Flexible Recommendations over Rich Data

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ABSTRACT

CourseRank is a course planning tool aimed at helping students at Stanford. Recommendations comprise an integral part of the system. However, implementing existing recommendation methods leads to fixed, pre-specified recommendations that cannot adapt to each particular student's changing requirements and do not help exploit the full extent of the available learning opportunities at the university. In this paper, we describe the concept of a flexible recommendation workflow, i.e., a high-level description of a parameterized process for computing recommendations. The input parameters of a flexible recommendation process comprise the "knobs" that control the final output and hence support flexible recommendations. We describe how flexible recommendations can be expressed over a relational database and we present our prototype system that allows defining and executing different, fully-parameterized, recommendation workflows over relational data. Finally, we describe a user interface in *CourseRank* that allows students to make use of two flexible recommendation workflows.

1. INTRODUCTION

Recommendation systems, such as Google News [10], Amazon [15] and MovieLens [17], are popping up everywhere, to provide advice on movies, travel, and leisure activities. The systems help users sort through the huge amounts of available data, and receive content and services that are of interest to them. Since the appearance of the first recommendation systems [11, 19, 21], many approaches have been proposed both by the industry and academia. However, most recommendation methods *perform on the basis of assumptions 'hard-wired' into the system and they support only a predefined and fixed set of recommendations which may not always capture the real-time user information needs* [4]. Giving the end-user the ability to customize their recommendations may be very important in order to provide more accurate, personalized recommendations. For example, *CourseRank* is a course planning tool for Stanford University students that helps students choose courses. Recommendations comprise an integral part of the system. Providing only fixed recommendations does not help build personalized plans that are customized to each particular student's changing requirements and exploit the full extent of the available learning opportunities the university offers.

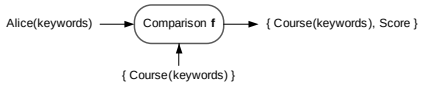
1.1 The CourseRank System

Traditionally, university students base their schedules on word-of-mouth knowledge and the brief course descriptions found in bulletins or academic guides, rather than on more comprehensive assessments. *CourseRank* [1], under development in Stanford's Infolab, is a social tool for course planning that helps students make informed choices and take advantage of the available learning options. It displays official university information and statistics, such as bulletin course descriptions, grade distributions, and results of official course evaluations. Furthermore, students can anonymously rank courses they've taken, add comments, and rank the accuracy of each others' comments. They can also shop for classes, get personalized recommendations, and organize their classes into a quarterly schedule or devise a four year plan. *CourseRank* also functions as a feedback tool for faculty and administrators, ensuring that information is as accurate as possible. Faculty can also modify or add comments to their own courses, and can see how their class compares to other classes. To support this functionality, *CourseRank* maintains a database that stores rich information, such as the courses offered, the instructors, the students, comments and ratings given by the students to courses and instructors, course material, and so forth. Figure 2 provides a small snapshot of the database schema.

A little over a year after its launch, *CourseRank* is already used by more than 6,200 Stanford students, out of a total of about 14,000 students. The vast majority of *CourseRank* users are undergraduates, and there are only about 7,000 undergraduates at Stanford. Thus, it is safe to say that *CourseRank* is already used by a very large fraction of Stanford undergraduates.

Supporting Recommendations. Existing recommendation approaches can be categorized on the basis of how recommendations are generated: (a) *content-based* methods recommend to the user items similar to the ones the user preferred in the past, and (b) *collaborative filtering* recommend to the user items that people with similar preferences liked in the past.

Following a content-based approach in *CourseRank*, we could consider that each course is represented by the set of topics that it covers (Courses.Description), and each student is



(a) Content-based paradigm

(b) Collaborative filtering paradigm

Figure 1: Classical recommendation paradigms.

Departments(DepID, DepCode, Name)
Courses(CourseID, DepID, Title, Description, Units, Url)
CourseSched(CourseID, Year, Term, InstrID, Location, TimeSlot, Days)
Instructors(InstrID, Name, Url)
Students(StudID, Name, Class, GPA)
StudentStudies(StudID, StudyPrgID)
StudyPrograms(StudyPrgID, ProgramName, Classification, DepID)
StudentHistory(StudID, CourseID, Year, Term, Grade, Rating)
Comments(StudID, CourseID, Year, Term, Text, Rating, Date)

Figure 2: Extract from *CourseRank*'s database

represented by a list of the topics from the courses she has attended. When a student, say Alice, logs into the system, the system matches courses, based on their topics, to the topics that interest this student. The result would be a list of courses, each one with a score showing how closely the course matches Alice's interests and the top courses would comprise the system's recommendations. Standard functions for computing such scores include the cosine similarity, the Jaccard metric, and so forth. A high-level representation of this recommendation process is illustrated in Figure 1(a).

