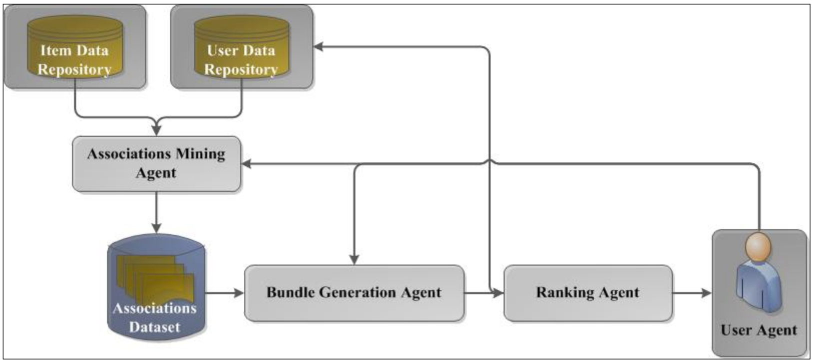


Fig. 2. Agent interactions for dynamic generation of product bundles

3.2 Bundling Multi-Agent System Architecture

The proposed agent system architecture comprises of four basic types of agents, which interact in order to generate and customize personalized product bundles (Fig. 2). Specifically, the proposed architecture includes the following agent types:

- **Associations Mining Agent** (AMA), which is responsible for the generation of associations and relationships between products. It accepts as input the users' historical data and product information, and extracts the substitution and complementarity associations between the products by executing the Associations Mining Algorithm (cf. Sec. 3.3). Subsequently, the collection of associations is stored in tabular form in a structure termed 'associations dataset'.
- **Bundle Generation Agent** (BGA), which accepts as input the associations dataset created by AMA and generates a list of product bundles using the Bundle Generation Algorithm (cf. Sec. 3.4).
- **Ranking Agent** (RA), which accepts as input the list of proposed bundles and based on the user purchase history stored in e-Furniture repository, it executes the Ranking Algorithm (cf. Sec. 3.5) and creates a personalized list of bundles for the respective user.
- **User Agent** (UA), which implements the user interface.

3.3 Associations Mining Agent

AMA detects substitution and complementarity associations between product items in the system repository. Substitution associations are measured by the substitution score which takes values in the range [0,1] and reflects the degree to which two items are similar and can substitute each other. An example of substitutable items could be two different wireless handheld devices that have similar features but are offered by different broadband providers. On the other hand, complementarity associations reflect the degree to which an item enhances the purchasing possibility of another when offered together in a bundle. For example, complementary items for a wireless handheld device might be a wireless plan, a subscription to some broadband provider or a carrying case.

Initially, AMA identifies the primary product items drawn from the product repository either based on a user request or automatically according to predefined settings, such as identifying items with highest sales at regular time intervals or during off-peak processing times. Primary product items can also be identified by users by selecting items from particular product categories. For example, if bundles having as a primary item a sofa are to be generated, the bundle mining system can select the primary product items from the sofa category of products. Furthermore, primary items can also be identified by using one or more keywords in a search, such as 'sofa' or 'three seated', or they can be a product item that the user has explicitly selected.

Subsequently, AMA generates the substitution associations between the primary items by performing an analysis of their attributes, for example by using the cosine similarity measure [11] or a semantic similarity comparison method such as the one proposed in [12]. Items that have more attributes in common have stronger substitution associations and they are given higher association scores, while items that have fewer attributes in common receive lower scores or an association may not be created for them at all. For example, two wireless handheld devices with touchscreen and Wi-Fi connectivity have higher substitution score than two wireless handheld devices with touchscreen but where only one of them has Wi-Fi connectivity. In the proposed approach, we use the cosine similarity metric to compare products considering that each item's attributes are defined in free textual descriptions.

After having determined the substitution associations between primary items, AMA generates the complementarity associations between each primary item and one or more complementary items. Complementarity associations are measured by the complementarity score which takes values in the range [0, n], where n is the total number of customer usage history recordings in the system repository.

Algorithm 1. Mining product associations

```
Require: ItemsNumber, ItemtoSearch
Ensure: SubstDataset, CompleDataset
for i=0 to ItemNumber do
PrimaryItems ← search_primary_items(ItemtoSearch)
end for
for i=0 to ItemNumber do
    for j=0 to ItemNumber do  //calculate using cosine similarity
    SubstDataset ← calculate_substitution_associations(PrimaryItems)
    end for
end for
for i=0 to ItemNumber do
    while next in purchase history do //calculate using Apriori algorithm
    CompleDataset ← calculate_complementarity_associations(PrimaryItems)
    end while
end for
```

Complementarity associations can be created between items that were purchased together, a method known as Market Basket Analysis [13]. For example, users who purchase a certain type of a wireless handheld device tend to purchase certain accessories and service options in a single transaction. Moreover, complementary items may also be limited to certain categories, such as ‘headsets’ and ‘car kits’. Such associations can be commonly identified using association rule mining algorithms, such as Apriori [14], AprioriTid [15] and Eclat [16]. In our approach, we currently employ the Apriori algorithm because it has wide popularity and it is easy to implement.

