Database Management System Support for Collaborative Filtering Recommender Systems

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Dedication

I dedicate this thesis to my beloved son Yossuf.

Abstract

Recommender systems help users identify useful, interesting items or content (data) from a considerably large search space. By far, the most popular recommendation technique used is collaborative filtering which exploits the users' opinions (e.g., movie ratings) and/or purchasing (e.g., watching, reading) history in order to extract a set of interesting items for each user. Database Management Systems (DBMSs) do not provide in-house support for recommendation applications despite their popularity. Existing recommender system architectures either do not employ a DBMS at all or only uses it as a data store whereas the recommendation logic is implemented in-full outside the database engine. Incorporating the recommendation functionality inside the DBMS kernel is beneficial for the following reasons: (1) Many recommendation algorithms take as input structured data (users, items, and user historical preferences) that could be adequately stored and accessed using a database system. (2) The In-DBMS approach facilitates applying the recommendation functionality and typical database operations (e.g., Selection, Join) side-by-side. That allows application developers to go beyond traditional recommendation applications, e.g., "Recommend to Alice ten movies", and flexibly define *Arbitrary Recommendation* scenarios like "Recommend ten nearby restaurants to Alice" and "Recommend to Bob ten movies watched by her friends". (3) Once the recommendation functionality lives inside the database kernel, the recommendation application takes advantage of the DMBS inherent features (e.g., query optimization, materialized views, indexing) provided by the storage manager and query execution engine. This thesis studies the incorporation of the recommendation functionality inside the core engine of a database management system. This is a major departure from existing recommender system architectures that are implemented on-top of a database engines using either SQL queries or stored procedures. The *on-top* approach does not harness the full power of the database engine (i.e., query execution engine, storage manager) since it always generates recommendations first and then performs other database operations. Ideas developed in this thesis are implemented inside RecDB ; an open-source recommendation engine built entirely inside PostgreSQL (open source relational database system).

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Chapter 1

Introduction

1.1 Recommender Systems

"What end-users really want?" a question asked by almost every business, online retail store, or content provider. The answer to this question helps users find interesting items (e.g., products, movies, books). In a pursuit to such an answer, researchers have been crafting novel technologies that provide a personalized experience to end-users. Among such technologies, recommender systems have been widely used in both industry [1, 2, 3, 4] and academia [5, 6, 7, 8, 9, 10, 11, 12]. The purpose of recommender systems is to help users identify useful, interesting items or content (data) from a considerably large search space. For example, recommender systems have successfully been used to help users find interesting books and media from a massive inventory base in Amazon [4], movies from a large catalog in Netflix [13] and Movielens [9], TV programs from TV Genuis [14], college courses in CourseRank [15], or even food from Freshdirect [16], among other applications.

A recommender system exploits the users' opinions (e.g., movie ratings) and/or purchasing (e.g., watching, reading) history in order to extract a set of interesting items for each user. Collaborative filtering [6, 17, 18, 19, 20, 21] comes as one of the most popular recommendation methods proposed in the literature. Collaborative filtering recommendation algorithms consist of two main phases: (1) A computationally expensive offline *model generation* phase that uses community opinions (i.e., user rating triples represented as (*user*, *item*, *rating*)) in order to derive meaningful correlations

between users or items, and (2) An online *recommendation generation* phase that uses the model to produce recommendations.

With its wide use, recommender systems have been mostly applied only to, now classical, web applications of retail stores (e.g., Amazon and Netflix) that manage to have somehow static set of objects that are infrequently updated. In such applications, the recommendation changes very slowly over time [22, 21]. Hence, it is enough to periodically (e.g., weekly) rerun the offline model generation phase. The scope of most work within recommender systems has been from a *user-centric* perspective, e.g., providing users with quality [17, 23] and trustworthy recommendations [24]. There is a *scarcity* of work that studies recommenders from a systems perspective, i.e., measuring query processing efficiency of different architectures. Herlocker et al. in their 2004 detailed evaluation of recommender systems state [17]:

"We have chosen not to discuss computation performance of recommender algorithms. Such performance is certainly important, and in the future we expect there to be work on the quality of time-limited and memory-limited recommendations."

We are living in the era of staggering web use growth and ever-popular social media applications (e.g., Facebook [25], Twitter [26]) where: (a) users are expressing their opinions over a diverse set of items (e.g., Facebook "likes") faster than ever. Hence, weeks, days, or even hours to rebuild the recommendation model is not acceptable [3], (b) there is an urge need to support arbitrary recommendations that do not only fit the prior user ratings, but also fit the user profile and context, e.g., context-aware recommender systems [33, 34, 35, 36], and (c) users and items spatial locations play a major role in the quality of the recommendation result as has been indicated by New York times [27] and Foursqaure [28] as well as various academic studies [29, 30, 31, 32].

1.2 Database Management Systems

A Database is a collection of data that typically describes entities and interactions among these entities, e.g., flight reservations, product purchases, student grades, part inventory system. A Database Management System (DBMS) is a software artifact that enables storing, maintaining, and accessing data efficiently [37]. For more than four decades, DBMSs have been a major contributor to the information technology world.

A modern DBMS consists of two main modules: (1) A storage manager that adopts a suitable storage layout to physically represent the data, stores the data on a persistent storage medium, and provides efficient access methods for the stored data. (2) A query execution engine that parses the incoming query, optimizes it into an execution plan, and finally executes the query.

DBMSs do not provide in-house support for recommendation applications despite their popularity. Existing recommender system architectures either do not employ a DBMS at all or only use it as a data store whereas the recommendation logic is implemented in-full outside the database engine. Incorporating the recommendation functionality inside the DBMS kernel is beneficial for the following reasons: (1) Many recommendation algorithms take as input structured data (e.g., users, items, and user historical preferences) that could be adequately stored and accessed using a database management system. Recent work from the data management community has shown that many popular recommendation methods (including collaborative filtering) can be expressed with conventional SQL, effectively pushing the core logic of recommender systems within the database management system (DBMS) [38]. (2) The In-DBMS approach facilitates applying the recommendation functionality and typical database operations (e.g., Selection, Join) side-by-side. That allows application developers to go beyond traditional recommendation applications, e.g., "Recommend to Alice ten movies", and flexibly define *Arbitrary Recommendation* scenarios like "Recommend ten nearby restaurants to Alice" and "Recommend to Bob ten movies watched by her friends". (3) Once the recommendation functionality lives inside the database kernel, the recommendation application takes advantage of the DMBS inherent features (e.g., query optimization, materialized views, indexing) provided by the storage manager and query execution engine.

1.3 Contribution and Organization

The overarching goal of this thesis is to conduct research, develop requisite knowledge to advance the state-of-the-art and usage of recommender systems. This thesis is the first of its kind to study the integration of both the recommender system and database management system. Given this outlook, this document is organized as follows:

- Chapter 2 gives an overview of collaborative filtering recommenders and analyzes the straightforward approach of implementing a collaborative filtering recommender using a database management system.

- Chapter 3 presents the architecture of RecDB ; an In-DBMS recommender system that incorporates the recommendation functionality inside the database kernel. This chapter also explains RecDB 's SQL interface for creating and querying recommenders as well as describes two RecDB case studies (i.e., Movie Recommendation, Point-of-Interest Recommendation).

- Online updates come from new or deleted items (e.g., news item, microblog entries) or ratings (e.g., Facebook likes, comments over news). With online updates, recommender systems can easily evolve with their contents, and hence be able to produce accurate and fresh recommendation results. Chapter 4 studies online maintenance mainly for neighborhood-based collaborative filtering recommender models and introduces RecStore ; an online recommender maintenance module integrated with the database storage engine.

- Chapter 5 studies the integration of the recommendation generation process inside the database query executor. This part of the thesis presents RecQuEx ; a query execution engine that (a) Encapsulates recommender systems functionality inside a set of pipeline-able query operators that integrate well with other database system operators, and (b) Employs a set of query optimization strategies that rely on composite query operators that include the recommendation functionality.

- Chapter 6 describes an extension to RecDB that considers context pre-filtering scenarios. This chapter explains the scalability needs of maintaining multiple context pre-filtering recommenders and presents a solution that completely builds such recommenders in an analogous way to building index structures inside the core database engine.

- Chapter 7 presents LARS ; a system that takes advantage of the ubiquitous location information in enhancing the result of recommender systems. This part of the thesis achieves the following goals: (a) Going beyond the commonly used rating triple (*user*, *item*, *rating*), which forms the basis of current collaborative

filtering methods to support *spatial user ratings for non-spatial items*, represented as a four-tuple (*ulocation*, *user*, *rating*, *item*), (b) Supporting *non-spatial user ratings for spatial items*, represented as a four-tuple (*user*, *rating*, *ilocation*, *item*).

- Chapter 8 highlights research works relevant to this thesis. Finally, Chapter 9 concludes the thesis findings and introduces a set of future research directions.

The approach in this thesis is clearly distinguished from all previous approaches for recommender systems. This thesis incorporates the recommendation functionality inside the core engine of a database system to leverage its power in indexing, query processing, and optimization. This is a major departure from existing DBMS-based recommender system architectures that are implemented on-top of a database engine using either traditional SQL queries or stored procedures [38]. The *on-top* approach does not harness the full power of the database engine since it always generates recommendations first and then performs other database operations. The ideas developed in this thesis are implemented inside RecDB [39]; an open-source recommendation engine built entirely inside PostgreSQL [40].

Scope. This thesis assumes a shared-memory/shared-disk database management system architecture [41]. However, the presented ideas could be extended to a shared-nothing distributed database system architecture. Moreover, This thesis does not focus on introducing a novel recommendation model with higher accuracy. It instead focuses on performance aspects that include query execution latency as well as storage and maintenance overhead.

Chapter 2

Recommender Systems and Databases

A Recommender system [5, 76, 8, 7, 10, 77, 11, 12] takes as input a set of users U, items I, and ratings (history of users opinions over items) R and estimates a utility function $\mathcal{F}(u, i)$ that predicts how much a certain user $u \in U$ will like an item $i \in I$ such that i has not been already seen by u [6]. To estimate such utility function, many recommendation algorithms have been proposed in the literature [6] that can be classified as follows: (1) Non-Personalized: this class of algorithms leverages statistics and/or summary information to recommend the same interesting (e.g., the most highly rated) items to all users. (2) Content-based Filtering: analyzes the items' content information and recommends to a user a set of items similar (in content) to those she liked before. (3) Collaborative Filtering: harnesses the historical preferences (tastes) of many users to predict how much a specific user would like a certain item. Collaborative filtering recommenders falls into two main categories: (a) Neighborhood-based [6, 19]: that leverages the similarity between system users or items to estimate how much a user like an item. (b) Matrix Factorization [21, 42]: that linear algebra techniques to predicts how much a user would like an unseen item. This chapter gives an overview of Collaborative Filtering (CF) Recommenders, with more emphasis on neighborhood-based CF techniques. The chapter also describes the straightforward approach to incorporating the collaborative filtering recommenders inside the Database Management System

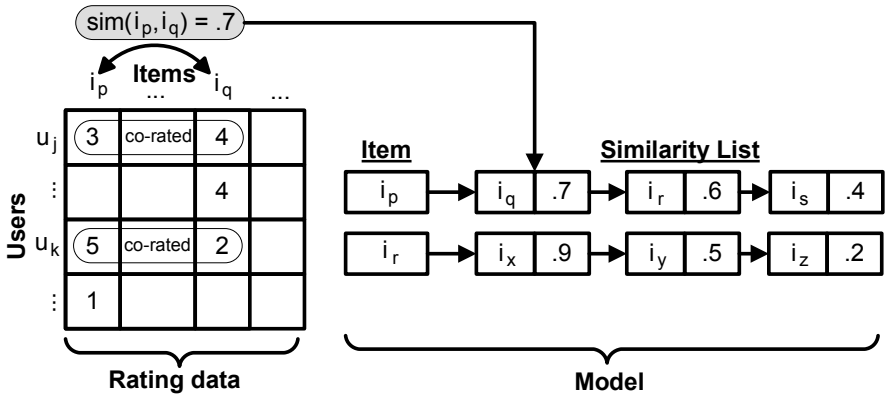


Fig. 2.1: Item-based Model Generation

(DBMS).

2.1 Collaborative Filtering

This section provides an overview of collaborative filtering, the primary family of recommendation algorithms we are concerned with in this thesis. Collaborative filtering assumes a set of n users $\mathcal{U} = \{u_1, ..., u_n\}$ and a set of m items $\mathcal{I} = \{i_1, ..., i_m\}$. Each user u_j expresses opinions about a set of items $\mathcal{I}_{u_j} \subseteq \mathcal{I}$. In this Chapter, we assume opinions are expressed through an explicit numeric rating (e.g., one through five stars), but other methods are possible (e.g., hyperlink clicks, Facebook "likes"). An active user u_a is given a set of recommendations $\mathcal{I}_r$ such that $\mathcal{I}_{u_a} \cap \mathcal{I}_r = \emptyset$, i.e., the user has not rated the recommended items. The recommendation process is usually broken into two phases: (1) an offline *model generation* phase that creates a model storing correlations between items or users, and (2) an online *recommendation generation* phase that uses the model to generate recommended items. There are several methods to perform collaborative filtering including item-based [21], user-based [19], regression-based [21], or approaches that use more sophisticated probabilistic models (e.g., Bayesian Networks [42]).

Below we describe the details of item-item [21], user-user [19] collaborative filtering, and singular value decomposition (a matrix factorization method) three popular recommendation methods in use today (e.g., Amazon [4]).

2.1.1 Offline Model Generation

The offline model generation phase analyzes the entire user/item rating space, and uses statistical techniques to find correlated items and/or users. These correlations are measured by a *score*, or weight, that defines the strength of the relation.

Item-Item collaborative filtering

The item-item model builds, for each of the m items $\mathcal{I}$ in the database, a list $\mathcal{L}$ of *similar* items. Given two items i_p and i_q, we can derive their similarity score $sim(i_p, i_q)$ by representing each as a vector in the user-rating space, and then use a similarity function over the two vectors to compute a numeric value representing the strength of their relationship. Figure 2.1 depicts this item-item model-building process. Conceptually, we can represent the ratings data as a matrix, with users and items each representing a dimension, as depicted on the left side of Figure 2.1. The similarity function, $sim(i_p, i_q)$, computes the similarity of vectors i_p and i_q using *only* their co-rated dimensions. In our example u_j and u_k represent the co-rated dimensions. Finally, we store i_p, i_q, and $sim(i_p, i_q)$ in our model, as depicted on the right side of Figure 2.1. The similarity measure need not be symmetric, i.e., it is possible that $sim(i_p, i_q) \neq sim(i_q, i_p)$.

Many similarity measures have been proposed in the literature [43, 21]. On of the most popular measures used is the cosine distance, calculated as:

$$sim(i_p, i_q) = k \frac{\vec{i_p} \cdot \vec{i_q}}{\|\vec{i_p}\| \|\vec{i_q}\|} \tag{2.1}$$

Here, items i_p and i_q are represented as vectors in the user-rating space, and k represents a dampening factor that discounts the influence of item pairs having high scores, but only a *few* common ratings [44]; given the co-rating count between two items as $corate(i_p, i_q)$, k is defined as:

$$k = \begin{cases} 1 & corate(i_p, i_q) \geq 50 \\ corate(i_q, i_q)/50 & otherwise \end{cases} \tag{2.2}$$

Model Truncation. It is common practice in recommender systems to reduce the model size by truncating the similarity list $\mathcal{L}$ for each object [44, 21] (e.g., item or user). For the item-item model, truncation means storing in $\mathcal{L}$ only a small fraction of similar

items for each of the m items in the database. Such a practice has positive performance implications, as a smaller $\mathcal{L}$ implies a more efficient recommendation generation process (per Equation 2.4). Also, for the item-item method, it has been observed that truncating $\mathcal{L}$ has minimal impact on the *quality* of recommendations [21]. Truncation is also beneficial to the user-user method from both an efficiency and quality standpoints [44]. In general, the criteria used for truncating $\mathcal{L}$ is unique to each recommender system. However, two common approaches are: (1) store the k most similar items to an item i, where ($k << m$), and (2) store only items l that have a similarity score (i.e., $sim(i, l)$) greater than a threshold $\mathcal{T}$.

User-User collaborative filtering

The user-user model is similar in nature to the item-item paradigm, except that the model calculates similarity between users (instead of items). This calculation is performed by comparing user vectors in the item-rating space. For example, in Figure 2.1, focusing on the user/item matrix, users u_j and u_k can be represented as vectors in item space, and compared based on the items they have co-rated (i.e., i_p and i_q). The user-user model primarily uses cosine distance and Pearson correlation as similarity measures [42], much like that of the item-item paradigm with the exception that similarity is measured in item space rather than user space.