Adopting a collaborative approach, we could take into account the ratings students assign to courses (Comments.Rating). In order to recommend courses to Alice, the system will first find students that are similar to Alice, i.e., with similar ratings for the same courses. The output of this first step is a list of (top N) users ordered on their similarity scores. A typical function for computing user similarity is the Pearson correlation [19]. Then, these users collectively determine the ratings for the courses not taken by Alice. For example, course ratings could be computed as the weighted average of the students' ratings for this course. Figure 1(b) illustrates this recommendation process, which has been implemented in *CourseRank*. Figure 3 shows a screen from *CourseRank* that displays recommendations based on this approach.

Limitations. Supporting recommendations following one of the classical approaches allows *CourseRank* to offer only fixed, 'canned' recommendations that change only when there is a significant change either in the information the system keeps for the users or in the courses offered. For example, recommendations would change if Alice rated new courses and became similar to a different set of users that could offer new recommendations to her. Likewise, in a content-based system, if Alice took a number of courses on new topics, the system could recommend courses on these topics.

Offering standard advice cannot capture a student's (and a person's, in general) evolving information needs. Furthermore, often we seek recommendations on items that do not depend explicitly (as in content-based approaches) or implicitly (as in collaborative approaches) on our past choices but we are willing to see other alternatives; for example, what courses would be recommended to our best friend. Current recommendation systems operate on a set of fixed assumptions that shape the desired recommendations but the user cannot specify or modify any of them. Below, we highlight these assumptions and give examples from *CourseRank* of how they may generate inaccurate or inflexible recommendations for the students.

- *The system always assumes that the target of the recommendations is the current user.*

  Recommendations explicitly (content-based approach) or implicitly (collaborative approach) match this user's representation in the system. For example, if a student has attended many Computer Science courses, a content-based recommendation system can recommend other CS courses. However, if this student is also interested in taking some Sociology courses, the system cannot generate any recommendations for such courses that would match the system's past knowledge on the student (i.e., her past CS courses).

- *The system always assumes a fixed pool of courses, from which recommendations will be drawn.*

  For example, in Figure 3, *CourseRank* provides a general list of recommendations for our hypothetical student, Alice, containing a course on Robotics and a course on Spanish language. Other interesting courses on Spanish have not surfaced in this general list of recommendations. Moreover, Alice cannot request recommendations targeted to Spanish language courses. Taking this one step further, since the database stores information about many entities apart from courses, a student may wish to ask for recommendations for different entities, such as instructors, course material for CS courses, etc.

- *In collaborative filtering, recommendations are based on the opinions of a fixed set of users.*

  For example, in our initial *CourseRank* implementation, all students act as potential recommenders. In many cases, a student may not seek recommendations from the broad student community, because their shared interests may not be related to the user's current information need, but rather from a selective subset of experts w.r.t. to her current needs. For example, Alice would rather ask for recommendations on Spanish courses from Spanish Language students rather than any student in general, whereas for CS courses she is only interested in the opinions of her colleagues in Computer Science.

- *The system always assumes a fixed set of attributes for comparing courses or students.*

  Courses and students are compared on a fixed set of their attributes, ratings in collaborative filtering and keywords in the content-based case. Since *CourseRank*'s database contains a lot of attributes that describe the various entities, assuming that comparisons are performed only on ratings or keywords (or anything that is predefined in the system) is very restricting. For example, when Alice plans her CS courses, she may want recommendations from students who have taken similar courses and have similar grades but for dance classes, she wants recommendations from people with similar ratings for the shared dance classes.