Finally, AMA stores both substitution and complementarity associations in an associations dataset. The association mining steps are presented in Algorithm 1.

3.4 Bundle Generation Agent

BGA dynamically creates product bundles corresponding to product items selected by users by considering the substitution and complementarity product information stored in the associations datasets created by AMA.

Firstly, BGA identifies the primary product item selected by a user, and retrieves additional product items from the substitution dataset that have a substitution association with the identified primary item. A subset of these substitutable items is then retained in a substitutable product dataset by selecting a specific number of items with highest substitution association scores.

The next step for BGA is to search in the complementarity associations dataset for product items that have complementarity associations with the selected primary item and the selected substitutable items. A subset of these complementary items is then retained in a complementary product dataset, by retaining a specific number of items with highest complementarity association scores. For example, a user can select a wireless handheld device A and based on the substitution dataset BGA can identify as substitutable item a wireless handheld device B. Based on these two devices, BGA will then search in the complementarity dataset to find complementary products, for example those having complementarity score to either device A or device B above a given threshold, and can identify a headset and a carrying case for instance.

As a next step BGA creates product item bundles by combining the selected complementary items with the primary item and a number of substitutable items, considering all possible combinations. For example, two complementary items and a

Algorithm 2. Bundle generation

Require: ItemNumber, SelectedItem, SubstDataset, CompleDataset
Ensure: BundleList
for i=0 **to** ItemNumber **do**
    Substitute ← find_substitutes(SelectedItem, SubstDataset)
    Complementary ← find_ complementary(SelectedItem, CompleDataset)
end for
for i=0 **to** ItemNumber **do**
    BundleList ← bundle_items(SelectedItem, Substitute, Complementary)
end for

Algorithm 3. Ranking selected bundles

Require: BundleList, BundleNumber, CustomerHistory
Ensure: RankedList
for i=0 **to** BundleNumber **do**
    Affinity ← affinity(CustomerHistory, BundleList)
end for
for i=0 **to** BundleNumber **do**
    RankedList ← rank_items(Affinity, BundleList)
end for

substitutable item can form a bundle. In the aforementioned wireless handheld devices example the substitutable item is the wireless device B, and hence a bundle generated by BGA could include wireless device B together with the headset and carrying case.

Finally, the proposed bundles are forwarded to RA to be ranked according to user profile. The bundle generation steps are described in Algorithm 2.

3.5 Ranking Agent

RA is responsible for the personalization of the proposed bundles created by BGA, and ranks them according to each user's browsing and purchase history. Ranking is based on the concept of affinity of a customer C for purchasing a pair of products $\{P_i, P_j\}$, which has been introduced by Batra et al. in [1]. The Affinity index is a measure of the degree of a customer C preferring a particular product tion $\{P_i, P_j\}$, and can be calculated using the following formula:

$$Affinity(C, \{P_i, P_j\})$$
$$= Compatibility(\{P_i, P_j\}, R_c) * \max(Affinity(C, \{P_i\}), Affinity(C, \{P_j\}))$$

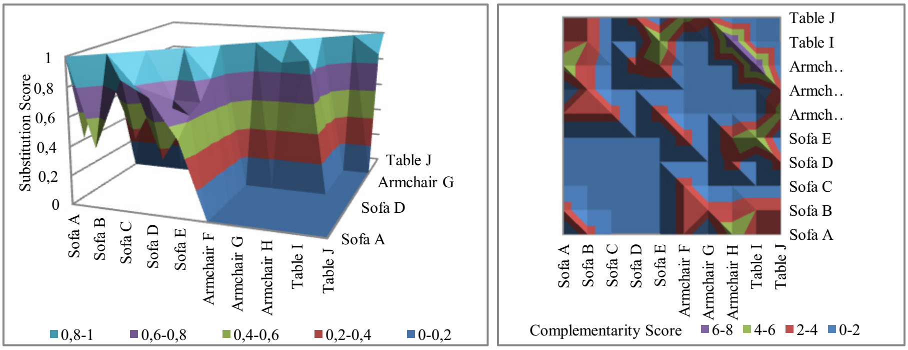
where R_c is a subset of R containing only the transactions and browsing data of customer C and $Compatibility(\{P_i, P_j\}, R_c)$ is a measure of preference of customer C for the particular pair $\{P_i, P_j\}$. The value of compatibility between a customer C and a pair of items $\{P_i, P_j\}$ can be estimated as the times customer C has viewed or inquired information online or purchased both P_i and P_j.