Matrix Factorization Recommenders

Matrix Factorization recommenders reduces the the user/item ratings space into two latent factor space matrices: (1) User Factors Matrix (p): contains a set of user vectors such that each user vector $p_u \in p$ denotes the weights that each user would assign to a set of item features (latent factors), and (2) Item Factors Matrix (q): consists of a set of item vectors such that each item vector $q_i \in q$ denotes the weights that qualifies how much each item belongs to a set of features (latent factors).

$$\min_{q^*,p^*} \sum_{(u,i)\in k} (r_{ui} - q_i^T.p_u)^2 + \lambda(||q_i||^2 + ||p_u||^2) \tag{2.3}$$

To learn the matrix factorization model, the system uses techniques like singular value decomposition (SVD), stochastic gradient descent, alternating least square to minimize the regularized squared error (see Equation 2.3).

2.1.2 Online recommendation generation

The online recommendation generation phase employs the ability to predict ratings for items that a user u_a has not yet rated. Rating predictions are produced by performing aggregation over the recommender models. These predictions can be used to (1) give the user their predicted score for a specific item on request, or (2) produce a set of (e.g., top-N) recommended items based on predicted rating scores.

Item-based collaborative filtering

Recommendation generation for the item-based cosine method produces the top-n items based on predicted score using two steps. (1) *Reduction*: cut down the model such that each item i left in the model is an item *not* rated by user u_a, while i's similarity list $\mathcal{L}$ contains only items l already rated by u_a. (2) *Compute*: the predicted rating $P_{(u_a,i)}$ for an item i and user u_a is calculated as a weighted sum [21]:

$$P_{(u_a,i)} = \frac{\sum_{l \in \mathcal{L}} sim(i,l) * r_{u_a,l}}{\sum_{l \in \mathcal{L}} sim(i,l)} \tag{2.4}$$

The prediction is the sum of the user's rating for a related item l, $r_{u_a,l}$, weighted by the similarity to the candidate item i. The prediction is normalized by the sum of scores between i and l.

User-based Collaborative Filtering

Rating prediction in the user-based recommender paradigm is similar in spirit to the item-based method. Recall that the similarity list $\mathcal{L}$ in the user-user paradigm is a list of similar users to a particular user u. A prediction $P_{(u_a,i)}$ for an item i given user u_a is calculated as [18]:

$$P_{(u_a,i)} = \overline{r}_{u_a} + \frac{\sum_{l \in \mathcal{L}} (r_{u_l,i} - \overline{r}_{u_l}) * sim(u_a, u_l)}{\sum_{l \in \mathcal{L}} |sim(u_a, u_l)|} \tag{2.5}$$

This value is the weighted average of deviations from a related user u_l's mean. In this equation, $r_{u_l,i}$ represents a user u_l's (non-zero) rating for item i, while $\overline{r}_{u_a}$ and $\overline{r}_{u_l}$ represent the average rating values for users u_a and u_l, respectively.

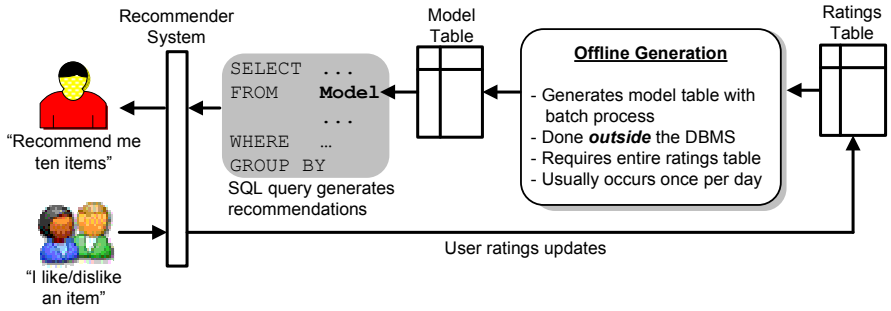


Fig. 2.2: Recommender System built on-top of a database system

Matrix Factorization Recommenders

For Matrix Factorization recommenders, the predicted rating valued $F(u,i)$ for each item i not rated by u is calculated as the dot product of both the user feature vector p_u and the item feature feature vector transpose (q_i^T) (see Equation 2.6).

$$F(u,i) = q_i^T . p_u \tag{2.6}$$

2.2 DBMS-based Collaborative Filtering

Recent work from the data management community has shown that many popular recommendation methods (including collaborative filtering) can be expressed with conventional SQL, effectively pushing the core logic of recommender systems within the database management system (DBMS) [38]. Ratings data can be stored in a relation *Ratings(userId,itemId,rating)*, where *userId* and *itemId* represent unique ids of users and items, respectively.

A straightforward solution implements the recommendation functionality *on-top* of the database management system, aka. *OnTop-DBMS*. This approach implements the whole recommender system functionality, that includes model building and recommendation generation, in the application layer as depicted in Figure 2.3. In other words, the application developer implements the recommendation functionality, uses the DBMS only as a storage medium, and communicates with the database using SQL. We call that the *OnTop-DBMS* approach (see Figure 2.3). This approach can be implemented as follows (refer Figure 2.2):

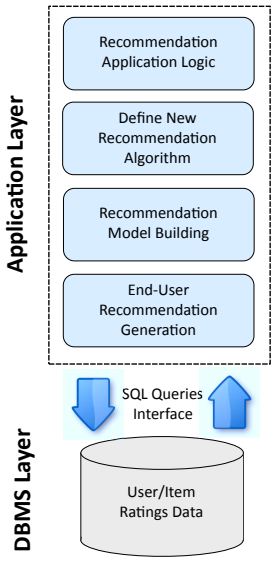


Fig. 2.3: OnTop-DBMS

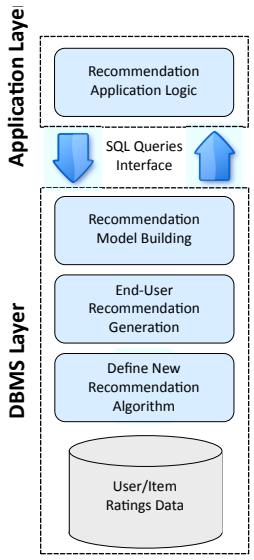


Fig. 2.4: In-DBMS

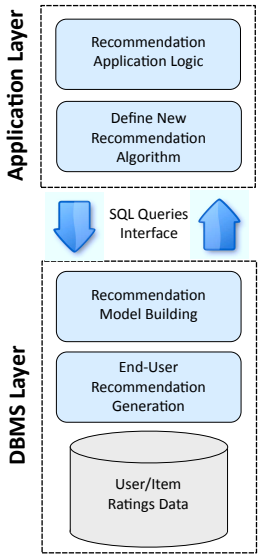


Fig. 2.5: Extensible In-DBMS

Model representation. The model can be represented by a three-column table *Model(item,rel_itm,score)* for the item-item collaborative filtering model, or *Model(user,rel_user,score)* for the user-user model (different schemas may be necessary for other methods). For matrix factorization algorithms, the model can be represented by two tables: a table that represents the user Feature vectors *UserFeature(user,feature,value)* and another table that contains the item feature vectors *ItemFeature(item,feature,value)*.

Recommender queries. A DBMS-based recommender uses SQL to produce recommendations. Figure 2.6 provides an SQL example of the process discussed in Section 2.1.2 (listed in two parts for readability). The first query finds all movies rated by a user X. The second query uses these results to produce recommendations for user X using Equation 2.4. The WHERE clause represents the *reduction* step, while the SELECT clause represents the *computation* step. The query assumes the *model* relation *M(itm,rel_itm,sim)* is already generated offline.

Critique. The OnTop-DBMS approach gives freedom to the application developer to tailor the recommendation algorithm that fits the application needs. Nonetheless, it

```
/* Find movies rated by REC_USER_X,
 * store in temp table usrXMovies */
CREATE TEMP TABLE usrXMovies AS
SELECT  R.mid as itemId, R.rating as rating
FROM    ratings R
WHERE   R.uid = REC_USER_X;

/* Generate predictions using weighted sum */
SELECT  M.itm as Candidate Item,
        SUM(M.sim * U.rating)/ SUM(M.sim) as Prediction
FROM    Model M, usrXMovies U
WHERE   M.rel_itm = U.itmId AND
        M.itm NOT IN (select itmId FROM usrXMovies)
GROUP BY M.itm ORDER BY Prediction DESC;
```

Fig. 2.6: Item-based recommender query

suffers from the following drawbacks: (1) Implementation Complexity: Since the application developer is responsible for the whole recommender system logic, the application development process ends up being tedious. A novice developer might not be able to handle the system performance and scalability issues. (2) Tremendous overhead of extracting the data from the database, loading it to a specialized recommendation engine [45], and then loading the produced recommendation back to the database. (3) The *OnTop-DBMS* approach does not harness the full power of the database kernel that includes query optimization, indexing. That may lead the recommendation application to perform unnecessary work, incurring high latency, especially when only a subset of the recommendation answer is required. (4) This approach does nothing to address the pressing problem of *online model maintenance*, as collaborative filtering still requires a computationally intense offline model generation phase when implemented with a DBMS.

On the other hand, the *In-DBMS* approach (see Figure 2.4) pushes the recommender system functionality (i.e., model building and recommendation generation) inside the DBMS kernel. Hence, the application developer just focuses on the application logic and relies on the DBMS to take care of the recommender system performance and scalability issues. However, the *In-DBMS* approach is sort of rigid as it mandates the

usage of specific recommendation techniques that are implemented a-priori inside the DBMS. In case the application developer wants to employ a different recommendation algorithm, she might either implement the new recommendation technique inside the DBMS or alternatively use the *OnTop-DBMS* approach.

To remedy that, the *Extensible In-DBMS* approach (see Figure 2.5) is similar to the *In-DBMS* approach, with the exception that the DBMS is extensible to new recommendation techniques, which could be declared by the application developer. The *Extensible* approach combines the advantages of both the *OnTop-DBMS* approach and the *In-DBMS* approach in such a way that it isolates the application developer from the system issues and at the same time allow her/him to define new recommendation techniques. For the aforementioned reasons, we set the *Extensible In-DBMS* approach as our system design goal in this thesis.

Chapter 3

Database Support for Recommender Systems

In this chapter, we introduce RecDB [1] – a collaborative recommender system built completely inside a database management system. RecDB provides an intuitive interface for application developers to build custom-made recommenders. To achieve that, we extend SQL with new statements to create and/or drop recommenders, namely `CREATE/DROP RECOMMENDER`. The system initializes and maintains each created recommender that consist of a recommendation model M which is queried to generate arbitrary recommendations to end-users. To query a created recommender, RecDB users specify the ratings table in the `FROM` clause and invokes the `RECOMMEND` clause; a SQL extension to denote the recommendation functionality.

3.1 RecDB Overview

Figure 3.1 highlights the RecDB architecture. When an end-user logs-on, the recommendation application issues a recommendation query (written in SQL) to RecDB via the application layer. RecDB employs its query execution engine RecQuEx that processes incoming queries and returns recommendation back to end-users. RecDB allows the application developer to create a priori recommenders and store them on disk. RecDB invokes the *offline model trainer* module that in turn builds a recommendation

[1] `http://www-users.cs.umn.edu/~sarwat/RecDB/`

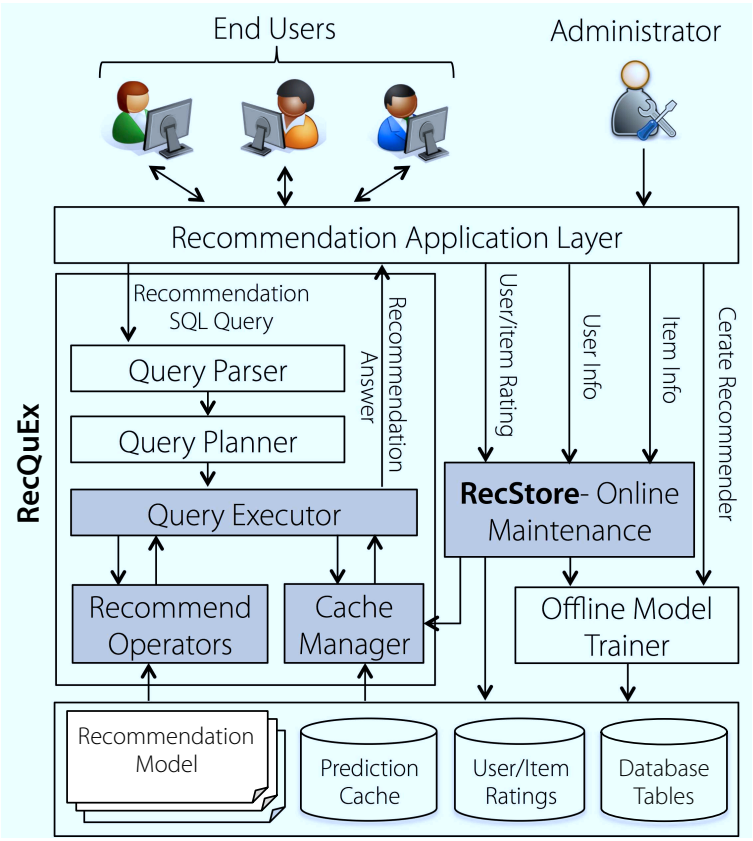


Fig. 3.1: RecDB Architecture

model for the input rating matrix `[Ratings Table]` using the recommendation algorithm specified in the `USING` clause. RecDB provides a storage layout that efficiently access the maintained user/item ratings data and the trained recommendation models. RecDB is also equipped with a recommender storage manager called RecStore that materializes the generated model on disk. When a new rating is inserted in the user/item ratings table, RecStore decides how to maintain the underlying recommendation model to provide online (up-to-date) recommendation to end-users.

The RecQuEx *query parser* parses and validates each incoming SQL recommendation query, and looks whether an existing recommender could be harnessed to execute the query. Afterwards, the query planner (optimizer) determines an efficient query execution plan that reduces the recommendation generation time. Therefore, the *query executor* processes the plan by accessing data via the recommender *storage manager*

User/Item Ratings Table

uid	iid	ratingval
1	1	1.5
2	2	3.5
2	1	4.5
2	3	2
3	2	1
3	1	2
4	2	1
4	3	2.5
...		

Users Profile

uid	name	City	Age	Gender
1	Alice	'Minneapolis, MN'	18	Female
2	Bob	'Austin, TX'	27	Male
3	Carol	'Minneapolis, MN'	45	Female
4	Eve	'San Diego, MN'	34	Female
...				

Movies Table

mid	name	Director	Genre
1	'Spartacus'	'Stanley Kubrick'	'Action'
2	'Inception'	'Christopher Nolan'	'Suspense'
3	'The Matrix'	'Lana Wachowski'	'Sci-Fi'
...			

Fig. 3.2: Recommender Input Data.

and employing the Item Scorer to predict the rating that the specified user would give to unseen items. RecQuEx employs a *caching module* that pre-computes the predicted rating for a set of user/item pairs and store them on disk to further reduce the recommendation generation latency.

The recommendation application may also update the recommender input data, user/item ratings, using traditional SQL update statements, e.g., `INSERT, UPDATE, DELETE`. In case a recommender is already created and initialized on-top of the updated ratings table, RecDB invokes RecStore which is responsible for efficiently updating the recommendation model, stored in the database, in order to provide online recommendation to end-users.

3.2 Using RecDB

Since RecDB is implemented inside a database management system, it hence accepts relational tables as input. The recommender input data mainly represents a user/item *Ratings* table that contains a set of users U and a set of items I and a set of ratings that each tuple represents a rating *ratingval* that a $u \in U$ assigned to an item $i \in I$.

Ratings represent users expressing their opinions over items. Opinions can be a numeric rating (e.g., one to five stars), or unary (e.g., Facebook "check-ins"). Also, ratings may represent purchasing behavior (e.g., Amazon). Figure 3.2 gives an example of movie recommendation data.

RecDB provides a tool to the system users to freely decide which attributes and recommendation algorithm to be used in building a recommender. To this end, the system allows its users to use a SQL-like clause to declare a new recommender by specifying the recommender input data source and recommendation algorithm. This section focuses on how users interact with the system. In particular, Section 6.1.1 explains the SQL clause for creating a new recommender, while Section 6.1.2 explains the SQL for querying a certain recommender. Internals of RecDB that enable such interface, i.e., indexing, maintenance, query processing and optimization, are described in later sections.