If recommendations are to help the students (users) in ex-

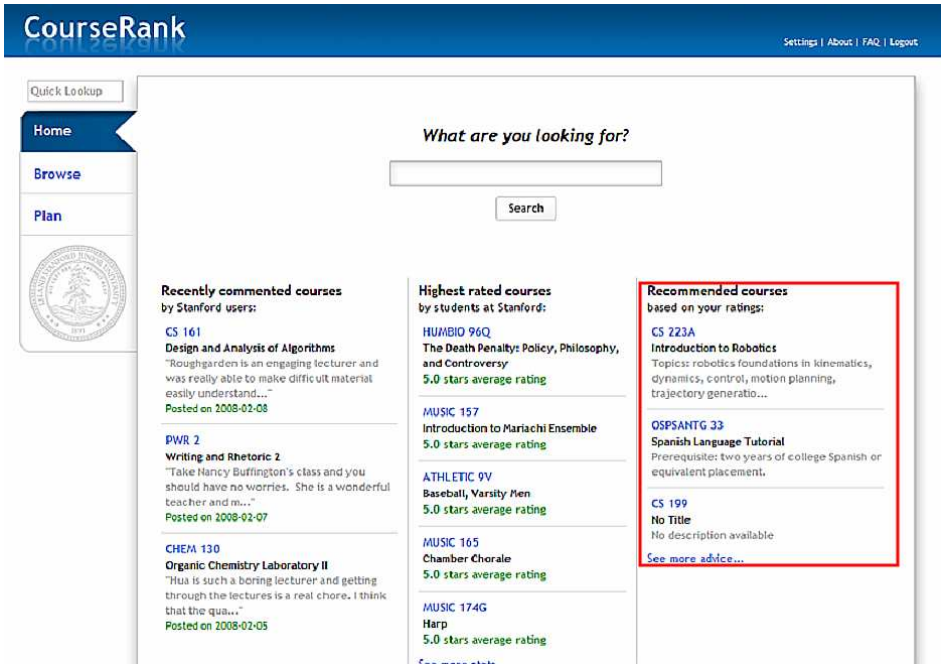


Figure 3: Fixed recommendations in *CourseRank*

ploring the full extent of their choices, then the users should have a more active role in asking for and shaping the desired recommendations. Motivated by the above, we propose *flexible recommendations*, i.e., recommendations that have a set of "knobs" that can be used to specify or "tune" the desired output of the recommendation process, and can be dynamically defined over rich data. To illustrate, in the same sense that a system can offer advanced search, where users can customize their queries by combining different parameters, conditions, and entities, a system should provide advanced recommendations, where users can tweak a number of "components" in order to explore different recommendations.

1.2 Contributions

In brief, the contributions of this paper are the following:

- We define the concept of a flexible recommendation workflow, i.e., a high-level description of a parameterized process for computing recommendations. The input parameters of a workflow allow one to control externally the final output of the recommendation process, and hence, generate *flexible recommendations* (Section 2).
- We describe how flexible recommendations can be expressed over a relational database (Section 3) and we present our prototype flexible recommendation engine that allows defining and executing recommendation workflows over relational data (Section 4).
- We describe a preliminary user interface in *CourseRank* that allows students to make use of two flexible recommendation workflows, a content-based one and a collaborative filtering one, defined and executed with the help of the prototype system in order to shape the course recommendations provided by the system (Section 5).

2. FLEXIBLE RECOMMENDATIONS

We define a *flexible recommendation workflow* $RW(I, P)$ as a high-level description of a process for computing recommendations for a set of objects I (e.g., courses, books, etc) based on a set of input parameters P. A recommendation workflow comprises a series of interconnected operators that describe how a recommendation is computed. In a workflow, sets of objects flow from one operator to the next, and are filtered, ranked, etc. in the process. The workflow is a "high-level" description in the sense that it does not contain actual code, but rather, it describes what code (operators) to call upon. The input parameters P of a workflow are essentially operator inputs that are exposed outside the workflow in order to allow one to control externally the final output of the recommendation process, and hence, generate *flexible recommendations*.

There are several possible types of operators that one could define and combine in a recommendation workflow. For example, one could use filters in order to exclude objects, blend operators for combining sets of objects or recommendations, and top-k operators that output only the top k objects based on some attribute of them. The core operator of any recommendation workflow is a *recommend operator* that rates the objects of a set by comparing them to the objects of another set.

Figures 1(a) and 1(b) could actually be seen as two recommendation workflows, except that the inputs and parameters are hardwired by the system. Furthermore, in classical recommendation systems there is usually no high-level description; the recommendation processing is implemented in low-level code that is hard to change. Below we illustrate some flexible recommendation workflows.

