Business Recommender Systems

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Besides the typical applications of recommender systems in B2C scenarios such as movie or shopping platforms, there is a rising interest in transforming the human-driven advice provided, e.g., in consultancy via the use of recommender systems. There are two main classes of recommender systems: information-filtering-based and knowledge-based systems. The former category selects items from a large collection of items based on user preferences and is further classified as collaborative-filtering recommenders and content-based filtering recommenders. The knowledge-based recommenders make recommendations by applying constraints or similarities based on domain or contextual knowledge. Common applications are in B2C scenarios such as e-commerce, tourism, news, movie, music, etc.

recommender systems | business recommender systems | consultancy | B2B recommendations | digital consultancy service

1. Introduction

Digitalisation leads to a transformation of internal business processes but also very notably of customer-facing services, while most attention is paid to services in the B2C domain, there is also a rising interest in digitalising knowledge-intensive services in the B2B domain, such as consultancy in general [1] and IT consultancy in particular [2]. Such transformation implies that a digital service (partially) takes over the role of a human consultant and that companies can use that service to help themselves to the required advice.

Obviously, such digital services will be able to give advice only for restricted domains; often, advice will consist of recommending items from a predefined set of solution components. Thus, digital consulting services can be thought of as recommender systems.

2. Business Recommender Systems

A recommender that suggests solution components to companies is different in several ways from the typical B2C recommenders that help users in finding, e.g., books, movies, or music that fit their preferences (see also [3]):

- Requirement-driven: A consultancy recommender needs to consider business requirements not personal preferences;

- Interdependent items: The recommended items are not simple, atomic and independent products (such as books, movies etc.) but interdependent and sometimes complex components of a larger solution;

- No profiles: While typical B2C recommenders are used repeatedly by the same person, a digital consultancy service has no chance to build up customer profiles through repeated interactions; companies will usually access the service only once. Thus, a profile of the company needs to be acquired within a single session by the recommender; one can regard it as forming a *query* that describes the situation of the company seeking advice.

Despite some of these differences, one can establish a "digital consultancy process" that will make it possible to apply traditional recommender techniques that have been designed for classical preference-based B2C scenarios. Such a process is based on the following considerations (see also **Figure 1**):