3.2.1 Creating a Recommender

To allow creating a new recommender, RecDB employs a new SQL statement, called `CREATE RECOMMENDER`, as follows:

```
CREATE RECOMMENDER <Recommender Name> ON <Ratings Table>
USERS FROM <Users ID Column>
ITEMS FROM <Items ID Column>
RATINGS FROM <Ratings Value Column>
USING <Recommendation algorithm>
```

The recommender creation SQL, presented above, has the following parameters: (1) `Recommender name` is a unique name assigned to the created Recommender. (2) `Ratings Table` is the table that contains the input user/item ratings data (e.g., see Figure 3.2). (3) `Users ID Column`, `Items ID Column`, and `Ratings Value Column` are the columns containing the users, items, and ratings data in the ratings table. (4) `Recommendation algorithm` is the algorithm used to build the recommender. Currently, RecDB supports three main recommendation algorithms (with their variants): (a) Item-Item Collaborative Filtering with Cosine (abbr. ItemCosCF) or Pearson Correlation (abbr. ItemPearCF) similarity functions, (b) User-User Collaborative filtering (abbr. UserCosCF / UserPearCF), and (c) Regularized Gradient Descent Singular Value

(c) User-Items Vector Table

UserID	uVector
Alice	{⟨'Spartacus',1.5⟩}
Bob	{⟨'Inception',3.5⟩;⟨'Spartacus',4.5⟩;⟨'The Matrix',2⟩}
Carol	{⟨'Inception',1⟩;⟨'Spartacus',2⟩}
Eve	{⟨'Inception',1⟩;⟨'The Matrix',2.5⟩}

(d) Item-Users Vector Table

Item	iVector
'Spartacus'	{⟨Alice,1.5⟩;⟨Bob,4.5⟩;⟨Carol,1⟩}
'Inception'	{⟨Bob,3.5⟩;⟨Carol,1⟩;⟨Eve,1⟩}
'The Matrix'	{⟨Bob,2⟩;⟨Eve,2.5⟩}

Fig. 3.3: Rating Table Storage Representation

Decomposition (abbr. SVD). If no recommendation algorithm is specified, RecDB employs by default the ItemCosCF algorithm.

Recommender Initialization. The initialization process consists of two steps: (I) *User/Item Rating Re-Arrangement*: RecDB first re-arranges the user/item rating matrix data on disk and stores it into the *vector representation* format. That format represents the user/item ratings matrix as a table, namely the *User Vector Table*. The user vector table consists of two columns: *UserID*: a unique user identifier and *uVector*: a set of Key-Value pairs $\langle iid, rating \rangle$ that contains evert item *iid* rated by the user and the respective *rating* value. The user vector table is indexed by a primary key index created on the *UserID* field. Figure 5.1 gives the *User Vector Table* for the ratings matrix given in Figure 3.2. To efficiently access item vectors instead of user vectors, we also store the user/item ratings matrix transpose, called *Item Vector Table*, that also consists of two columns: *ItemID* and *iVector* (see Figure 5.1).

(II) *Model Building*: In this step, RecDB employs a set of user defined functions that train a recommendation model *RecModel* using the input data. The format of the model depends on the underlying recommendation algorithm. For example, a recommendation model for the item-item collaborative filtering (cosine similarity measure) model (ItemCosCF) [6] represents a similarity list of the tuples $\langle i_p, i_q, SimScore \rangle$, where $SimScore$ is the similarity between items i_p and i_q.

3.2.2 Updating a Recommender

To get the most accurate result, *RecModel* should be updated with newly inserted rating by a user u assigned to an item i. However, doing so is infeasible as collaborative recommendation algorithms employ complex computational techniques that are very costly to update. The update maintenance procedure differs based on the underlying recommender algorithm, specified in the `CREATE RECOMMENDER` statement. Yet, most of the algorithms may call for a complete model rebuilding to incorporate any new update. To avoid such prohibitive cost, we decide to update the *RecModel* only if the number of new updates reaches to a certain percentage ratio $N\%$ (a system parameter) from the number of entries used to build the current model. We do so because an appealing quality of most supported recommendation algorithms is that as *RecModel* matures (i.e., more data is used to build it), more updates are needed to significantly change the recommendations produced from it.

3.2.3 Querying a Recommender

Once a recommender is created and initialized using the `CREATE RECOMMENDER` statement, users can issue SQL queries that harnesses the created recommender to produce recommendation to end-users, as follows:

```
SELECT    <Select Clause>
FROM      <Rating Table>
RECOMMEND <ItemID> TO <UserID> ON <RatingVal>
USING     <Recommendation Algorithm>
WHERE     <Where Clause>
```

Query Syntax. The `SELECT` and `WHERE` clauses are typical as in any SQL query. The `FROM` clause may directly accept a `[Ratings]` table with the same schema passed to the `CREATE RECOMMENDER` statement. The `RECOMMEND` clause is responsible for predicting how much the system users would like the unseen items. The application developer also needs to specify the ItemID (i.e., `<ItemID>`), UserID (i.e., `TO <UserID>`), and Rating Value (i.e., `ON <RatingVal>`) Columns.

Query Semantics. The `RECOMMEND` clause returns a set of tuples S such that each tuple $s \in S$; $s = \langle uid, iid, ratingval \rangle$ represents a predicted rating score (*ratingval*) that

a user (*uid*) would give to an unseen item (*iid*) based on the recommendation algorithm specified in the `USING` clause.

3.3 Case Studies

This section presents two case studies that manifest the usability of RecDB . Section 3.3.1 presents a movie recommendation application that delivers movie recommendation to end-users based on historical preferences. Section 3.3.2 highlights a Point-of-Interest (POI) recommendation application that recommends Point-of-Interests to end-users based on their spatial location.

3.3.1 Movie Recommendation

This section show how RecDB is used to build a movie recommendation application. The data set leveraged by this application consists of three tables: (1) `Users (uid, name, age, city, gender)`: contains information about all users. Each user tuple consists of a user ID, user name, age, home city, and gender. (2) `Movies (mid, name, director, genre)`: the set of movies saved in the database; each movie has a unique ID, name, director, and genre. (3) `Ratings (uid, mid, rating)`: The history of user ratings such that each rating represents how much a user liked a movie she/he watched.

Creating a Movie Recommender

To create Recommender 3 (given below), the system user leverages the `CREATE RECOMMENDER` SQL statement to declare `MovieRec`, a recommender that is created on top of the Users, Movies, and Ratings database tables. We specify the item-item collaborative filtering method to be applied to the declared recommender.

Recommender 1 MovieRec*: a ItemCosCF recommender created on the input data stored in the Ratings table of Figure 3.2.*

```
Create Recommender MovieRec On Ratings
Users From uid Item From iid Ratings From ratingval Using ItemCosCF
```

This SQL creates a recommender, named *MovieRec* inside RecDB . *Rec* is a traditional recommender that can be queried to recommend a set of movies for a certain user, e.g., *recommend me five movies.*

Movie Recommendation Generation

An example of a movie recommendation query is given below:

Query 1 *Return ten movies to user with ID 1 using the Item-Item Collaborative Filtering algorithm.*

```
Select R.uid, R.iid, R.ratingval
From Ratings as R
Recommend R.iid To R.uid On R.ratingVal Using ItemCosCF
Where R.uid=1 Order By R.ratingVal Desc Limit 10
```

In this case, RecDB uses the `MovieRec` recommender, which was created before using a `CREATE RECOMMENDER`. Since this recommender was created based on the age attribute, Query 11 will predict the ratings based on the algorithm passed to `ItemCosCF` algorithm. The query finally returns the Top-10 movies to user 1 in a descending order of the predicted rating value (`ratingval`).

3.3.2 Point-of-Interest (POI) Recommendation

Recently, applications like Yelp and Google maps have provided tools for end-users to express their opinions over visited items, e.g., restaurants. That motivated the use of recommender systems to suggest Point-Of-Interests (POIs) to end-users in urban areas. In this section, we present a use case that serves as an anecdotal evidence to prove the usefulness of RecDB . Consider the following scenarios:

Scenario 1 *Alice plans to visit 'Minneapolis' for business. She looks for Hotel recommendation in the 'Minneapolis' urban area.*

In Scenario 1, the system first needs to retrieve hotels that lie within the 'Minneapolis' area. Therefore, it predicts the rating that Alice would give to such hotels based on

the opinions of other users similar to her. In Scenario 2 (below), the system calculates the distance between Alice's current location and all restaurants. It also predicts a rating for each restaurant based on its similarity to restaurants already seen by Alice. The system finally ranks restaurants based on both the spatial proximity score and predicted rating score.

Scenario 2 *Alice arrived to 'Minneapolis'. She looks for nearby (personalized) restaurant recommendation.*

In order to support POI recommendation, we integrate RecDB with PostGIS [46]. PostGIS is an extension to PostgreSQL that provides a SQL interface for users to express spatial operations on geographical data. That way, users can spatially filter the recommended POIs to only return those POIs that resides in a specified urban area. That also allows users to rank POIs based on both its personalized recommendation score and spatial proximity to the querying user.

Creating POI Recommenders

The following SQL creates a recommender, named `POI-ItemCosCF-Rec`, on the input data stored in the HotelRatings table. `POI-ItemCosCF-Rec` can be accessed to predict a rating that users would give to POIs based on the ItemCosCF algorithm.

Recommender 2 POI-ItemCosCF-Rec*: an SVD recommender created on the HotelRatings table.*

```
Create Recommender POI-ItemCosCF-Rec On HotelRatings
Users From uid Item From iid Ratings From ratingval Using ItemCosCF
```

The following SQL creates another recommender, named `POI-SVD-Rec`, on the the RestaurantRatings table. `POI-SVD-Rec` can be accessed later to predict how much users would like POIs based on the SVD recommendation algorithm.

Recommender 3 POI-SVD-Rec*: a UserPearCF recommender created on the RestaurantRatings table.*

```
Create Recommender POI-SVD-Rec On RestRatings
Users From uid Item From iid Ratings From ratingval Using SVD
```

Generating POI Recommendation

After initializing the POI recommenders, users may issue location-aware recommendation queries. For instance, to produce POI recommendation as given in Scenario 1, users may issue the following SQL queries:

Query 2 *Predict the rating that user 1 would give to Hotels that exist in the 'Minneapolis' urban area.*

```
Select H.name, R.ratingval
From HotelRatings as R, Hotels as H, City as C
Recommend R.iid To R.uid On R.ratingVal Using ItemCosCF
Where R.uid=1 AND R.iid=H.vid AND C.name = 'Minneapolis' AND
ST_Contains(C.geom, H.geom)
```

In this case, RecDB uses the `POI-ItemCosCF-Rec` recommender, which was created before using a `CREATE RECOMMENDER`. Query 2 predicts the ratings that user 1 would give to unseen hotels using the `RECOMMEND` operator. However, the query leverages the `ST_Contains()` function (provided by PostGIS) to predict a rating only for those hotels that lie within the extent of the 'Minneapolis' urban area.

Query 3 *Recommend top-10 restaurants to user 1 that lies within a 500 meters distance of her current location based on the UserPearCF algorithm.*

```
Select V.name, V.address
From Ratings as R, Restaurants as V
Recommend R.iid To R.uid On R.ratingVal Using SVD
Where R.uid=1 AND R.iid=V.vid AND ST_DWithin(ULoc, V.geom, 500)
Order By R.ratingVal Desc Limit 10
```

Query 3 harnesses the `POI-SVD-Rec` recommender, created earlier and initialized inside RecDB , to predict the ratings that user 1 would give to restaurants that lie within 500 meters range from the user current spatial location. To this end, Query 3 invokes the `ST_DWithin()` geometry function to filter out restaurants that are not spatially within 500 meters from the user location.

Query 4 *Recommend top-10 restaurants that are close to user 1 current location based on the SVD algorithm.*

```
Select V.name, V.address
From Ratings as R, Restaurants as V
Recommend R.iid To R.uid On R.ratingVal Using SVD
Where R.uid=1 AND R.iid=V.vid
Order By CScore(R.ratingVal, ST_Distance(V.geom, ULoc)) Desc Limit 3
```

Query 4 combines both the predicted rating score calculated using the UserPearCF algorithm and the spatial proximity score using the PostGIS `ST_Distance()` function. The query finally returns the Top-3 restaurants.

Chapter 4

Online Recommendation Model Maintenance

To get fresh (most accurate) recommendation, the recommendation model should be updated with newly inserted user, item, or ratings data. A straightforward approach is to use DBMS views to support online model management. This approach has major drawbacks. (1) *Inflexibility* in supporting model truncation rules. For example, views lack support for efficiently maintaining the top-k related objects for each object (user or item) in the database. Furthermore, are incapable of understanding flexible truncation rules [47] (e.g., maintain the top-k related objects for the 100 most popular objects in the database, and only the top-m related objects otherwise, $k > m$). Such rules are beneficial to the quality of recommendation [6, 17, 22]. (2) *Inefficiency.* Using a regular view will incur serious query processing overhead. Essentially, this approach re-executes the expensive model-building step for *every* recommendation generation query. On the other hand, materialized views suffer from an update efficiency perspective. Depending on the view definition, a materialized view may require a complete refresh upon receiving an update to the base *Rating* table (e.g., complete refresh conditions in Oracle [48]). Furthermore, we cannot specify *how* and *when* updates to the view occur in order to tune update efficiency, e.g., update similarity scores *only* when the average item rating moves outside a threshold. As we will see, such update rules are necessary in providing efficient update support for some recommender models.

In this Chapter, we address the problem of providing online recommender model maintenance for DBMS-based recommender systems. We present RecStore , a RecDB module built *inside* the storage engine of a database system. RecStore enables online model support for DBMS-based recommender systems (e.g., [38]) through efficient incremental updates to *only* parts of the model affected by a rating update. Thus, updating the recommender model does not involve significant overhead, nor regeneration of the model from scratch. RecStore exposes the model to the query processor as a standard relational table, meaning that *existing* recommender queries can remain *unchanged*.

The basic idea behind RecStore is to separate the logical and internal representations of the recommender model. RecStore receives updates to the user/item rating data (i.e., the base data for a collaborative filtering models) and maintains its internal representation based on these updates. As RecStore is built into the DBMS storage engine, it outputs tuples to the query processor though access methods that transform data from the internal representation into the logical representation expected by the query processor.

RecStore is designed with extensibility in mind. RecStore 's architecture is generic, and thus the logic for a number of different recommendation algorithms can easily be "plugged into" the RecStore framework, making it a one-stop solution to support a number of popular recommender models within the DBMS. We provide a generic definition syntax for RecStore , and provide implementation case studies for various neighborhood-based [6, 42] collaborative filtering algorithms (e.g., item-based [21] and user-based [19]). We also discuss support for other non-trivial recommendation algorithms (e.g., [42, 49]).

RecStore is also adaptive to system workloads, tunable to realize a trade-off that makes query processing more efficient at the cost of update overhead, and vice versa. At one extreme, RecStore has lowest query latency by making update costs more expensive; appropriate for query-intense workloads. At the other extreme, RecStore minimizes update costs by pushing computation into query processing; appropriate for update-intense workloads. For particularly update-intense workloads, RecStore also performs load-shedding to process *only* important updates that significantly alter the recommender model and change the answers to recommender queries.

RecStore requires a small code footprint, which is advantageous to implementation in existing database engines. Our prototype of RecStore , built *inside* PostgreSQL [40], between the storage engine and query processor, requires approximately 600 lines of either modified or new code. Rigorous experimental study of our RecStore prototype using a *real* workload from the popular MovieLens [50] recommender system shows that RecStore exhibits desirable performance in *both* updates and query processing compared to existing DBMS approaches that support online recommender models using regular and materialized views.

The rest of this Chapter is organized as follows: Section 4.1 introduces the RecStore architecture. Section 4.2 describes the functionality of RecStore . Finally, Section 5.4 provides an experimental evaluation of RecStore .

4.1 RecStore Architecture

Figure 4.1 depicts the high-level architecture of RecStore , built inside the storage engine of a DBMS. RecStore consists of the following main components:

- **Intermediate store and filter**. The *intermediate store* contains a set of statistics, functions, and/or data structures that are efficient to update, and can be used to quickly generate part of the recommender model. The data maintained in the intermediate store is specific to the recommendation algorithm. Whenever RecStore receives ratings updates (i.e., insertions, deletions, or changes to the ratings table), it applies an *intermediate filter* that determines whether the update will affect the contents of the *intermediate store* (Section 4.2.1).