Example. Assume that we define two operators: (a) a filter operator $\phi(X, c)$ that takes as input a set of objects X and outputs only objects that meet the condition c, and (b) a recommend operator $\rho(X, Y, f, A)$ that rates the objects in X by comparing them to the objects in Y on some common attribute A with the help of a function f. These operators can be combined in several ways to build different flexible recommendation workflows. Figure 4 il-

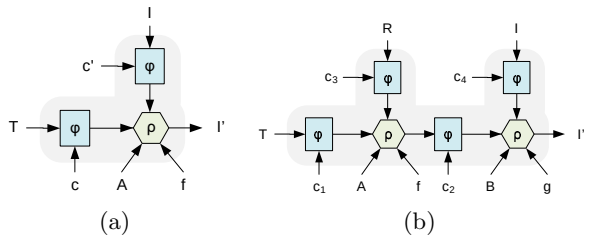


Figure 4: Flexible recommendation workflows.

lustrates two example workflows. The workflow depicted in Figure 4(a) generates flexible recommendations for a set of objects I, which may be filtered based on some criterion c', by comparing its objects with the objects of a set T on some common attribute A. Objects in T may be also filtered on some criterion. Consequently, this workflow represents a flexible content-based recommendation process with several parameters to shape the recommendations, i.e., $RW(I, c', T, c, A, f)$. By dynamically changing its inputs, this process can provide different recommendations. For example, a student (i.e., T: students) with id '1432' (c: id='1432') could ask for recommendations for courses (I: courses) on programming (c':"on programming") whose topics match her topics of interest (A: topics). In similar way, she could ask for course recommendations for her friend (c') or for dance (c) classes (I). Going one step further, T could be a set of objects, such as a group of friends and function f could compute the average score for each course over all students. In this way, the system could provide recommendations for courses that would match the interests of a group of students that want to take a class all together.

Figure 4(b) shows a workflow that provides flexible recommendations for a set of objects I in a collaborative-filtering fashion. For this purpose, the objects in I are rated w.r.t. the objects of a set R, which have been already rated w.r.t. a set T. Consequently, this workflow represents a flexible recommendation process $RW(I, c_4, R, c_3, B, g, c_2, T, c_1, A, f)$. Different recommendations can be obtained by changing the process inputs. For example, a student (T) named Alice (c_1) may want to see books (I) recommended based on the ratings (B) of students (R) with a CS major (c_3) that match with her on course ratings (A). Similarly, Alice could ask for sociology (c_4) courses (I) recommended based on the ratings (B) of sociology (c_3) students (R) that have similar grades (A) with a friend student in this department (c_1).

As illustrated in Figure 5, a *flexible recommendation system* contains a set of recommendation workflows, RW_1, RW_2, ..., RW_N. These are defined by an administrator or designer using the set of operators that are supported by the system. At run time, users can invoke any of these workflows (through some user interface) with the set of objects, for which recommendations are sought, and the rest of the parameters that are required by the process in order to generate customized recommendations. The system then executes the process over the underlying data and returns a set of recommendations.

3. FLEXIBLE RECOMMENDATIONS OVER RELATIONAL DATA

Since most structured data used by production systems (including *CourseRank*) is stored in relational databases, it

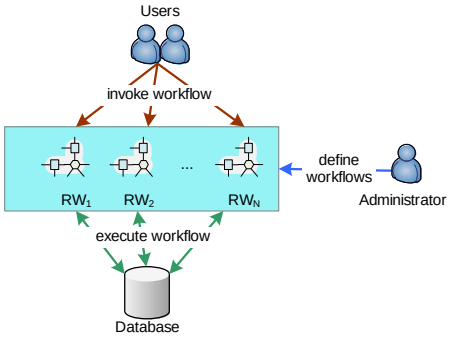


Figure 5: Flexible system workflow.

is desirable to have a workflow data model that is "close" to a relational model. If the objects that flow between operators are relations (i.e., sets of tuples), then we can use classical relational operators like joins, selections and projections to operate on the data. Reading and storing objects would be straightforward, since we would only need to read and write relations into the database. We would need to define new operators like recommend and blend, but they would also be defined over relations.

Unfortunately, relying on a "pure" relational data model for recommendation workflows is restrictive. The problem is that information about a single entity (e.g., student, course) may be dispersed over different relations due to database structuring and normalization. For example, we may want to compare students to the current user based on their ratings for the courses that they have in common. In *CourseRank*, as Figure 2 shows, there is a relation Students, where each tuple corresponds to a single student while information about the courses each student has taken is stored in a different relation, StudentHistory. A recommend operator that compares students to the current user would need to join together multiple relations, making it cumbersome to define the operator.