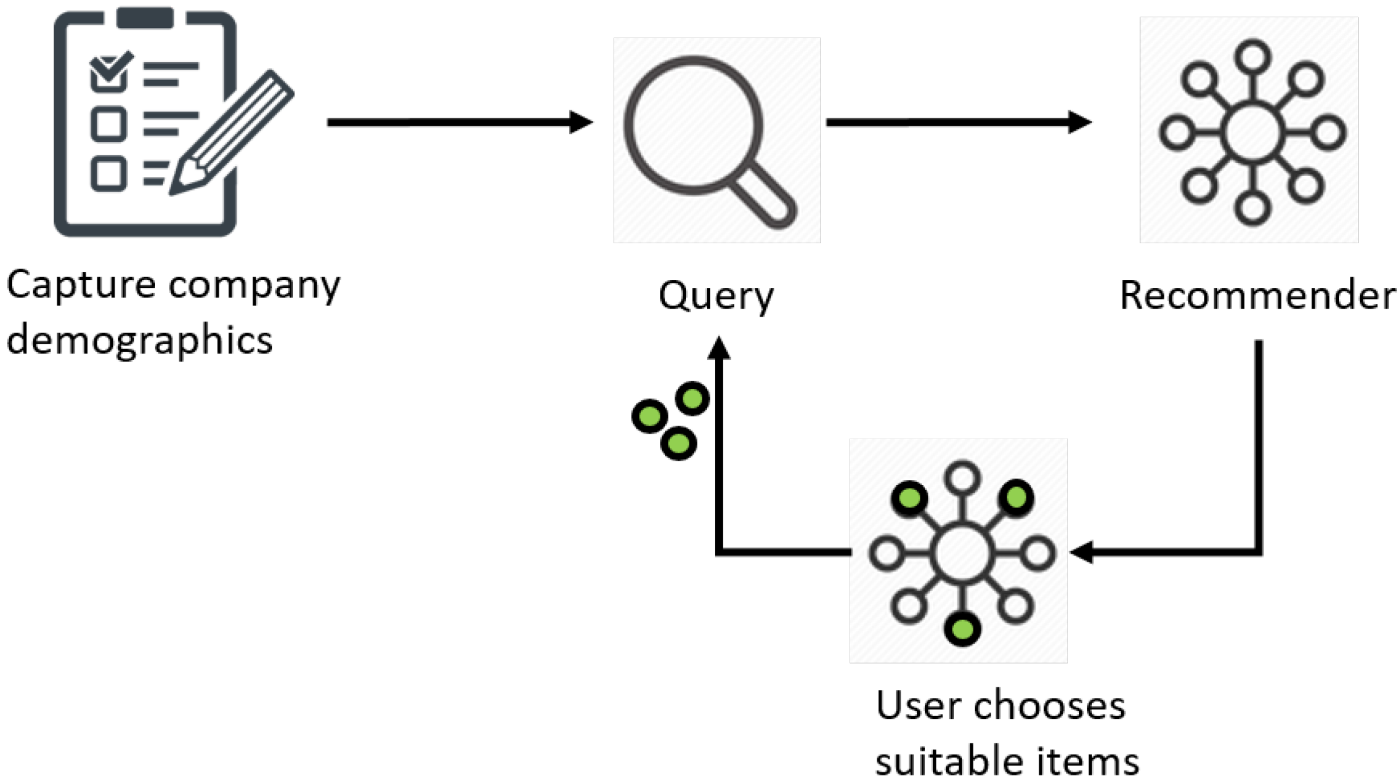

Figure 1. Iterative process for business consultancy recommenders.

- Many companies share the same requirements, just like many persons share preferences. The similarity of requirements often depends on the companies' demographics (e.g., size, industry, etc.). Thus, a first step in the digital consultancy process may be to capture company demographics and regard them as an initial company profile or **initial query**. This allows establishing a certain similarity between companies from the beginning.

- Later, the similarity of context and requirements manifests itself in accepting similar suggestions from the recommender. Since solutions will be complex, one may construct a repeated interaction with the recommender in the form of iterations: after entering the company demographics (step 1), the business user receives a first set of recommendations and selects from those some first elements of a solution. These elements are added to the initial company profile to form an **extended query**, and the recommender is invoked again. This process is repeated, each time with a more verbose query.

Following this iterative process will allow scholars to assess the *similarity* of company contexts by comparing queries of a company to those of previous users of the service, with an increasing degree of accuracy as the query is iteratively extended. Since similarity is at the heart of both content-based and collaborative filtering approaches [4], being able to assess similarities is an important prerequisite for applying these approaches. In addition, scholars build up company profiles during the process, which makes it possible to apply content-based filtering. The iterative refinement also makes it possible to take into account the interdependence of solution elements by identifying, in each new step, new elements that fit to the already selected elements.

Although collaborative and content-based filtering become applicable through the iterative process, they may not be the best choice because a) collaborative filtering does not lend itself readily to incorporating company demographics (or other forms of general context) and b) because both do not foresee the use of human-provided knowledge about the business domain, which might be helpful. In fact, previous research has argued for the use of case-based reasoning (CBR) in business recommenders [5] because CBR is a proven way of re-using solutions for business problems. Constraint-based recommenders [3] are another family of algorithms that have been put forward as a good way of satisfying business requirements.

2.1. Digitalisation of Consultancy Services

Digitalising consultancy services has been discussed recently [6]. For the domain of IT consulting, a “computer-executed consulting (CEC) service” is proposed by Werth et al. [2], which replaces, most notably, the two steps of (a) interviewing client representatives and (b) creating a report that summarises the interview results. The digital service is designed by human consultants and consists of (a) a series of questionnaires (replacing the interviews) and (b) an automated report creation module. Obviously, there is a rough correspondence between these components and the step of (a) formulating a query and (b) getting recommendations for that query in **Figure 1**. The proposed CEC service is general-purpose. Therefore, although it mentions the need for more intelligence in the report creation module and the option of using recommender systems, it does not discuss any details of how to use recommenders.

The application of recommender systems has been discussed for more specific consultancy tasks such as optimisation of product assortments [7], selection of cloud or web services [8][9][10], or adaptation of conditions in agriculture [11]. In all these cases, the set of possible items that can be recommended is known and well-defined, and the task consists of selecting and possibly orchestrating the items. In its simplest interpretation, the term “orchestration” simply means that the selected services should be well aligned with each other, e.g., for optimal cross-selling opportunities [7] or for obtaining a consistent complex cloud service configuration [10].

2.2. Business-Oriented Recommendations

With regard to recommender algorithms, business-oriented recommender systems have to deal with **complexity** in terms of company contexts (input) and solutions (output). Attempts to deal with such complexity can be divided into several categories:

- *Augmentations of content-based filtering:*

  Approaches in this category model both the input and output complexities and establish the degree to which both of them match. For instance, constraint-based recommenders [3][12] help model product features and constraints to be expressed about them and then ensure constraint satisfaction. Other approaches use tree-like structures to model items and user preferences [13] or use multiple levels on which queries and items are matched (such as recommending first providers and then actual services in a service recommender [14]).

  In content-based filtering, additional knowledge can be incorporated, e.g., into the function that determines the similarity between an item and the user profile. Often, this is knowledge about user context, item features and/or domain-specific constraints. For instance, refs. [15][16] use ontologies to represent and reason about item features and to apply this knowledge in a sophisticated similarity measure that takes into account “hidden relationships” [16]. Middleton et al. [17] use an ontology to represent user profiles and engage users in correcting the profiles before assessing profile–item similarities. The complexity of business contexts has also been highlighted in [18], where the authors focus on identifying the criteria for recommendations in business processes that will serve as inputs to knowledge-based recommenders.