- **Model store and filter**. The *model store* represents the materialized model that matches the exact storage schema needed by the recommender algorithm (e.g., *(itm, rel_itm, sim)* for the item-based model covered in Section 2.1). Any changes to the intermediate store goes through a *model filter* that determines whether it affects the contents of the *model store* (Section 4.2.1).

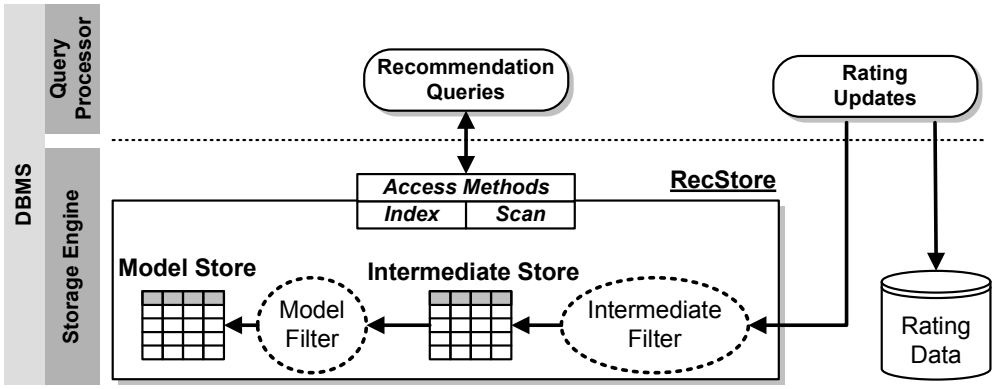


Fig. 4.1: RecStore Architecture

4.2 RecStore: Built-In Online DBMS-Based Recommenders

The main objective of RecStore is to bring online model support to existing recommender queries for various workloads and recommendation algorithms. This objective presents three main challenges that we address in the rest of this Chapter: (1) Efficient online incremental maintenance of the recommender model, i.e., avoiding expensive model regeneration with each update (Section 4.2.1). (2) The ability to adapt the system to various workloads, e.g., query or update-intensive workloads (Section 4.2.2). (3) The ability to support various existing recommender algorithms (Section 4.3).

4.2.1 Online Model Maintenance

This section describes the framework for online model maintenance within RecStore . The framework is extensible, and its specific functionality is determined by the underlying recommendation algorithm. While this approach may seem overly-tailored to each specific algorithm, we note that many algorithms, especially collaborative filtering, share commonalities in model structure. We defer such discussion until later in Section 4.3. For now, we use the example of the item-based cosine model to illustrate RecStore 's approach to providing online model maintenance, consisting of two steps.

Step 1: Intermediate Filter

We describe the functionality of the intermediate filter with an example using the item-based cosine algorithm described in Section 2.1. For this algorithm, the intermediate store contains a "deconstructed" cosine score (Equation 2.4), where we store for each item pair (i_p,i_q) that share at least *one* co-rated dimension (1) $pdot(i_p, i_q)$, their partial dot product, (2) $len_p(i_p, i_q)$ and $len_q(i_q, i_p)$, the partial length of each vector for only the co-rated dimensions, and (3) $co(i_p, i_q)$, the number of users who have co-rated items i_p and i_q. This data is stored as a six-column relation, where the first two columns store the item id pairs, while the last four columns store the four statistics just described.

RecStore employs an *intermediate filter* upon receiving a rating update $\mathcal{R}$. The intermediate filter performs three tasks in the following order. (1) *Filter.* This task determines whether $\mathcal{R}$ will be used to update entries in the intermediate store. If not, $\mathcal{R}$ is immediately dropped (but still stored in the ratings data). This step is required by the adaptive maintenance and load shedding techniques discussed later Section 4.2.2. In the general case this step will not drop any updates. (2) *Enumeration.* This task determines all intermediate store entries $\mathcal{E}$ that will change due to $\mathcal{R}$. For our item-based cosine example with a new rating for item i_p, $\mathcal{E}$ would contain all entries (i_p,i_q) for which items i_p and i_q are co-rated by the user u. (3) *Updates.* Finally, all statistics, functions, or data structures in the intermediate store associated with an entry $e \in \mathcal{E}$ are updated. These updates are then forwarded to the model filter. For our item-based cosine example, the stored statistics are updated as follows, assuming a new rating for item i_p with value s_p: $pdot(i_p, i_q) = pdot(i_p, i_q) + s_p \times s_q$, $len_p(i_p, i_q) = len_p(i_p, i_q) + s_p$, $len_q(i_q, i_p) = len_q(i_q, i_p) + s_q$, and $co(i_p, i_q) = co(i_p, i_q) + 1$.

Together, the intermediate filter and store are the keys to efficient online model maintenance in RecStore . The filter reduces update processing overhead by allowing RecStore to only process the updates necessary to maintain an accurate intermediate representation. The contents of the intermediate store keep computational overhead low for online maintenance by allowing RecStore to quickly update the intermediate store and, once updated, quickly derive a final model score from the intermediate representation.

Step 2: Model Filter

Upon receiving updates from the intermediate filter, the *model filter* executes the same three tasks as the intermediate filter (i.e., filter, enumeration, and updates), except applied to the model store instead of the intermediate store. Continuing our item-based cosine example, its model store contains entries of the form (i_p,i_q,sim(i_p,i_q)), i.e., the item-based model schema discussed in Section 2.1. The model filter uses the statistical updates from the intermediate store for item pairs (i_p,i_q) to update the similarity score in the model store entry (i_p,i_q, sim(i_p,i_q)) as follows per Equation 2.2: (1) If statistic $co(i_p, i_q) < 50$, then $sim(i_p, i_q)$ is updated as:

$$sim(i_p, i_q) = \frac{co(i_p, i_q) * pdot(i_p, i_q)}{50 * \sqrt{len_p(i_p, i_q)}\sqrt{len_q(i_p, i_q)}}$$

(2) If statistic $co(i_p, i_q) \geq 50$, we update $sim(i_p, i_q)$ as:

$$sim(i_p, i_q) = \frac{pdot(i_p, i_q)}{\sqrt{len_p(i_p, i_q)}\sqrt{len_q(i_p, i_q)}}$$

Updating the similarity score is the final step in the RecStore online maintenance process.

4.2.2 Adaptive Strategies for System Workloads

This section discusses how RecStore adapts to different workload characteristics. We first discuss generic maintenance strategies that help realize an update and query efficiency trade-off. We then discuss load-shedding for update-intensive workloads.

Update vs. Query Efficiency Trade-off

While the intermediate and model store are beneficial to RecStore , their sizes may lead to non-trivial maintenance costs. For instance, in item-item or user-user collaborative filtering, the size of the model can reach O(n^2), where n is the number of items (or users). In this case, RecStore could be responsible for updating and maintaining data for O(n^2) items (or users) in its intermediate and model store, leading to burdensome maintenance costs. In this section, we explore a trade-off: reducing the storage and maintenance of data in the intermediate store and model store (i.e., the *internal maintenance* approach) in return for sacrificing query processing (i.e., recommendation generation) efficiency.

RecStore can be tuned to realize an efficiency trade-off between updates and query processing. The basic idea is to maintain α entries in the intermediate store, β entries in the model store, and require the invariant that $\alpha \geq \beta$, i.e., all entries in the model store are also maintained in the intermediate strore. Both values cannot be greater than $\mathcal{M}$: the total possible number of entries, a model-specific value (e.g., for item-based models $\mathcal{M} = \mathcal{I}^2$).

Low values of α and β imply low incremental update latency as the filters udpate fewer entries in the intermediate and model stores. On the other hand, during query processing, the access algorithms must service requests from the query processor by producing model values in the following order of efficiency: (1) directly from the model store if the entry is maintained there. (2) If the entry is not maintained in the model store but maintained in the intermediate store, the model value is produced *on-demand* from the intermediate store (e.g., from the intermediate statistics covered in Section 4.2.1 for the item-based cosine algorithm). (3) If the entry is not maintained in the intermediate nor the model store, the model value must be produced *on-demand* using the base ratings data (e.g., using Equation 2.1 for the item-based cosine algorithm). Thus, as α and β decrease, query processing latency increases as more model values must be produced *on demand*. Larger values of α and β have a reverse effect on update and query processing efficiency.

Using the maintenance parameters α and β allows RecStore to be tuned for a wide range of workloads. More update-intense workloads can lower values of α and β at the cost of increasing recommender query latency. Meanwhile, query-intense workloads can use larger values of α and β at the cost of increasing update overhead. We now explore several strategies for α and β settings; experimental analysis for these strategies is given in Section 5.4.

- **Extreme Approaches**. Two extreme approaches can be taken by RecStore : (1) *Materialize all*. In this approach $\alpha = \beta = \mathcal{M}$, meaning RecStore 's intermediate and model stores maintain all required model information. RecStore filters just apply the conditions imposed by the specific similarity functions upon receiving a rating update. Recommendation generation, i.e., the query processing functionality that generates recommended items, is most efficient at this extreme. However, storage and maintenance costs are at their highest with this approach.

(2) *Materialize none*. In this approach $\alpha = \beta = 0$, and basically mimics the use of regular DBMS views that we recompute model values *on demand*. In this approach there is no need for the intermediate store, model store, nor filters. Recommendation generation for this approach is very expensive, but incurs *no* storage and maintenance costs as nothing is maintained.

- **Intermediate Store Only**. In this approach $\alpha = \mathcal{M}$ and $\beta = 0$. This approach (abbr. *Intermediate Only*) represents a middle ground between *Materialize All* and *Materialize None*, where we materialize the intermediate store in full for all required model information, while not maintaining the model store. This means that the initial filter will be applied on all incoming updates as described in Section 4.2.1, while there is no filter for the model store. The recommendation generation process for a requested object o (e.g., item or user) needs to rebuild part of the model store that includes o using the fully maintained intermediate store. This rebuilding process makes this approach incur higher query processing cost compared to the *Materialize All* approach, but much lower query processing cost than the *Materialize None* approach. On the other hand, storage and maintenance costs are lower than the *materialize all* approach, as the model store is nonexistent.

- **Full Intermediate Store and Partial Model Store**. This approach (abbr. *Partial Model*) sets $\alpha = \mathcal{M}$ and $\beta = N$, and represents a middle ground between the *Materialize all* and *Intermediate Only* approaches. This approach materializes only a *portion* of the model store, i.e., only N objects (e.g., items or users), while materializing the intermediate store in full. We employ *hotspot detection* (described in Section 4.2.2) to select the N items in the model store. This approach directs the initial filter will be applied to all incoming updates. All updates made to the intermediate store are still forwarded to the model filter as described in Section 4.2.1, however, the model filter only accepts updates for the qualifying N objects, and their their related objects, that are maintained in the model store. The query processing and storage/maintenance overhead for this approach lies between the *Materialize all* and *Intermediate Only* approaches.

- **Partial Intermediate Store and Partial Model Store**. This approach sets

$\alpha = K$ and $\beta = N$, and is similar to the *Partial Model* approach, except that we also partially materialize the intermediate store. The model store still maintains data for N objects, while the intermediate store maintains data for K objects. These K and N objects are derived using *hotspot detection* (described next in Section 4.2.2). This approach directs the initial filter only accepts incoming updates for the K objects (items of users), and their their related objects, that qualify for storage in the intermediate store. The model filter remains unchanged from the *Partial Model* approach. The query processing and storage/maintenance overhead for this approach lies between the *Partial Model* and *Intermediate Only* approaches.

HotSpot Detection

For the approaches that use partial materialization, α and β should ideally be set to ensure the maintenance of model *hotspots*, i.e., popular or frequently accessed entries. This setting assures efficient query processing over popular model entries, while sacrificing higher query latency for less popular model entries. We use two methods to detect hotspots. (1) *Most accessed*. Keep the α and β most accessed entries from the model determined by simple usage statistics from the access methods. (2) *Most rated*. Keep the α and β most popular entries in the model determined by association with the *most ratings* (e.g., most-rated movies, users who rate the most movies).

Load Shedding

For the special case of update-intense workloads where the system is incapable of processing all ratings updates, RecStore is capable of load-shedding. The goal of load-shedding is to process *only* updates that significantly alter the recommender model, thus changing the answer to recommender queries. Load-shedding techniques are model-specific, and RecStore executes these techniques in a special filter before the intermediate filter.

As an example, consider the item-based cosine method, where an update should only be processed if it changes the order in the model similarity lists. In this case, altered order in any similarity list can potentially change the answer to a recommender query per Equation 2.4. An effective heuristic approach to achieve this goal is to process

```
DEFINE RECSTORE MODEL ItmItmCosine
FROM    Ratings R1, Ratings R2
WHERE   R1.itemId <> R2.ItemId AND R1.userId = R2.userId
WITH INTERMEDIATE STORE:
   (R1.itemId as item, R2.itemId as rel_itm, vector_lenp,
    vector_lenq, dot_prod, co_rate)
WITH INTERMEDIATE FILTER:
  ALLOW UPDATE WITH My_IntFilterLogic(),
  UPDATE vector_lengthp AS R1.rating*R1.rating,
  UPDATE vector_lengthq AS R2.rating*R2.rating,
  UPDATE dot_prod AS R1.rating*R2.rating,
  UPDATE co_rate AS 1
WITH MODEL STORE:
   (R1.itemId as item, R2.itemId as rel_itm, COMPUTED sim)
WITH MODEL FILTER:
  ALLOW UPDATE WITH My_ModFilterLogic(),
  UPDATE sim AS
    if (co_rate < 50)
       co_rate*dot_prod/50*sqrt(vector_len1)* sqrt(vector_len2);
    else
       co_rate/sqrt(vector_len1)* sqrt(vector_len2);
```

Fig. 4.2: Registering a recommendation algorithm

updates that change intermediate store entries with a co-rating count (i.e., the statistic $co(i_p, i_q)$) below a pre-set threshold $\mathcal{T}$. The intuition here is that low co-rated items have less terms defining their cosine distance, thus an update will likely alter the score significantly compared to more highly co-rated items. Of course, more sophisticated statistical techniques can apply. However, any load-shedding approach should remain simple to evaluate and maintain due to its mission-critical purpose.

4.3 RecStore Extensibility

RecStore provides a generic extensible architecture capable of supporting different recommendation algorithms. This section first demonstrates how to register a recommendation algorithm with RecStore . We then provide various case studies demonstrating how RecStore accommodates other item-based collaborative filtering methods. Finally, we discuss how RecStore supports recommendation algorithms beyond "neighborhood-based" collaborative filtering.

4.3.1 Registering a Recommender algorithm

We provide a syntax for registering a new recommender algorithm model within RecStore . Figure 4.2 gives an example for registering the item-based cosine algorithm. Registration begins by first defining the model name, and then providing a *from* and optional *where* clause to specify the base data used in the model. For the item-based cosine model, the base data comes from the *Ratings* relation, and the where-clause defines a relational constraint (in the form of a self-join) declaring that model entries are (non-equal) items that are co-rated by the same user. The major clauses are:

- **WITH INTERMEDIATE STORE:** defines the data in the intermediate store; in this case the intermediate statistics for the item-based cosine algorithm.
- **WITH INTERMEDIATE FILTER:** defines the intermediate filter in two parts. (1) *Allow Updates With* defines the logic for filtering incoming updates (task 1 discussed in Section 4.2.1), currently contained in a user-defined function. (2) *Update* defines how to compute data in the intermediate store when given a rating update that is *not filtered*; the logic can be given directly or contained in a user-defined function.
- **WITH MODEL STORE:** defines the name and schema of the model store, this schema is exposed to the rest of the DBMS and used by the recommender queries. Any attributes computed from data in the intermediate store are given the *COMPUTED* prefix. Our example item-based cosine follows the schema discussed in Section 4.2.1, where the value *sim* is a computed attribute.
- **WITH MODEL FILTER:** follows the same syntax as the intermediate filter, with the exception that the *compute* clause defines how to update the model store values using data from the intermediate store.