Instead, we consider an *extended relational model*, that lets us represent our application entities with a single relation. For instance, a tuple in an extended relation can contain base information on a student (e.g., name, major), plus the set of courses the student has taken.

Extended relations. A relational database comprises a set of stored relations. A stored relation has a set of stored tuples described by a set of attributes. An attribute can be instantiated to a single, numerical or categorical, value. We define an *extended relation*, which has a set of extended tuples described by a set of stored attributes and a set of extended attributes. An *extended attribute* is instantiated to a relation derived from another stored relation. Consequently, under our semantics, an attribute value can be scalar or a relation. Note that only stored (flat) relations can be part of a tuple, allowing only one level of nesting. We think that one level of nesting is sufficient to capture the needs of most recommendation operators, so we avoid the complexities of a full-fledged nested relational model.

Extend operator. Since extended relations are not stored in the database, we define an *extend operator* that can be used in a recommendation workflow. This operator allows "extending" each tuple from one relation with the set of joining tuples from a different relation. In other words, for each tuple t in the first relation, the operator creates an extended attribute. The t attribute is instantiated to a relation con-

Students

StudID	Name	Class	Reputation
1	Paul Little	2009	A
2	John Doe	2010	A

Ext_Students

StudID	Name	Comment(CourseID, Rating, Date)		
1	Paul Little	C1	5	2 Feb 2008
		C2	6	3 Dec 2007
2	John Doe	C1	5	15 Mar 2007
		C2	6	12 Dec 2007
		C5	6.6	22 Jun 2007
		C7	7	22 Jun 2007

Figure 6: The relation Students extended with course information.

taining tuples from another relation that join with t. For example, each student can be extended with an attribute that describes the courses she has taken. Similarly, a department can be extended with the courses it offers, etc.

Figure 6 shows an instance of the Students relation and an example of an extended relation, where the set of courses for each student is "viewed" as an additional attribute of the student. A recommend operator can now take as input this extended relation, and for each tuple generate a score indicating how well the student matches the target user (as discussed in the example of Section 2).

In the following section, we present our prototype flexible recommendation engine that allows defining and executing relational recommendation workflows.

4. FLEXIBLE RECOMMENDATION ENGINE

Our goal is to build an engine for flexible recommendation processing and optimization over relational databases. There are generally two options: (i) build a middleware layer, i.e., implement the processing outside the core of the database system or (ii) extend the database query engine with the processing capabilities required for flexible recommendations. We chose the middleware solution for portability and implementation ease. Figure 7 shows the architecture of our current *CourseRank* working system. It is implemented in Java on top of MySQL.

Workflow Manager. This component allows an administrator to define different recommendation workflows and end-users (through the user interface, see Section 5) to invoke any of the defined workflows with different inputs and receive customized recommendations. This component hides the details of how flexible recommendations are generated, such as the details of the algorithms and structures used to implement the functionality of the operators that comprise a recommendation workflow, the execution order of operators, which can be different from the workflow definition in order to optimize the process, and so forth.

Operator Manager. The Operator Manager implements the operators that can be used for defining relational recommendation workflows. Apart from exposing the classical relational operators, i.e., selections, projections and joins, it implements additional operators: the extend operator, as described in the previous section, and the recommend and top-k operators described in Section 2. We also plan to add a blend operator that will unify recommendations generated from different workflows or different instantiations of the same workflow.

The extend operator allows "extending" in a transparent

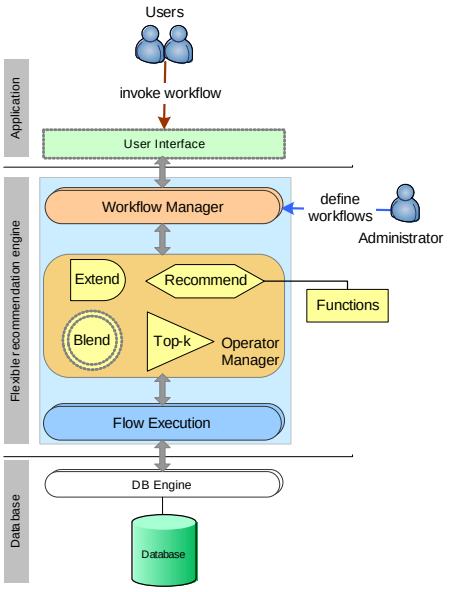


Figure 7: Prototype flexible recommendation engine

way any tuple from one relation with its set of joining tuples from a different relation. For example, students can be extended with their courses. In this way, the set of courses for each student can be "viewed" as an additional attribute of the student that can be handled by the recommend operator irrespective of the database structure. Note that the extend operator does not materialize a new relation. The joins implied by the extended relation are only executed only when tuples are actually requested by some downstream operator.