- *Augmentations of collaborative filtering:*

  Case-based recommenders [5][19] can be seen as a special form of collaborative filtering since they recommend items used in solutions of companies that are similar to the current company. However, instead of only considering already chosen items, case-based recommenders’ similarity measures take into account context variables that describe, e.g., company demographics and other relevant aspects of the company’s problem and/or initial situation.

  Since case-based reasoning is an approach based on problem-solving from past experience, case-based recommenders have been implemented in domains that most benefit from contextual information coming from past experience. For example, [20] explored case-based recommenders to recommend personalized financial products to the customers of a banking organisation. The authors of [21] argue that case-based recommenders are much more suitable for a complex domain of smart-city initiatives as they can utilize a rich range of domain-specific attributes.

- *Graph-based recommenders:*

> Recommender algorithms based on graph structures [22][23][24] have been put forward because of their ability to accommodate a wide variety of forms of contexts in a flexible way without much effort. Random walks [25][26][27] are a predominant type of algorithm to provide recommendations based on graph structures. Because of their simplicity, graphs also have limitations, e.g., in modeling and matching simple string-valued attributes of input cases or in modeling certain forms of complex solution structures. The possibility of using graph-based recommenders to “mimick” traditional recommender approaches, such as collaborative or content-based filtering, has been explored by Lee et al. [28]. For this, one needs to assign different weights to different types of graph relations.

Obviously, all of these approaches employ and model various types of knowledge. An overview of the different kinds of knowledge that recommenders may use can be found in [3][29]. What distinguishes the business recommenders from most others is the use of *domain knowledge*. Often, this knowledge is obtained from human experts [3][29][30].

2.3. Evaluation of Business-Oriented Recommenders

It is important to evaluate the performance of recommenders, more so when the recommendations are expected to be comparable to those of human experts. A common and popular metric for recommender evaluation is accuracy. Herlocker et al. [31] classify recommender accuracy into three categories: predictive accuracy, classification accuracy and rank accuracy. However, accurate recommendations may not always indicate useful recommendations. Hence, recommenders may be evaluated based on additional metrics such as diversity, novelty, coverage, serendipity, etc. [32][33]. Some of these metrics are subjective to user preferences and are used to improve user engagement in B2C scenarios.

In the context of B2B recommendations, however, not every metric is relevant. For IT consultancy, for instance, the recommendations are dependent on the domain of the customer, and accuracy in terms of ranking the recommendations is more value-adding for the customers than providing novel or diverse suggestions. Consequently, an item should always be added to the recommendations if it is *relevant*, even if it is not *novel*. The customers expect the recommender to provide recommendations ordered by relevance and usefulness, with the most relevant suggestions at the top. The top recommendations then can be iteratively tuned by adjusting the input to the recommender (query). Thus, for the evaluation of the recommender outputs, scholars adopted the relevance judgement approach to evaluate *rank accuracy* using the metric Mean Average Precision (MAP) [34]. MAP is commonly used to evaluate the quality of ranking by calculating the average precision at every rank for a query and then computing the mean of all average precisions for all the queries. Metrics such as diversity and coverage may be relevant in occasional cases, e.g., for customers from a new industry (not considered in past consultations) or customers that expect non-standard solutions.

2.4. Hybrid Recommenders

Forming hybrid recommenders [35][36] is an active field of research since combinations of different approaches can often help to combine the strengths and/or avoid the weaknesses of the combined approaches. For instance, content-based filtering can be combined with collaborative filtering, e.g., to mitigate the so-called cold-start problems associated with collaborative filtering, i.e., problems with recommending newly introduced items or serving new users: new items can be recommended immediately by content-based techniques as long as they have a meaningful description that can be matched against user profiles. Besides cold start problems, hybridisation can be used, e.g., to augment similarity in collaborative filtering with the reasons behind user preferences and thus give it a stronger CBR flavour [37]. Another motivation for using hybridisation is to improve the quality of recommendations. For example, Rivas et al. [38] combine CBR recommendations with multi-agent systems to improve the accuracy of recommendations. Further possible complementary strengths and weaknesses of knowledge-based and knowledge-weak recommenders are discussed in [39].

In order to effectively combine the strengths of individual recommendation techniques, Burke [35] has proposed seven different hybrid strategies: weighted, mixed, switching, feature combination, cascade, feature augmentation and meta-level. These strategies are still being successfully applied to address various problems in recommender systems. For instance, Rebelo et al. [40] have used the cascade strategy to improve the *novelty* and *diversity* of recommendations; Alshammari et al. [41] have applied the switching strategy to address the problem of *long-tail recommendations*; Hu et al. [42] have combined algorithms in a cascading fashion to improve the *personalization* of recommendations; and Gatzioura et al. [43] have implemented a meta-level hybrid recommender to explore metrics such as *coherence* and *diversity* in music recommendations.

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