4.3.2 Item-Based Collaborative Filtering

We now discuss RecStore registration for two other item-based collaborative filtering algorithms [21], namely probabilistic and Pearson item-based recommenders. We

	Probabilistic	**Pearson**
Intermediate Store	len(i_p): partial vector length of for i_p freq(i_p): no. ratings for i_p sum(i_p,i_q): sum of scores for i_p given co-rated item i_q	mean(i_p): mean rating score for i_p stddev(i_p): standard dev. for i_p freq(i_p): no. ratings for i_p sum(i_p): sum of ratings for i_p sumsq(i_p): sum or ratings squared for i_p coprodsum(i_p,i_q): sum of product deviation from mean for i_p given co-rated dimension i_q
Intermediate Filter	Update sum$_q$(i_p,i_q) only where user u co-rated i_p and i_q, always update other statistics. Update logic sum(i_p,i_q)=sum(i_p,i_q)+s_p; len(i_p)=len(i_p)+s_p^2; freq(i_p)=freq(i_p)+1	Always update mean(i_p), stddev(i_p), freq(i_p), sum(i_p), sumsq(i_p).Only update coprodsum(i_p,i_q) if user u co-rated i_p and i_q, *and*mean(i_p) has not changed greater than Δ since last coprodsum(i_p,i_q)recalculation. Update logic freq(i_p)=freq(i_p)+1; mean(i_p)=$\frac{s_p}{freq(i_p)}$ + $\frac{(freq(i_p)-1)mean(i_p)}{freq(i_p)}$; sum($i_p$)=sum($i_p$)+$s_p$; sumsq($i_p$)=sumsq($i_p$)+$s_p^2$; stddev($i_p$)=$\frac{\sqrt{freq(i_p)*sumsq(i_p)-sum(i_p)^2}}{freq(i_p)}$; coprodsum($i_p$,$i_q$)=coprodsum($i_p$,$i_q$)+$(s_p - mean(i_p))(s_q - mean(i_p))$
Model Store	(i_p,i_q,$sim(i_p, i_q)$)	(i_p,i_q,$sim(i_p, i_q)$)
Model Filter	Update entry (i_p,i_q,$sim(i_p, i_q)$) for each statistical update for pair (i_p,i_q) Update Logic $sim(i_p, i_q)$= $\frac{sum_q(i_p,i_q)}{\sqrt{len(i_q)}*freq(i_p)*(freq(i_q))^\alpha}$	*Update* entry for each (i_p,i_q,$sim(i_p, i_q)$) for each statistical update affecting pair (i_p,i_q). Completely *recalculate* coprodsum(i_p,i_q) if mean(i_p) has changed greater than threshold Δ. Update Logic If mean(i_p) has changed less than Δ, $sim(i_p, i_q)$=$\frac{coprodsum(i_p,i_q)}{stddev(i_p)stddev(i_q)}$, otherwise $sim(i_p, i_q)$=$\frac{coprodsum(i_p,i_q)=\sum_{u\in\mathcal{U}_c}(s_p-mean(i_p))(s_q-mean(i_p))}{stddev(i_p)stddev(i_q)}$

Table 4.1: Realizing probabilistic and Pearson item-based collaborative filtering

demonstrate each use case assuming a user u has provided a new rating value s_p for an item i_p.

Item-based probabalistic recommender. This algorithm is similar to our running example of the item-based cosine recommender, except the similarity score $sim(i_p, i_q)$ is measured as the conditional probability between two items i_p and i_q as follows.

$$sim(i_p, i_q) = \frac{\sum_{u\in\mathcal{U}_c} r_{u,i_q}}{Freq(i_p) \times (Freq(i_q))^\alpha} \tag{4.1}$$

Here, r_{u,i_q} represents a rating for item i_q normalized to unit-length, $Freq(i)$ represents the number of non-zero ratings for item i, and α is a scaling factor [43].

The second column of Table 4.1 provides an approach to implementing the item-based probabilistic algorithm in RecStore . The intermediate store contains (1) the partial vector length for item i_q (len(i_q)), (2) the total number of ratings for i_p (freq(i_p)), and (3) the item-pair statistic maintains the running sum ratings for item i_p given that it is co-rated with an item i_q (sum(i_p,i_q)). The intermediate filter updates all single-item statistics, while only updating the pair statistic for which items i_p and i_q are both rated by user u. Each statistic update requires constant time. The *model filter*, upon receiving changes to the intermediate statistics, updates the similarity score $sim(i_p,i_q)$ for pairs i_p,i_q in constant time using the intermediate statistics (equation given in the last row, second column of Table 4.1).

Item-based Pearson recommender. This algorithm is similar to the item-based cosine algorithm, except it measures the similarity between objects using their Pearson correlation coefficient as follows.

$$sim(i_p, i_q) = \frac{\sum_{u \in \mathcal{U}_c}(R_{u,i_p} - \overline{R}_{i_p})(R_{u,i_q} - \overline{R}_{i_q})}{\sigma_{i_p}\sigma_{i_q}} \tag{4.2}$$

$\mathcal{U}_c$ represents users who co-rated items i_p and i_q, R_{u,i_p} and R_{u,i_q} represent a user's ratings, and $\overline{R}_{i_p}$ and $\overline{R}_{i_q}$ represent the average rating for items i_p and i_q, respectively. σ_{i_p} and σ_{i_q} are the standard deviations for i_p and i_q

The third column of Table 4.1 provides an approach to implementing the Pearson algorithm in RecStore . The intermediate store maintains for an item i_p its mean rating value for an item (mean(i_p)), its standard deviation of rating values (stddev(i_p)), the total number of ratings for i_p (freq(i_p)), the sum of ratings for i_p (sum(i_p)), and the sum of the squared rating values for i_p (sumsq(i_p)). The intermediate store also maintains *coprodsum*(i_p,i_q): the sum of the product of deviations from the mean (i.e., the numerator in Equation 4.2) for an item pair (i_p,i_q) given that they share at least one co-rated dimension. The *intermediate filter* updates all single-item statistics (those maintained for i_p only). The statistic *coprodsum(* i_p,i_q) is incremented by the product of the deviation of user u's score for i_p (i.e., s_p) from the *newly* calculated *mean*(i_p), and the deviation of i_q (i.e., s_q) from the stored mean for item i_q (*mean*(i_q)). Note that previous rating scores for i_p in the sum deviated from different means, since *mean*(i_p) changed with this update. In essence, we are willing to forgo this difference in *accuracy* as long as *mean*(i_p) has not changed by at least a value Δ since the last calculation of

coprodsum(i_p,i_q). What we gain in this trade-off is efficiency, since updating *coprodsum*(i_p,i_q) is more efficient than recalculating the sum from scratch.

The *model filter* updates the similarity score *sim*(i_p,i_q) for pairs i_p,i_q in the model store using one of two algorithms (both given in the last row, third column of Table 4.1). (1) If the value *mean*(i_p) had not changed by Δ since the last recalculation of *coprodsum*(i_p,i_q), then we can update *sim*(i_p,i_q) efficiently by dividing *coprodsum*(i_p,i_q) by the product of the standard deviations. Otherwise, we must *recalculate* the value of *coprodsum*(i_p,i_q) from scratch for each entry using the current value of *mean*(i_p).

4.3.3 User-based Collaborative Filtering

The model for user-based collaborative filtering [19] is similar to the item-based approach, except that the model stores groups of similar users (as described in Section 2.1). Thus, the use cases previously discussed for the item-based approach can apply *directly* to the user-based approach, with the exception that similarity is measured over user vectors in the item rating space.

4.3.4 Non-"neighborhood-based" Collaborative Filtering within RecStore

Many other recommendation algorithms use models that are *not* similarity-based lists, as is the case with the "neighborhood-based" collaborative filtering techniques we have explored. In general, RecStore can support these different recommendation techniques as long as their models can be represented by sufficient statistics to update the model incrementally. For instance, recommendation algorithms that use sophisticated probabilistic models (e.g., Bayesian Networks [42], Markov decision processes [51]) *do not* lend themselves well to incremental updates, due to the computationally intense optimization process used to learn their parameters. On the other hand, algorithms that use linear regression to learn a rating prediction model [21] can fit easily within RecStore . In this case, the intermediate store can maintain the general linear model statistics: X (the regression design matrix), X^T (X transposed) and f (the regressand). It is known that these statistics are *incrementally updatable* and *sufficient* to learn unknown regression coefficients by solving the system of equations [52]: $X^T X\beta = X^T f$,

where β represents the learned regression coefficients. The source for these statistics depends on the recommendation algorithm. Examples include ratings vectors [21], a multi-dimensional ratings base (e.g., multi-dimensional recommenders [35]), or item attributes (e.g., content-based recommenders [53]).

4.4 Experimental Evaluation

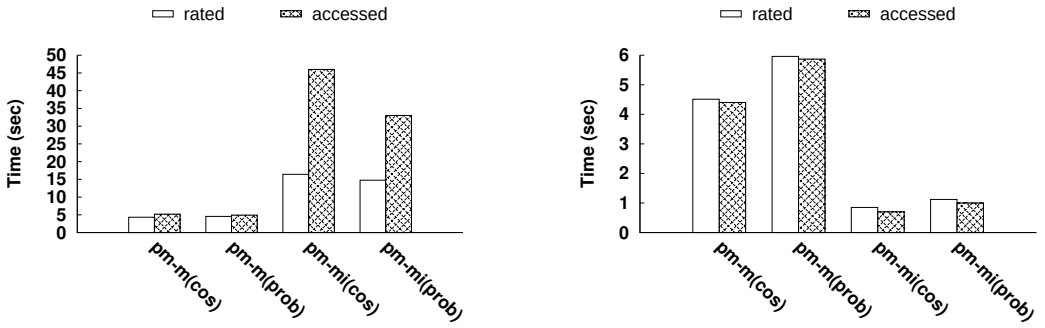
This section experimentally evaluates the performance of a prototype of RecStore implemented in between the storage engine and query processor of the PostgreSQL 8.4 database system [40] using the real-world Movielens 10M rating data set [50]. We test various RecStore adaptive maintenance strategies based on α and β proposed in Section 4.2.2: materialize all (abbr. ***matall***) where $\alpha = \beta = \mathcal{M}$, intermediate only (***ionly***) where α=$\mathcal{M}$ and $\beta = 0$, partial model hotspot maintenance where α=$\mathcal{M}$ and β is set to 20% of all movies (***pm-m***), and partial intermediate and model hotspot maintenance (***pm-mi***) where α and β are set to 40% and 20% of all movies. We also compare against regular (***viewreg***) and materialized DBMS views (***viewmat***). The ***viewreg*** approach is implemented using a regular PostgreSQL view, but since PostgreSQL does not support materialized views, we provide a fair simulation of ***viewmat*** within RecStore by maintaining a materialized *Model* store without the use of an intermediate store.

We provide experiments for: (1) Partial maintenance strategies (Section 4.4.1), (2) update efficiency (Section 4.4.2), (3) query efficiency using the query given in Figure 2.6 (Section 4.4.3), and (4) a *real* recommender system workload trace consisting of interleaved queries and updates (Section 4.4.4). Each experiment is run for both the *cosine* and *probabilistic* item-based recommendation algorithm (details of both algorithms given in Section 4.3).

The experiment machine is an Intel Core2 8400 at 3Ghz with 4GB of RAM running Ubuntu Linux 8.04. Our performance metric is the *elapsed time* over an average of five runs reported by the PostgreSQL EXPLAIN ANALYZE command.

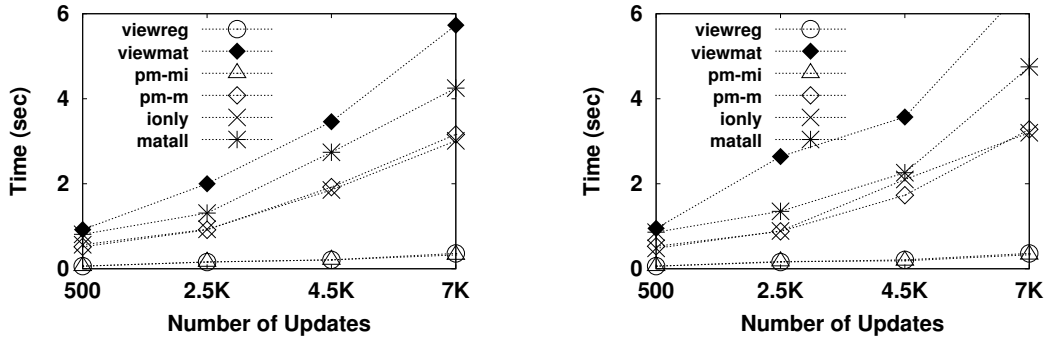
4.4.1 Hotspot Detection Strategies

This experiment studies the effectiveness of our two hotspot detection strategies covered in Section 4.2.2: *most-rated* (abbr. ***rated***) and *most-accessed* (abbr. ***accessed***). We



(a) Query (b) Update

Fig. 4.3: Hotspot Detection



(a) Cosine (b) Update

Fig. 4.4: Update Efficiency

use a real workload trace consisting of the continuous arrival of both ratings updates and recommender queries against the MovieLens system [9, 50]. We start with a *Ratings* table that already contains 950K ratings, and report the *total* time necessary to process 1K ratings updates interleaved with 40 recommendation generation queries for different users. Figures 4.3(a) and 4.3(b) report performance for ***rated*** and ***accessed*** using both the ***pm-mi*** and ***pm-m*** approaches implementing the *cosine* and *probabilistic* algorithms. The *update* performance is relatively similar between the ***rated*** and ***accessed*** strategies for all cases. However, the *query* performance of ***rated*** over ***accessed*** exhibits a 50% speedup, as ***rated*** is able to keep model data in the intermediate and model store requested by the recommendation generation queries. Thus, in the rest

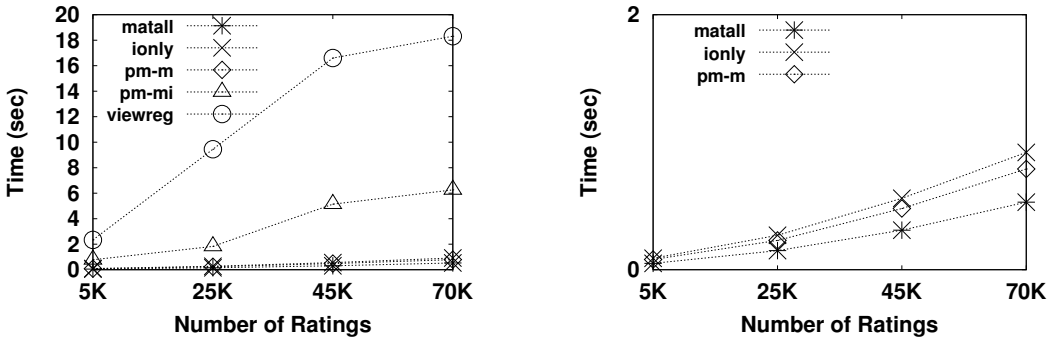
of this section, we employ the ***rated*** strategy for both ***pm-mi*** and ***pm-m***.

4.4.2 Update Efficiency

This experiment studies update efficiency and scalability. We start with a *Ratings* table already containing 950K rating tuples, and measure the total time it takes to process 500, 2.5K, 4.5K, and 7K updates, respectively. Figures 4.4(a) and 4.4(b) give the results for the *cosine* and *probabilistic* algorithms, respectively. For both algorithms, all approaches exhibit the same relative performance. The materialized view (***viewmat***) incurs the most overhead of all approaches. This performance is due to the need, on every update, to recalculate the model score from scratch using the ratings data. The RecStore ***matall*** strategy, on the other hand, incurs less update overhead compared to ***viewmat*** due to its intermediate store, that helps it to efficiently update the model store. This experiment confirms that RecStore overcomes the update efficiency drawback of materialized views. Both ***ionly*** and ***pm-mi*** exhibit better performance, with ***ionly*** doing slightly better due to not having to maintain a partial model store. Both ***matnone*** and ***pm-mi*** exhibit the best performance due to the low (or non-existent) storage and maintenance costs.