The recommend operator comes with a library of functions for performing correlations (e.g., Pearson), similarity comparisons (e.g., Jaccard), and aggregations, such as average and weighted average. The operator is responsible for providing the right inputs when calling these functions. The library is extensible, so new types of recommendations can always be supported.

Flow Execution. The Flow Execution component is responsible for the execution of a recommendation workflow and it contains the code for implementing the recommend, the extend and the top-k operators. This component constructs the SQL queries that are required in order to: (i) bring into memory tuples that need to be processed, (ii) realize the extension of tuples required by the extend operator, and (iii) materialize any results that are shared in a particular recommendation workflow. The SQL queries are executed by the underlying DB engine. The Flow Execution component assembles results in memory and performs any extra processing required, such as applying any library function used by a recommend operator.

In the current *CourseRank* version, a workflow is executed exactly as defined. We are currently working on workflow optimization, where operators can be reordered and executed using different run-time strategies (e.g., exploiting an index). Such optimization is analogous to what a query engine does in a traditional database system, except that now we have to handle new operators and extended relations.

5. A FLEXIBLE USER INTERFACE

A flexible recommendation interface should allow the user

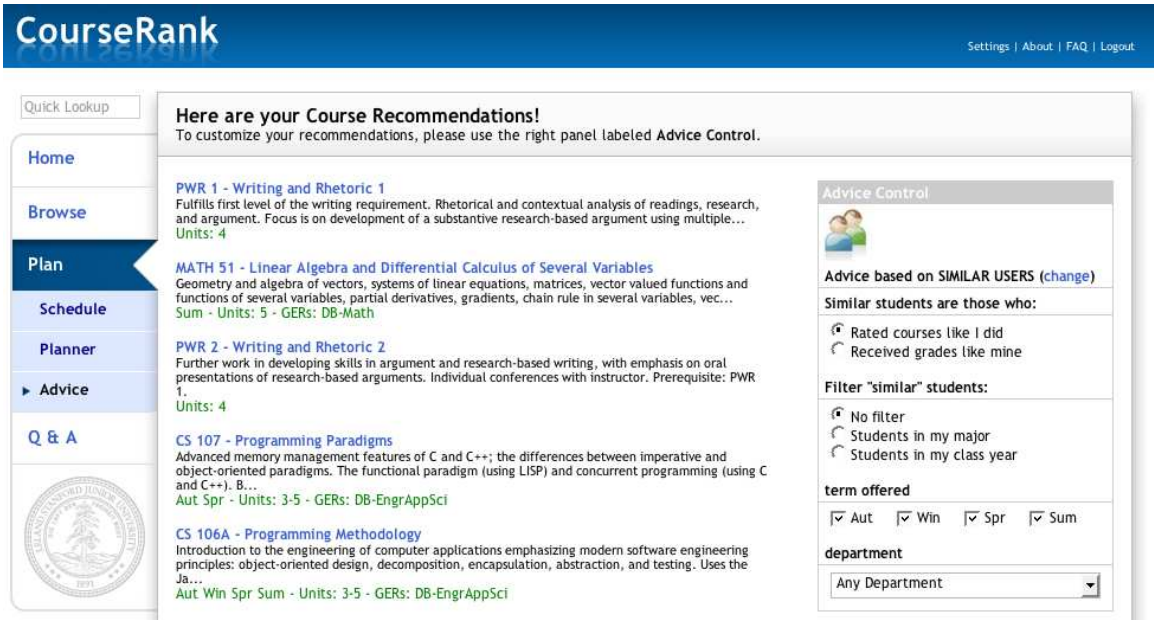


Figure 8: Snapshot of advice page's collaborative recommendation workflow. (Default)

to select a recommendation workflow, to set the parameters, and then to see the recommendations generated. Below we outline the challenges of creating such an interface.