For a single product, $Affinity(C, \{P_i\})$ can be calculated using the following formula:

$$Affinity(C, \{P_i\}) = \frac{Support(P_i)}{\max(Support(P_m))}$$

where P_m refers to all products selected or purchased by customer C, $Support(P_i)$ expresses the number of times customer C has selected or purchased product P_i and $max\ (Support(P_m))$ expresses the maximum number of the times customer C has selected or purchased a particular product.

The produced product bundles list is then sorted in decreasing order of the calculated Affinity index. Finally, a subset of the ranked bundle list, for example a predefined



(a) (b)

Fig. 3. Substitution (a) and complementarity (b) pairwise association indices (10 products)

number of highest rank bundles, is selected and presented to the user. The steps for ranking product bundles are described in Algorithm 3.

4 Discussion

The proposed approach has been implemented in the e-Furniture system and we are currently experimenting with customer transaction data obtained from the partner individual web sites and ERP systems. For an indicative sample of 10 representative furniture products the viewing and transaction behavior of 5 representative registered customers resulted in the substitution and complementarity associations shown in Fig. 3. We only considered substitution associations between items in the same category, only between sofas for instance, and we used the cosine similarity measure to generate the substitution associations.

Table 1. List of the proposed and personalized product bundles for customers A and B

Bundle	Non-personalized Bundle List	Total Score	Ranked for Customer A	Affinity for Customer A	Ranked for Customer B	Affinity for Customer B
1	Sofa D Armchair H	4	Sofa E Armchair H	3	Sofa A Armchair H	4
2	Sofa D Table J	4	Sofa A Armchair H	1,33	Sofa A Table J	1
3	Sofa E Armchair H	3,8	Sofa E Table J	1	Sofa D Armchair H	0,57
4	Sofa E Table J	3,8	Sofa D Armchair H	0,67	Sofa E Armchair H	0,57
5	Sofa A Armchair H	3,77	Sofa D Table J	0,67	Sofa D Table J	0,29
6	Sofa A Table J	3,77	Sofa A Table J	0	Sofa E Table J	0

As an exemplar bundling scenario we considered two customers, A and B, both selecting to view sofa D. Based on the substitution and complementarity relations depicted in Fig. 3 a non-personalized product bundle list was created (Table 1) where bundles are ranked according to their total score as proposed in [6]. The total score is the algebraic sum of the substitution and complementarity scores and takes values in the range [0, n+1]. Finally, the Affinity index of each bundle was calculated based on customer historical data and the final personalized product bundles for customers A and B were created as shown in the third and fourth columns of Table 1 respectively.

As can be seen from Table 1 the ranking of the product bundles generated with our approach is different for each customer. This is because the preferences of customers A and B for the respective bundles, expressed in terms of the respective affinities, differ considerably. For example, sofa D and armchair H would be the first proposal according to [6] where no personalization takes place. However, according to each customer's historical data, reflected in the values of the respective affinity indices, customers A and B seem to have higher preferences for sofas E and A respectively. Our proposed approach takes this into account by ranking first the bundles comprising sofa E and sofa A for customers A and B respectively. Consequently, since our ranking is based on the affinity of each individual customer the ranked bundle lists produced with our proposed method are more likely to match customer preferences.

5 Conclusions

In this paper we introduced an approach for dynamic generation of personalized product bundles in enterprise networks using agents. The created bundles include a primary item, obtained either by explicit user input or from a generated substitution list, and a number of complementary items selected from a generated complementarity list. The produced bundles are then personalized by ranking them for each user based on individual user data.

The initial results look promising and we now plan to carry out extensive evaluation of our approach by comparing the results with other approaches and test its acceptance through the users' feedback. An issue that needs to be addressed is the complexity incurred when product numbers and features increase. We plan to address this by employing approximation methods for similarity matching and complementarity identification. Furthermore, an issue of concern is the lack of actual transaction data for new customers and partners in the network. Therefore, we plan to explore methods to personalize the generated bundles for customers lacking historical data, for example by using data from customers with similar profiles. Finally, in our current work bundling is based only on product information stored in a central repository. Additional research issues arise when considering obtaining product information directly from partner distributed repositories, including semantic compatibility of product representations and performance of distributed product searches.

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