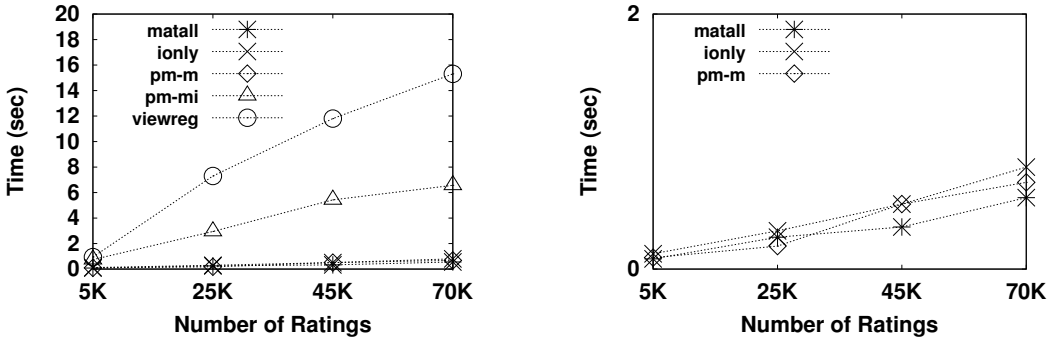
4.4.3 Query Efficiency

This experiment studies query efficiency and scalability. We measure the time to perform the recommender query given in Figure 2.6 for a user X as the number of tuples in the *Ratings* table increases from 5K to 70K. We choose user X as the user that has rated the *most* movies. Figures 4.5(a) and 4.6(a) give the results for the *cosine* and *probabilistic* recommendation algorithms, respectively. The ***viewreg*** approach (a regular DBMS view) performs very poorly, as it must calculate all requested model scores *from scratch* from the ratings relation. The ***pm-mi*** approach exhibits performance between ***matnone*** and the rest of the approaches, as it must service a fraction of its requests from the ratings data, similar to ***viewreg***. Figures 4.5(b) and 4.6(b) zoom in on the ***matall***, ***ionly***, and ***pm-m*** approaches for the *cosine* and *probabilistic* models, respectively. As expected, the ***matall*** approach exhibits the best query processing performance as it must only retrieve values from the model store. Both ***ionly*** and ***pm-m***



(a) Cosine (b) Cosine Zoomed

Fig. 4.5: Query Efficiency



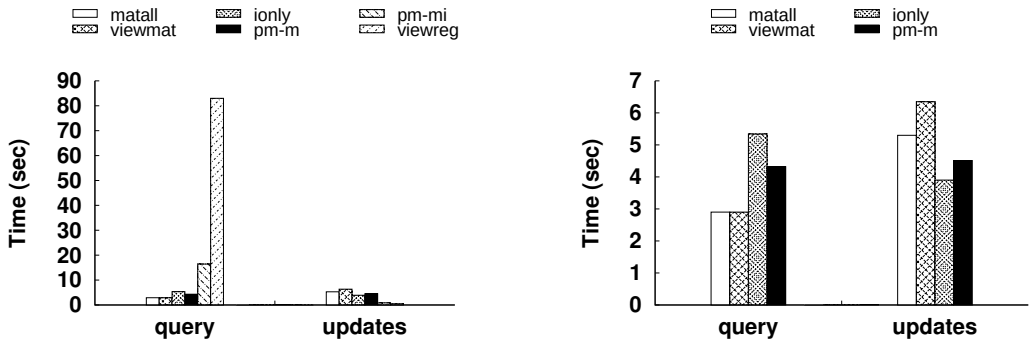
(a) Probabilistic (b) Probabilistic Zoomed

Fig. 4.6: Query Efficiency

exhibit close performance to ***matall***. We do not plot the ***viewmat***, since it exhibits the *same* performance as ***matall***, as the query operates over a completely materialized model relation for both approach. Due to both query and update performance, we can conclude that RecStore provides better support for *online* recommender systems compared to existing DBMS approaches (***viewmat*** and ***viewreg***).

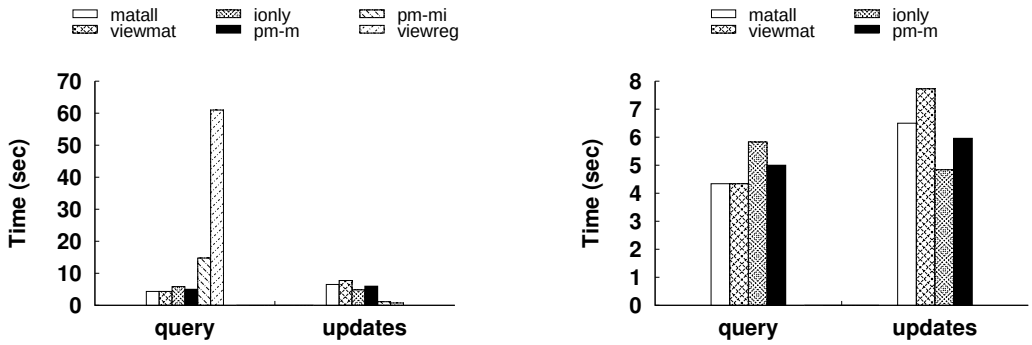
4.4.4 Update + Query Workload

This experiment uses our real recommender system workload trace (described in Section 4.4.1) to test *comprehensive* update and query processing performance. Figures 4.7(a) and 4.8(a) give the results of both query and updates for the *cosine* and



(a) Cosine (b) Cosine Zoomed

Fig. 4.7: Real Workload



(a) Probabilistic (b) Probabilistic Zoomed

Fig. 4.8: Real Workload

probabilistic algorithms, respectively. Both ***viewreg*** and ***pm-mi*** exhibit poor query processing performance for the workload, with ***viewreg*** performing almost an order magnitude worse than other approaches. While the ***viewreg*** performance is expected, the ***pm-mi*** performance is more surprising. Both ***viewreg*** and ***pm-mi*** exhibit the best update performance out of all approaches, as confirmed by our previous experiments (Section 4.4.2). However, the query processing performance of ***viewreg*** makes it an unattractive alternative, while the update/query processing tradeoff for ***pm-mi*** is a borderline choice due to its high query processing penalty. Figures 4.7(b) and 4.8(b) remove the ***viewreg*** and ***pm-mi*** numbers to zoom in on the other approaches for the *cosine* and *probabilistic* models, respectively. Both the ***matall*** and ***viewmat*** approaches

exhibit the same query processing performance that is superior to ***ionly*** and ***pm-m***. As for updates, we note again that ***matall*** (RecStore) provides more efficient update performance over ***viewmat*** (materialized views). Meanwhile, ***pm-m*** and ***ionly*** show superior update performance to ***matall*** and ***viewmat***, with ***ionly*** providing the best performance.

In this experiment, we can observe the update/query processing trade-off discussed in Section 4.2.2 for high values of α and β (***matall***) compared to lower values of α and β (***ionly*** and ***pm-mi***). Thus, for slightly more update-heavy recommender systems, the ***ionly*** or ***pm-mi*** is preferable due to efficient updates with little query processing penalty. Meanwhile, for more query-heavy systems, the ***matall*** approach is preferable with tolerable update penalty.

Chapter 5

Recommendation Query Processing and Optimization

A main challenge is how to efficiently execute queries over an initialized recommender. One solution is to implement a *Stored Procedure* that performs the recommendation query functionality over the initialized recommender. However, this approach is very limiting since it does not provide much flexibility for the database engine to optimize incoming queries. This section discusses RecQuEx a RecDB module built inside the database query execution engine for internal processing of recommender queries. RecQuEx encapsulates the recommendation functionality into a new family of query operators, termed Recommend. Being a query operator allows the recommendation functionality to be a part of a larger query plan that includes other query operators, e.g., selection, projection, and join. It also means that the recommendation functionality will be treated as a first class citizen operation, allowing a myriad of query optimization techniques that can be integrated to speed up recommendation queries.

To further reduce the recommendation application latency, RecQuEx pre-computes the predicted rating scores and caches the corresponding {*user,item,rating*} entries inside the database system. Storing and Maintaining the predicted rating for all {*user,item,rating*} entries may preclude system scalability. Hence, RecQuEx adaptively decides, based on the query/update workload, which entries to maintain with the main goal to reduce the overall recommender storage and maintenance overheard

(a) Item-Item Similarity Matrix

Item	ItemNeighbors
'Spartacus'	{⟨'Spartacus',0.5⟩;...}
'Inception'	{⟨'Spartacus',0.5⟩;⟨'The Matrix',1⟩;...}
'The Matrix'	{⟨'Inception',1⟩;⟨'Spartacus',0.2⟩;...}

(b) User-User Similarity Matrix

User	UserNeighbors
'Alice'	{⟨Bob,0.5⟩;⟨Carol,0.5⟩;...}
'Bob'	{⟨Alice,0.5⟩;⟨Eve,1⟩;...}
'Carol'	{⟨Alice,1⟩;⟨Eve,0.2⟩;...}
'Eve'	{⟨Bob,0.2⟩;⟨Carol,0.2⟩;...}

Fig. 5.1: Item-Item (User-User) Collaborative Filtering Model

without compromising the recommendation generation performance.

Experiments, based on actual system implementation inside PostgreSQL, using real data extracted from MovieLens [54] (Movie Recommendation Application) and Foursquare [55] (Point-of-Interest Recommendation Application), show that RecQuEx exhibits high performance for large-scale recommendation scenarios.

In summary, this chapter introduces the following: (1) RecQuEx – a unified approach for processing recommendation requests inside the database engine. (2) A family of novel query operators, called Recommend, that realize the recommendation algorithms inside the database query processor (Section 5.1). (3) Recommendation-aware operators that further optimize the recommendation operation with other operators (*selection*, *join*, and *ranking*) (Sections 5.3.1 and 5.3.2). (4) A materialization scheme that caches the pre-computed predicted rating scores to further reduce the recommendation latency (Section 5.3.3).

5.1 Recommendation Operators

RecQuEx employs three main versions of the Recommend operator; one for each recommendation algorithm. Each operator take as input a ratings table and return a set of tuples S such that each tuple $s \in S$; $s = \langle uid, iid, ratingval \rangle$ represents a predicted rating score *ratingval* for each item *iid* unseen by user *uid*. This section first describes

Algorithm 1 ItemCF-Recommend

```
1: /* load User Vector Table block by block in Memory */
2: for each user u ∈ UserVector do
3:    UserItems ← List of User u rated items in ItemNeighborhood
4:    /* load Item Neighborhood Table block by block in Memory */
5:    for each item i ∈ ItemNeighborhood do
6:       ItemNeighbors ← List of item similar to item i in ItemNeighborhood
7:       if item i ∈ UserItems then
8:          r_{u,i} ← Rating that u gave to i
9:       else
10:         CandItems ← ItemNeighbors ∩ UserItems
11:         if CandItems not equal φ then
12:            r_{u,i} ← Predict(u,i, UserItems, ItemNeighbors)
13:         else
14:            r_{u,i} ← 0
15:      EMIT ⟨u, i, r_{u,i}⟩
```

the recommendation operators and then explains how they are integrated in the SQL query pipeline.

5.1.1 Item-Item Collaborative Filtering Operator

RecQuEx stores the item-item similarity list as a table, called the *Item Neighborhood Table*. This table consists of two columns: (1) *ItemID*: a unique item identifier and (2) *ItemNeighbors*: a set of Key-Value pairs ⟨*iid,simscore*⟩ that contains every item *iid* that belongs to *ItemID* neighborhood. The Item Neighborhood Table is indexed by a primary key index created on the *ItemID* field. Figure 5.1(a) gives an example of the *Item Neighborhood Table*. RecQuEx adopts the same storage layout for the user-user collaborative filtering algorithm, but in this case stores the *User Neighborhood table* instead of items (see Figure 5.1(b)).

For an incoming query, the query planner invokes the ItemCF-Recommend operator when the `USING` clause specify the Item-Item Collaborative Filtering Algorithm (i.e., `ItemCosCF` or `ItemPearCF`). Algorithm 1 gives the pseudocode of the ItemCF operator. The ItemCF operator accesses both the *user vector table* (*UserVector*) and an *item neighborhood table* (*ItemNeighborhood*). The operator then returns a set of tuples S such that each tuple $s \in S$; $s = \langle u, i, r_{u,i} \rangle$ represents a user u, item i (unseen by

user *uid*), and a rating $r_{u,i}$. ItemCF fetches *UserVector* block by block to retrieve each tuple $\langle u; \{(i_1, r_{u,i_1}), ..., (i_m, r_{u,i_m})\}\rangle$. In a nested-loop fashion, the algorithm scans *ItemNeighborhood* block by block and saves the currently retrieved block in an in-memory buffer. If an item i is already rated by u, we set $r_{u,i}$ to the rating that u already assigned to i. In case u did not rate i, we first determine whether the set of similar items to i *ItemNeighbors* intersects the set of items rated by u (i.e., *UserItems*). If there in no overlap, the algorithm sets $r_{u,i}$ to 0. Otherwise, ItemCF invokes `Predict()` to estimate the rating value $r_{u,i}$. Finally, ItemCF emits the tuple $\langle u, i, r_{u,i}\rangle$ up in the query pipeline. The `Predict` procedure takes as input the user u, item i, the items rated by u *UserItems*, and the set of items similar to i *ItemNeighbors*. It then employs an aggregate function to estimate how much user u would like item i and returns a predicted rating accordingly. Example is given below:

Query 5 *Predict the rating that users would give to unseen items based on the Item-Based Collaborative Filtering Algorithm.*

```
Select R.uid,R.iid, R.ratingval
From Ratings as R
Recommend R.iid To R.uid On R.ratingval Using ItemCosCF
```

By specifying the `Recommend` clause and the `Ratings` table in the `From` clause, RecQuEx figures that an ItemCosCF recommender, i.e., GeneralRec, is already created and initialized. Hence, the system accesses `GeneralRec` via the ItemCF operator to perform the recommendation functionality.

5.1.2 User-User Collaborative Filtering Operator

To generate recommendation using user-user collaborative filtering, RecQuEx employs a variant of the Recommend operator named, called UserCF. UserCF is similar to ItemCF except that it accesses the following data structures: the *item vector table* (*ItemVector*) and the *user neighborhood table* (*UserNeighborhood*). The operator finally returns a set of tuples S such that each tuple $s \in S$; $s = \langle u, i, r_{u,i}\rangle$ represents a user u, item i (unseen by user *uid*), and a rating $r_{u,i}$. Algorithm 2 gives the pseudocode of the UserCF operator.

Algorithm 2 UserCF-Recommend

```
1: /* load User Neighborhood Table block by block in Memory */
2: for each user u ∈ UserNeighborhood do
3:    UserNeighbors ← List of users similar to u in UserNeighborhood
4:    /* load Item Vector Table block by block in Memory */
5:    for each item i ∈ ItemVector do
6:       ItemUsers ← List of Users that rated i
7:       CandUsers ← UserNeighbors ∩ ItemUsers
8:       if CandUsers not equal φ then
9:          r ← Predict(u,i, ItemUsers, UserNeighbors)
10:      else
11:         r ← 0
12:      EMIT ⟨u, i, r⟩
```

(a) Item Factor Table

Item	ItemFeatures
'Spartacus'	{⟨Feature1,0.5⟩;⟨Feature2,-0.7⟩;⟨Feature3,0.1⟩}
'Inception'	{⟨Feature1,0.4⟩;⟨Feature2,0.8⟩;⟨Feature3,-0.1⟩}
'The Matrix'	{⟨Feature1,0.5⟩;⟨Feature2,0.5⟩;⟨Feature3,0.6⟩}

(b) User Factor Table

User	UserFeatures
'Alice'	{⟨Feature1,0.5⟩;⟨Feature2,-0.1⟩;⟨Feature3,0.1⟩}
'Bob'	{⟨Feature1,0.3⟩;⟨Feature2,0.7⟩;⟨Feature3,0.1⟩}
'Carol'	{⟨Feature1,0.5⟩;⟨Feature2,0.6⟩;⟨Feature3,-0.3⟩}
'Eve'	{⟨Feature1,-0.4⟩;⟨Feature2,0.1⟩;⟨Feature3,-0.1⟩}

Fig. 5.2: Matrix Factorization Model

5.1.3 Matrix Factorization Operator

To access matrix factorization models, RecQuEx is equipped with a variant of the Recommend operator called MatrixFact. The MatrixFact operator accesses the following data structures: (1) *user factor table* (*UserFactor*): a table that contains the set of system users and their feature vectors and (2) an *item factor table* (*ItemFactor*): a table that contains the set of system items and their feature vectors (see Figure 5.2). Similar to previous operators, MatrixFact also returns a set of tuples S such that each tuple $s \in S$; $s = \langle u, i, _{u,i} \rangle$ represents a user u, item i and a rating r. Algorithm 3 gives the pseudocode of the MatrixFact operator. In a block nested loop manner,

Algorithm 3 MatrixFact-Recommend

```
1: /* load User Features Table block by block in Memory */
2: for each user u ∈ UserFactorVector do
3:    uFeatures ← List of latent factors (features) learned for user u
4:    /* load Item Features Table block by block in Memory */
5:    for each item i ∈ ItemFactorVector do
6:       iFeatures ← List of latent factors (features) learned for item i
7:       r_{u,i} ← DotProduct(iFeatures, uFeatures)
8:       EMIT ⟨u, i, r_{u,i}⟩
```

MatrixFact scans *UserFactor* block by block to fetch the feature vector of each user u. Then, MatrixFact scans *ItemNeighborhood* block by block to retrieve the feature vector for each item i. If an item i is already rated by u, we set $r_{u,i}$ to the rating that u already assigned to i. The algorithm calculates the dot product of both *uFeatures* and *iFeature* and that represents the value of the predicted rating $r_{u,i}$. ItemCF emits the tuple $\langle u, i, r_{u,i} \rangle$ up in the query pipeline.