- *Design an interface that does not confuse users.*

  Flexible recommendations are a new concept, so a user interface that provides this customizability could lead to confusion. If we were to include in our user interface an *advice panel* that allowed the user to customize recommendations, then we would want all users to recognize quickly both the purpose of the panel and how to use it.

- *Allow the user to select a recommendation workflow and set parameters.*

  Supporting multiple workflows could lead to confusion if not done carefully. The interface should make clear that a single workflow is active at a time, and given a particular workflow, the user should be able to set the relevant parameters. Since users are used to default recommendations, the advice panel should be preset with a default workflow and appropriate parameters.

- *Place the "advice panel" in appropriate positions.*

  We can show the advice panel when users explicitly ask for recommendations, but the panel might belong elsewhere as well. For example, we may want to integrate advice with search by ordering search results in a manner consistent with the user's preferences. In our initial prototype we have a separate advice page, but we anticipate that the integration of advice with search will reveal interesting challenges.

- *Decide what information to show with recommendations.*

  Given a set of recommendations, the user may be interested in why a particular item was recommended. In a social network such as *CourseRank*, the user may also want to know which users have previously experienced the recommended item. Showing information on other users presents privacy challenges, so for now we have refrained from presenting any explanations.

- *Use feedback to improve the system.*

  To improve recommendations, we need some way to measure the quality of our suggestions. A user can implicitly indicate that a recommended course is good by adding it to her *CourseRank* schedule or even by simply clicking the recommending item. We save for future work exploring different evidence of recommendation quality.

5.1 Overview of Current Prototype

We describe our current *CourseRank* prototype interface, which is still in the preliminary stages. For now, to receive recommendations, the user must explicitly request them by clicking a top-level link (tab) labeled *Advice*. After clicking the link, the user is shown recommendations created with a default collaborative recommendation workflow, as shown in Figure 8. The user experience thus far is consistent with the typical user experience in most recommendation systems. If the user is not satisfied with the recommendations, then the subtitle of the page shown after clicking *Advice* says:

To customize your recommendations, please use the right panel labeled Advice Control.

Thus, users who would like to customize their recommendations are directed to our *advice panel* on the right, allowing those users to customize recommendations. We currently offer two recommendation workflows: a collaborative workflow and a content-based workflow. Notice how in Figure 8's advice panel, there is an icon of two people, indicating that the collaborative workflow is currently active. Under this icon, there is the corresponding explanatory text:

Advice based on SIMILAR USERS

To switch between recommendation workflows, the user can simply click the *change* link. Now, instead of displaying people, the icon will display a stack of books (Figure 9). The text under this icon will also change to read:

Advice based on COURSE HISTORY

The two workflows currently supported by our interface are discussed in more detail below.

Collaborative workflow. By default the user is directed to the advice panel preset to the collaborative workflow. The

Figure 9: Snapshot of content-based recommendation workflow.

original, default *CourseRank* advice was generated using the collaborative workflow with course ratings as the basis for calculating similarity among users. Thus, to ease users into our flexible recommendation system, we set the default options of the advice panel to correspond with the original method. It is easy to customize recommendations; the user simply has to click on an option in the advice panel, and the list of recommended courses will dynamically change to reflect the newly selected option.

The advice panel has two sets of parameters: those for recommendation operations and those for filtering returned recommendations. In the first set, we currently support two parameters for the collaborative workflow. The first one allows the user to specify how similarity between two students should be calculated. By default, similarity between two users is calculated using a formula involving the users' course ratings. We allow the user to change this similarity formula to one based on grades. The other collaborative workflow parameter allows the user to filter the set of similar students in order to get more appropriate recommendations. For example, the user may be interested in recommendations based on students in her major. Alternatively, she may want recommendations based on those students in her class year. Thus we give the user the option to filter the group of similar students before these similar students are used to generated recommendations. In the second set of parameters, there are two parameters that are used to filter the returned recommendations. In both the collaborative and content-based modes, these parameters are the same. One parameter allows the user to filter courses by term offered. The other allows filtering by department.

Content-based workflow. In the content-based workflow, the advice panel exposes different workflow-specific parameters. The first parameter allows the user to specify how similarity between courses should be calculated. By default, similarity is calculated using both the course titles and course descriptions, but the user can request that similarity be calculated using only course titles. In certain situations, this option may yield more accurate results.

The second parameter allows the user to specify a subset of the user's course history that should be used to generate recommendations. By default, the user's whole course history is used, but this may not always be appropriate. For example, if the user is interested in recommendations within his major, he may want advice generated based on only the courses he has taken within the major. Thus, this parameter allows the user to specify that only courses taken in her major should be considered. Similarly, the system can also consider only courses taken outside the major.

Evolving Interface. There are many parameters that we would like the user to be able to control in order to customize recommendations. However, we did not want to confuse the user or overwhelm him with complexity. Thus, we have only chosen a subset of the possible parameters to include in our advice panel.

As users work with the system, we will track the usage of the advice panel to see which parameters are most popular and which could be replaced by others we have been considering. Designing the interface is an ongoing operation.

6. RELATED WORK

Since the appearance of the first papers on collaborative filtering [11, 19, 21], a lot of work has been done from improving and evaluating recommendation methods [2, 13, 18, 22] to designing trustworthy recommender systems [6, 16].

Recommendation approaches are broadly classified into the following categories [5]:

- *Content-based recommendations*: The user is recommended items similar to the ones the user preferred in the past;
- *Collaborative recommendations*: The user is recommended items that people with similar tastes and preferences liked in the past;
- *Hybrid approaches*: These methods combine collaborative and content-based methods.

Traditionally, recommendation systems deal with applications that have two types of entities, users and items (e.g., movies, Web pages) and they recommend top N items to a user following a content-based or a collaborative filtering paradigm. For example, the content-based component of the Fab system [5], which recommends Web pages to users, represents Web page content with the 100 most important words. Similarly, the Syskill & Webert system represents documents with the 128 most informative words [18]. This is a very restrictive view of the world. Many applications use much richer data with large amounts residing in databases. Different types of entities may co-exist in a single database, such as authors, books, customers, publishers, represented by rich sets of attributes. Therefore, being able to ask recommendations that can dynamically incorporate different parts of a database and be targeted to different entities is very useful. However, existing methods do not allow such flexibility and they provide canned recommendations.

Furthermore, using a fixed approach to recommendations can also be restrictive, since a single approach may not be appropriate for every occasion. For example, in content-based methods, the user is limited to see items that are similar to those already rated. Methods to address this problem include the use of genetic algorithms [22] or filtering out items if they are too similar to those seen before [8]. On the other hand, collaborative methods, grouped in memory-based [9, 12, 19] and model-based ones [7, 14], provide serendipitous recommendations. However, collaborative filtering has its own problems, such as the inability to recommend new items [5]. Several recommendation systems use a hybrid approach by combining collaborative and content-based methods, which helps to avoid certain limitations of content-based and collaborative systems [5, 7, 20]. Still, these methods may not provide a complete solution,

since in many cases, different recommendations may be required under different circumstances.

The inherent limitations of recommendation systems have been acknowledged [4] and some extensions have been recently proposed, such as incorporating multi-criteria ratings into recommendation methods [2] and supporting multi-dimensional recommendations [3]. In this paper, we propose moving away from the canned recommendation paradigm to flexible, customizable recommendations that can be expressed over rich data. Choosing the entities to be involved in a particular recommendation setting, using different, single or multiple, pieces of information to compare those entities, changing the comparison functions are some of the different knobs that can be used to shape recommendations based on the domain, the user preferences and the context.

7. CONCLUSIONS AND FUTURE WORK

In this paper, we have seen through our course planning tool, *CourseRank*, how existing recommendation methods lead to fixed, pre-specified recommendations that cannot adapt to each particular student's changing requirements and do not help exploit the full extent of the available options. These observations have shown the need to support flexible recommendations. We have defined the concept of a flexible recommendation workflow, i.e., a high-level description of a parameterized process for computing recommendations. The input parameters of a workflow allow one to generate flexible recommendations. We have seen how flexible recommendations can be expressed over a relational database and we have presented our prototype system that allows defining and executing recommendation workflows over relational data. We built a user interface in *CourseRank* that allows students to make use of two workflows defined and executed with the help of this system.

Building a flexible recommendation engine over relational data presents many challenges. We are currently working on adding a blend operator and on workflow optimization, where operators can be reordered and executed using different run-time strategies. We are interested in making an extensible platform that will allow expressing and experimenting with different types of flexible recommendations. Furthermore, building user interfaces for flexible recommendations is an ongoing operation. Finally, expressing flexible recommendations in a declarative language would be another interesting research direction.

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