5.2 Query Pipeline Integration

The Recommend operators are non-blocking (pipeline-able) database operators that follows the iterator model adopted by almost all existing relational database engines (i.e., PostgreSQL in our case). The non-blocking nature means that other operators in the query pipeline can receive results from the Recommend operator before it is done with all of its predictions. Being a pipeline-able operator allows a seamless integration with other query operators in a database query processor. However, as the Recommend operator only applies to a recommender and does not apply to normal database relations, it should always be pushed down to the bottom of the query pipeline. In this section, we discuss the integration of the Recommend operator in the bottom of a query pipeline with selection, join, and ranking operators.

5.2.1 Selection

Two cases might happen when a selection predicate is applied to the recommendation answer: (1) *Case 1: uid or iid selection predicate*, where the selection predicate is applied

to the user or item identifiers, and (2) *Case 2: ratingval selection predicate*, where the selection predicate is applied to the predicted rating value *ratingval*. RecQuEx deals with these two cases as follows:

Cases 1 and 2: *uid or iid* selection predicate. The following query gives an example of an *iid* selection predicate query over a recommendation result.

Query 6 *Predict the ratings that user uid* $= 1$ *would give to items 1 to 5 using the ItemCosCF algorithm.*

```
Select R.iid, R.ratingval From Ratings as R
Recommend R.iid To R.uid On R.ratingval Using ItemCosCF
Where R.uid=1 And R.iid In (1,2,3,4,5)
```

This kind of query is very frequent, where in many cases a user would like to only know the recommendation score for a specific item (e.g., a movie in Netflix) or for a set of few items (e.g., a set of few books in Amazon). A straightforward execution of such queries uses the query plan in Figure 5.3, which performs well only if the predictive selectivity is very low. For highly selective predicates (e.g., Query 6) above), the Recommend operator performs lots of unnecessary work fetching all items data from disk and calculating their predicted rating scores, while only few items are needed.

Case 3: *ratingval* selection predicate. Query 7 gives an example of a *ratingval* selection predicate query over a recommendation result. This is a very common query, where in many cases the user is only concerned about those items that have a recommendation score above a certain threshold, e.g., *report to me all items that would have my score as 4 or more out of 5.*

Query 7 *Predict the rating that user uid* $= 1$ *would give to unseen items and list only items with predicted rating value larger than or equal 0.5.*

```
Select R.uid, R.iid, R.ratingval From Ratings as R
Recommend R.iid To R.uid On R.ratingval Using ItemCosCF
Where R.uid=1 And R.ratingval >= 0.5
```

Figure 5.3(a) gives the query plan of the above query, where we first apply the RECOMMEND operator on the given recommender. Then, the recommender operator output is fed to a selection operator with the predicate $R.ratingval \geq 0.5$ to filter out those items that do not contribute to the final answer.

5.2.2 Join

Query 8 in Section 5.2 gives an example of a recommendation query, where the output of the recommender operator needs to be joined with another query to get the movie names instead of their identifiers and to only retrieve Action movies. This is a very common query in any recommender system. For example, Netflix and Amazon always return the item information, not the item identifiers. Also, a Netflix user may opt to receive movie recommendation for a certain movie genre.

Query 8 *Predict the rating that user (uid = 1) would give to* action *movies.*

```
Select R.uid, M.name, R.ratingval
From Ratings as R, Movies as M
Recommend R.iid To R.uid On R.ratingval Using ItemCosCF
Where R.uid=1 And M.iid = R.iid And M.genre='Action'
```

Figure 5.3(b) gives the query plan of the above query, where the ITEMCF-RECOMMEND operator is applied directly to the *GeneralRec* recommender. In the meantime, the `Movies` table goes to a selection operator (i.e., filter) with the predicate *"genre='Action'"* to pass only action movies. The output of the RECOMMEND operator is joined with the output of the selection operator using a traditional join operator with the predicate *"Movies.iid = GeneralRec.iid"* to come up with the movie names for action movies along with ratings produced from *GeneralRec*.

5.2.3 Ranking

Query 9 gives an example of a ranking query where we need to return only the top-10 recommended items. This is a very important query as it is very common to return to the user a limited number of recommended items rather than all items with their scores.

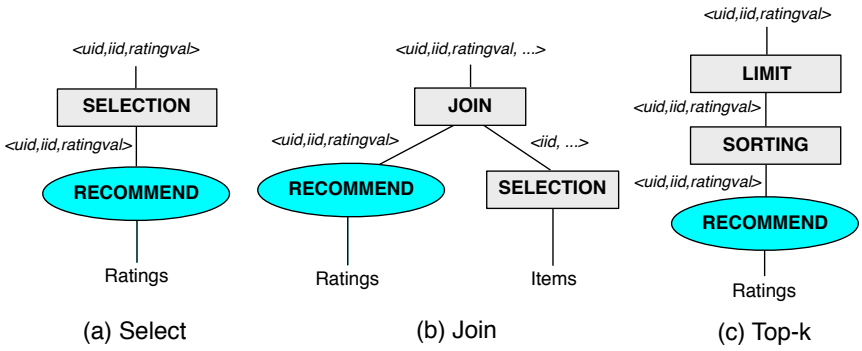


Fig. 5.3: Recommend Query Plans

Query 9 *Recommend the top 10 movies, with highest recommendation score, for user* $uid = 1$.

```
Select R.uid, R.iid, R.ratingval From Ratings as R
Recommend R.iid To R.uid On R.ratingval Using ItemCosCF
Where R.uid=1 Order By R.ratingval Limit 10
```

Figure 5.3(c) gives the query plan of the above query, where the RECOMMEND operator is applied directly on the *GeneralRec* recommender. The output of the RECOMMEND operator is all fed into a sorting operator to sort all the entries in descending order based on the predicted rating score. Then, the top 10 movies are returned back through the Limit operator.

5.3 Optimization Strategies

Since the recommendation operators (presented earlier) need to be always pushed to the bottom of the pipeline, the query processor might perform unnecessary work calculating the recommendation score for items that will never make it to the final query answer. This may happen due to integrating recommendation with other database operations. This section addresses the challenge of reducing the amount of unnecessary work with the ultimate goal of reducing the recommendation query response time. To this end, RECQUEX goes beyond the recommendation operators (explained earlier) to defining

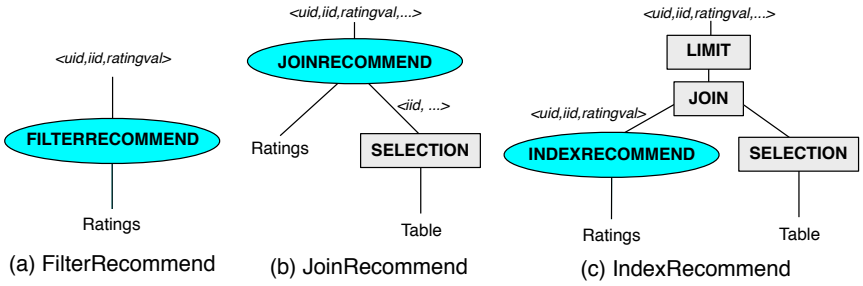


Fig. 5.4: Optimized Recommend Query Plans

more sophisticated operators for common recommender functionality, e.g., top-k recommendation, and joining with other tables. Although such functionality can be simply expressed using any of the RECOMMEND operators, as described in Section 5.1, it would be more efficient to have specialized query operators for such common queries. This section discusses a major part of RECQUEX query optimizer, which is composed of a set of recommender-aware operators that correspond to common recommender functionalities.

5.3.1 Selection Optimization

A straightforward execution of queries that combines recommendation and selection employs the query plan in Figure 5.3(a), which performs well only if the predicate selectivity is very low. For highly selective predicates (e.g., Query 6), the aforementioned RECOMMEND operators perform lots of unnecessary work fetching all items data from disk and calculating their predicted rating scores, while only few items are needed.

Since in many cases, the predicate selectivity is very high; It is very common to generate recommendation for a single user or predict the rating for only one item, RECQUEX employs a variant of the RECOMMEND operator, called FILTERRECOMMEND. Instead of calculating the predicted rating scores for all user/item pairs, the family of FILTERRECOMMEND operators takes the filtering predicate as input and prunes the predicted rating score calculation for those items that do not satisfy the filtering predicate. To achieve that, we modify Algorithms 5 to iterate and calculate the recommendation only for items that satisfy the uid/iid selection predicate.

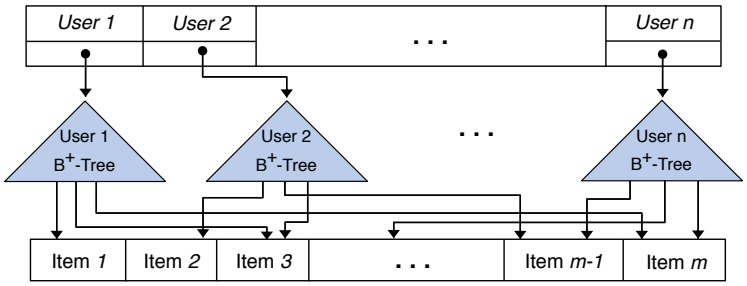


Fig. 5.5: RecScore Index Structure

5.3.2 Join Optimization

The straightforward plan for executing queries that combine recommendation and join (Figure 5.3b) may be acceptable only if there is no filter over the joined relation, or the filter has very low selectivity. Otherwise, if the filter is highly selective, the RECOMMEND operators will end up doing redundant work predicting the rating scores for all user/item pairs, while only few of them are needed. It is very common to have a very selective filter over the items table, e.g., only *Action* movies.

To efficiently support such queries, RECQUEX employs the JOINRECOMMEND operator. Besides the user u and a recommender R, the JOINRECOMMEND operator takes a joined database relation rel (e.g., `Movies`) as input, combines their tuples, and returns the joined result. Analogous to index nested loop join, JOINRECOMMEND employs the input relation rel as the outer relation. For each retrieved tuple $tup \in rel$, the algorithm calculates the predicted rating score for item i with iid equal to $tup.\texttt{iid}$ in the same way it was calculated in the RECOMMEND algorithm (Algorithm 5). The algorithm then concatenates $\langle uid,iid,ratingval \rangle$ and tup and the resulting joined tuple $\langle tup,iid,ratingval \langle$ is finally added to the join answer S. The algorithm terminates when there are no more tuples left in rel. Figure 5.4b gives the query plan for Query 8, when employing the JOINRECOMMEND operator.

5.3.3 Optimization through Pre-Computation

Recommendation applications are rather interactive and real time in nature which necessitates mitigating the recommendation generation latency. To further optimize query

execution performance, RecQuEx pre-computes the predicted ratings for user/item pairs and save them in a data structure, named *RecScoreIndex*.

Data Structure. *RecScoreIndex* (see Figure 5.5) is basically a hash table where each entry is represented by $\langle u, RecTree_u \rangle$, as the user identifier and a pointer to a B^+-tree that indexes the pre-computed predicted rating scores of all items unseen by the user. The predicted rating scores are pre-computed based upon the recommendation model *RecModel* trained using the recommender algorithm. $Rectree_u$ is built for each user u, where the predicted rating score *ratingval* is the key $Rectree_u$ leaf nodes contain pointers to the corresponding items. That means that items in the leaf nodes of $Rectree_u$ are sorted in a descending order of their predicted rating value.

Operator. RecQuEx accesses *RecScoreIndex* using an optimized recommendation operator, named IndexRecommend. The optimized operator reduces the amount of work performed by the recommendation operators by directly accessing the pre-computed predicted rating scores saved in *RecScoreIndex*. Algorithm 4 gives the pseudocode of the IndexRecommend query operator. Besides the ratings table, the algorithm takes as input a user predicate (*uPred*), item predicate (*iPred*), and *ratingval* predicate (*rPred*). The algorithm runs in three main phases: (1) *Phase I: User ID Filtering*: In this phase, IndexRecommend fetches each user u that satisfies *uPred* by looking up the given user IDs in the *RecScoreIndex* hash table. (2) *Phase II: Rating Value Filtering*: In this phase, IndexRecommend traverses the $RecTree_u$ corresponding to each user u retrieved in the first phase to satisfy the ratingVal predicate $rPred$ (3) *Phase III: Item ID Filtering*: In this phase, the algorithm fetches items one-by-one in the leaf level of $RecTree_u$. The algorithm filters out those items that do not satisfy the item predicate (*iPred*). Finally, IndexRecommend emits each tuple $\langle u, i, r_{u,i} \rangle$ that passes the three phases up in the query pipeline.

Query 10 needs to join the `GeneralRec` recommender with the `Movies` table to only select *Action* movies and then return the top 5 *Action* movies to user 1. The following two plans are deemed correct: (1) Apply the JoinRecommend operator on recommender `GeneralRec` and table `Movies` first and then perform a traditional top-k operation on the join result. (2) If a *RecScoreIndex* is maintained, the system may apply the IndexRecommend operator to retrieve items in sorted order and then perform the join operation on the returned items to retrieve *Action* movies (see Plan in Figure 5.4c).

Algorithm 4 IndexRecommend

```
1:  /* Phase I: Retrieve Users One by One in RecScoreIndex*/
2:  for each user u ∈ RecScoreIndex that satisfies uPred do
3:     RecTree_u ← Fetch user u RecTree pointer
4:     /* Phase II: Traverse RecTree to satisfy the ratingval predicate rPred */
5:     TreeNode←Traverse(RecTree_u,rPred)
6:     /* Phase III: Fetch Items One by One at the leaf nodes of RecTree_u */
7:     for each item i ∈ FetchNextItem(TreeNode) do
8:        if item i satisfies iPred then
9:           r_{u,i} ← the predicted Rating of i stored in the node
10:       EMIT ⟨u, i, r_{u,i}⟩
```

Query 10 *Recommend the top* 5 *Action movies to user uid* = 1 *using the SVD Algorithm.*

```
Select M.name, R.ratingval
From Ratings as R, Movies M
Recommend R.iid To R.uid On R.ratingval Using SVD
Where R.uid=1 And M.iid=R.iid And M.genre='Action'
Order By R.ratingval Desc Limit 5
```

5.3.4 Scalability

Most recommendation applications (e.g., Amazon, Google News) deal with large user base and large pool of items. For the system to scale up, i.e., accommodate more users and items, it must minimize the maintenance cost and reduce the overall storage occupied by the recommender data structure. Maintaining the *RecScoreIndex* every time maintenance is triggered for *RecModel* exhibits the lowest query response time because each incoming recommendation query may directly access the pre-computed recommendation scores stored in *RecScoreIndex*. However, the maintenance cost as well as the storage overhead incurred by materializing all *RecScoreIndex* entries may lead to a severe scalability bottleneck, especially with large amounts of user/item pairs.

Main idea. Since recommendation queries are personalized for each user, the system collects statistics about the demand of each user, and leverages these statistics to take the materialization decision. RecQuEx stores those ⟨user,item,ratingval⟩ triplets

in *RecScoreIndex* that correspond to highly demanding users. That mitigates the overall recommendation generation latency as queries directly access the pre-computed predicted ratings in *RecScoreIndex*. Since the generated recommendation represents a set of items, the system also collects statistics that quantifies each item's consumption rate. The system then determines whether an item is highly consumed, i.e., frequently rated/updated, and only maintains entries in *RecScoreIndex* that correspond to those highly-consumed items.

Statistics

To take the materialization decision, RecQuEx maintains the following statistics for each created recommender T: (1) *Users Histogram:* A hash table indexed by the user ID that contains the following fields for each user $u \in U$: (a) *Queries Count (QC_u)*: represents the number of issued recommendation queries by u since T is created. (b) *Query TimeStamp TS_u*: time stamp of the last recommendation query issued by u. (c) *User Demand Rate (D_u)*: represents the rate of queries issued by user u. (2) *Items Histogram:* A table hashed by the item ID and contains the following fields for each item i: (a) *Updates Count UC_i*: represents the number of updates applied, i.e., ratings insertion, to item i in recommender T since the recommender is created. (b) *Update TimeStamp TS_i*: time stamp of the last update transaction performed over item i, (c) *Item Consumption rate (P_i)*: represents the rate of updates performed on item i. (3) *Maximum User Demand (D_{MAX})*: the maximum user demand rate D_u of a user u among all users in recommender T. (4) *Maximum Item Consumption (P_{MAX})*: the maximum item consumption rate P_i of an item i among all items in recommender T.

Caching Algorithm

Using the statistics maintained for a recommender T, the main role of the cache manager is determining which user/item/rating triplets need to be cached in *RecScoreIndex*. To achieve this goal, the cache manager runs asynchronously every fixed period of time (e.g., 5 mins) in the background and performs the following steps:

STEP 1: Statistics Maintenance. It first retrieves the set of users U' such that each user $u \in U'$ has (TS_u) larger than the last time the cache manager was invoked. We also retrieve the set of items I' such that each item $i \in I'$ has (TS_i) larger than

Algorithm 5 Caching Algorithm

```
1: Function CacheManager (Recommender T)
2: U' ← All users in recommender T with TS_u larger than TS_mat
3: I' ← All items in recommender T with TS_i larger than TS_mat
   /* STEP 1: Statistics Maintenance */
4: for each item i ∈ I' do
5:    Maintain P_i ← UC_i / (TS_now − TS_init)
6:    If P_i>P_MAX then Maintain P_MAX←P_i
7: for each user u ∈ U' do
8:    Maintain P_i ← QC_u / (TS_now − TS_init)
9:    If D_u>D_MAX then Maintain D_MAX←D_u
   /* STEP 2: Materialization Decision */
10: for each user/item pair {u,i} ∈ {U'×I'} do
11:    if i is unseen by u then
12:       Hot_u,i ← (D_u/D_Max) × (P_i/P_Max)
13:       if Hotness Ration Hot_u,i ≥ HOTNESS-THRESHOLD then
14:          Append user/item pair {u,i} to Admission List
15:       else
16:          Append user/item pair {u,i} to Eviction List
```

the last time the cache manager was executed. The cache manager then calculates *User Demand Rate* D_u for each user $u \in U'$, as follows: $D_u = \frac{QC_u}{TS_{now} - TS_{init}}$; such that TS represents the current system timestamp. In addition, RecDB maintains *Maximum Demand* by setting D_{MAX} to D_u in case D_u value is larger than current D_{MAX} value. Therefore, the materialization manager calculates *Item Consumption Rate* P_i for each item $i \in I'$, as follows: $P_i = \frac{UC_i}{TS_{now} - TS_{init}}$; such that TS represents the current system timestamp. The system also maintains *Maximum Demand* by setting P_{MAX} to P_i if P_i value is larger than current P_{MAX}.

STEP 2: Decision Making. This step leverages the maintained statistics to decide whether the entry corresponding to a user/item pair needs to be materialized. To this end, the cache manager maintains two in-memory lists: (1) *Admission List*: a list that contains the user/item pairs that require materialization, and (2) *Eviction List*: a list that contains those user/item pairs that need to be dematerialized. For each user/item pair $\{u,i\}$ such that $u \in U'$ and $i \in I'$, we calculate the hotness ratio $Hot_{u,i}$ ($0 \geq Hot_{u,i} \leq 1$), as follows: $Hot_{u,i} = \frac{D_u}{D_{Max}} \times \frac{P_i}{P_{Max}}$; such that $\frac{D_u}{D_{Max}}$ and

Users Histogram

User	QC_u	TS_u	D_u
Alice	100	10	100/(15-10)= 20
Bob	10	12	10/(15-10)≈ 2

Items Histogram

Item	UC_i	TS_i	P_i
Spartacus	1000	12	1000/(15-10)≈ 200
Inception	10	12	10/(15-10)≈ 2
The Matrix	100	10	100/(15-10)= 20

User/Item Pair Hotness Ratio

User u	**Item** i	$Hot_{u,i}$
Alice	Spartacus	$(20/20) \times (200/200) = 1$
Alice	Inception	$(20/20) \times (2/200) = 0.01$
Alice	The Matrix	$20/20 \times (20/200)$ 0.01
Bob	Spartacus	$(2/20) \times (200/200)$ 0.1
Bob	Inception	$(2/20) \times (2/200) = 0.001$
Bob	The Matrix	$(2/20) \times (20/200) \approx 0.01$

Table 5.1: Materialization Manager Example

$\frac{P_i}{P_{Max}}$ represent the normalized user demand rate and item consumption rate, respectively. The hotness ratio $Hot_{u,i}$ determines whether the entry, corresponding to $\{u,i\}$, is eligible for materialization. If $Hot_{u,i}$ is greater than or equal to a system parameter `HOTNESS-THRESHOLD` (value between 0 and 1), we add the user/item pair $\{u,i\}$ to the admission list, otherwise we append them to the eviction list. The `HOTNESS-THRESHOLD` exhibits a tradeoff between: (1) Query latency, and (2) System Scalability (Storage Overhead and Maintenance Cost). In other words, when `HOTNESS-THRESHOLD` is equal to 0, RecDB tends to fully materialize all *RecScoreIndex* entries, and when set to 1, *RecScoreIndex* is not materialized at all.

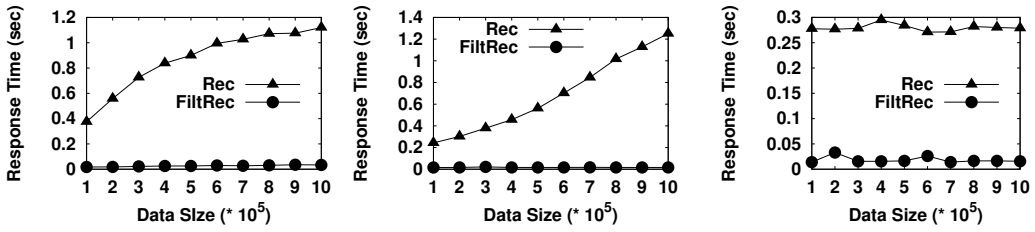
RecScoreIndex Maintenance. When maintenance is triggered for *RecModel*, the system retrieves all user/item pairs in the *Eviction List* and batch deletes all corresponding entries in *RecScoreIndex*. The system also retrieves the user/item pairs in the *Admission List* and batch inserts them in *RecScoreIndex*. Finally, RecDB maintains the recommendation score *RecScore* for all materialized entries.

Example. Table 5.1 depicts an example that illustrated the materialization manager dynamics triggered for a cell C. The table gives Cell C *Users Histogram* and *Items Histograms* at the time the materialization manager is invoked at timestamp 15. As it turns out from the table, *Users Histogram* contains two users: *Alice* and *Bob*, and *Items Histogram* contains three items (i.e., Movies): *Spartacus*, *Inception*, and *The Matrix*. The *User Demand* for *Alice* is calculated as $D_{Alice} = QC_{Alice}$ / (15-TS_{Alice} = 20). Similarly, D_{Bob} is equal to $\approx$ 3.33. The item consumption rate $P_{Spartacus}$ for *Spartacus* movie is evaluated as $UC_{Spartacus}$ / (15-10) = $\approx$ 200), and the same calculation is applied to other movies. Table 5.1 also manifests the hotness ratio calculated by the materialization manager for the user/item pairs. Assume that all movies are unseen by both *Alice* and *Bob* and *RecScoreIndex* only contains the entry t_1 that corresponds to user *Bob* and movie *Inception*. Let `HOTNESS-THRESHOLD` be set to 0.5, in this case the entry t_1 is added to cell C *Eviction List* as $Hot_{Bob,Inception}$ =$\approx$ 0.001 is less than `HOTNESS-THRESHOLD`. In contrast, entry t_2, corresponding to user *Alice* and movie *Bob*, is added to the *Admission List*.

5.4 Experimental Evaluation

This section presents a comprehensive experimental evaluation of RecQuEx based on an actual system implementation [39] and integration with PostgreSQL 9.2. All proposed operators are implemented using the iterator model adopted by PostgreSQL for operator implementations. We evaluate RecQuEx using two real datasets described as follows: *(1) MovieLens*: a real movie recommendation dataset [54] that consists of 6040 users, 3883 movies, and one million (1M) ratings. Each movie has name and genre attributes. The ratings data contains historical ratings (in a scale from 1 to 5) that users have assigned to movies. *(2) Foursquare*: a real venue (e.g., restaurant) recommendation dataset extracted [55] from Foursquare website, and consists of 150K users, 90K venues, and 1M ratings. Each user has a spatial location that represents where that user lives. Each item has also a spatial location.

We run our experiments for the following five popular recommendation algorithms, all supported by RecQuEx : (1) ItemCosCF: Item-Item Collaborative Filtering (CF)



(a) ItemCosCF (b) UserPearCF (c) SVD

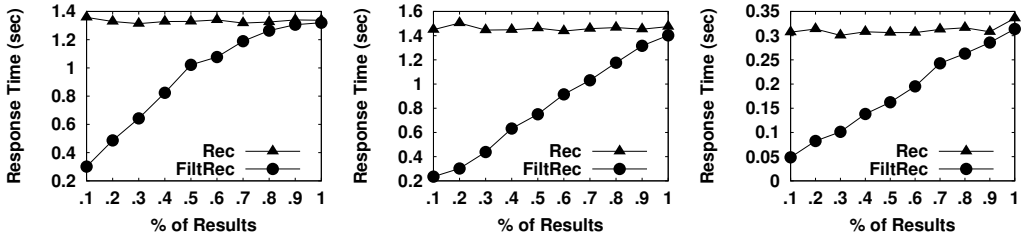
Fig. 5.6: Selection: Varying Data Size (MovieLens)

with cosine distance used to measure similarity among items. (2) ItemPearCF: item-item CF with pearson correlation similarity measure. (3) UserCosCF: user-user CF with cosine distance similarity. (4) UserPearCF: user-user CF with pearson correlation similarity. (5) SVD: Regularized Gradient Descent Singular Value Decomposition.

All experiments were performed on a machine with 3.6 Ghz Quad-Core processor, 16 GB RAM, 500 GB storage, and running Ubuntu Linux 12.04. The default dataset is MovieLens.

5.4.1 Recommender Queries

In this section, we evaluate the query execution performance in terms of the query response time. We consider the following four different approaches for query execution that are applied only when possible: (1) Rec: a query plan that only relies on the RECOMMEND operator to execute recommendation queries (Figure 5.3). (2) FiltRec: a query plan that leverages the FILTERRECOMMEND operator to optimize recommendation queries with a predicate over *iid* (Figure 5.4(a)). (3) IndRec: a plan that exploits the INDEXRECOMMEND operator as well as the *RecScoreIndex* to either (a) process a recommendation query with a predicate over *RecScore* (see Figure 5.4(b)), or (b) execute a ranking (Top-k) query (Figure 5.4(d)). (4) JoinRec: a plan that employs the JOINRECOMMEND operator to join a recommendation with a database table (Figure 5.4(c)). For space constraints, we plot only the results of three recommendation algorithms, namely, *ItemCosCF*, *UserPearCF*, and *SVD*.



(a) ItemCosCF (b) UserPearCF (c) SVD

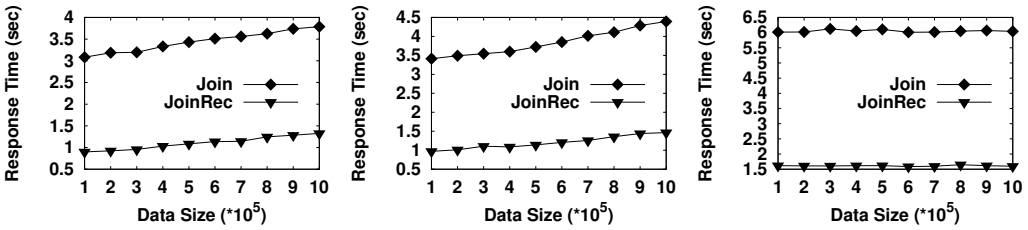
Fig. 5.7: Selection: Varying Selectivity (MovieLens)

Selection: iid Predicate (Query 6)

In this section, we study the performance of recommendation queries with selection predicate applied to the recommender *iid* field (e.g., Query 6 in Section 5.3.1). Unless mentioned otherwise, the query selectivity is set to 25% and the data size is 1M ratings.

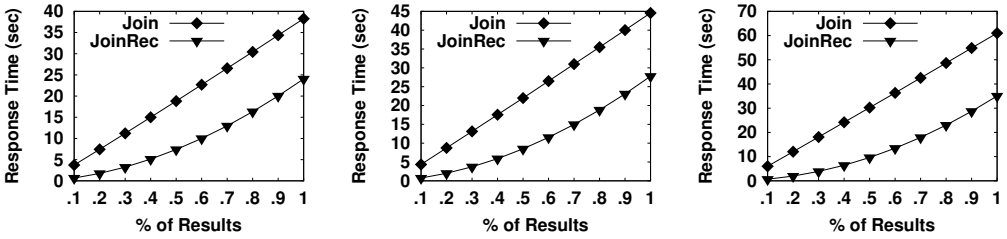
Varying data size. Figure 5.6 studies the impact of data size on the query execution performance. We vary the data size from 100K to 1M ratings, executing a set of 100 synthetically generated queries using *ItemCosCF*, *UserPearCF*, and *SVD* recommendation algorithms. For all recommender algorithms, *FiltRec* outperforms *Rec* by at least an order of magnitude. This is obvious since *FiltRec* applies the *iid* filtering predicate before calculating the predicted recommendation score for an item, which saves a huge amount of effort wasted by *Rec* in applying the RECOMMEND operator first on all items and then performing the predicate filtering step. In the meantime, the query response time increases as the data size gets bigger since we need to retrieve more recommendation model entries in *ItemCosCF* and *UserPearCF*. In the *SVD* case, the response time remains unchanged.

Varying Selectivity. Figure 5.7 gives the impact of *iid* predicate selectivity on the average query response time. As it turns out from the figure, as we increase the percentage of reported items (decrease selectivity), the average query response time in *Rec* remains constant since the RECOMMEND operator predicts the recommendation score for all items anyway before applying the *iid* predicate. On the other hand, *FiltRec* query response time increases linearly with the percentage of reported items until it reaches the same performance as *Rec* when 100% of items are reported. That happens because



(a) ItemCosCF (b) UserPearCF (c) SVD

Fig. 5.8: Join: Joined Recommender Data Size (Foursquare)



(a) ItemCosCF (b) UserPearCF (c) SVD

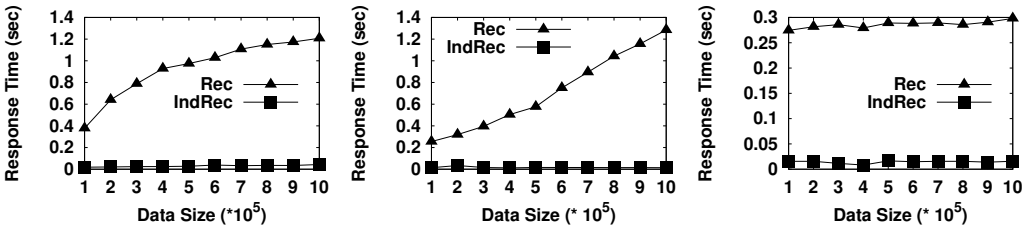
Fig. 5.9: Join: Joined Table (*rel*) Selectivity (Foursquare)

FiltRec, when 100% of items are returned, performs the same amount of recommendation score calculation as *Rec*. However, for higher selectivity (i.e., lower % of results), *FiltRec* outperforms *Rec* by more than an order of magnitude. With *iid* selection, a typical selectivity would be very high, i.e., less than 1%, which shows better performance for *FiltRec* over *Rec*.

Join (Query 8)

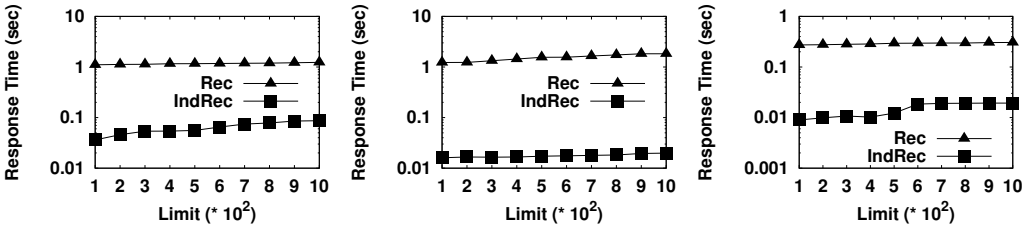
This section studies the performance of recommendation queries that involve joining the recommendation answer with other database tables in the *Foursquare* dataset (e.g., Query 8 in Section 5.2). The joined table has a selection predicate that filters out unwanted items. Unless mentioned otherwise, the selectivity for the join selection predicate is set to 25% and the data size is 1M ratings.

Varying data size. In this experiment, we build recommenders with different data sizes (100K to 1M ratings), and we generate a workload of 100 join queries that join the created recommender and the movies table. Figure 5.8 shows that `JoinRec` scales



(a) ItemCosCF (b) UserPearCF (c) SVD

Fig. 5.10: Ranking: Varying Data Size (MovieLens)

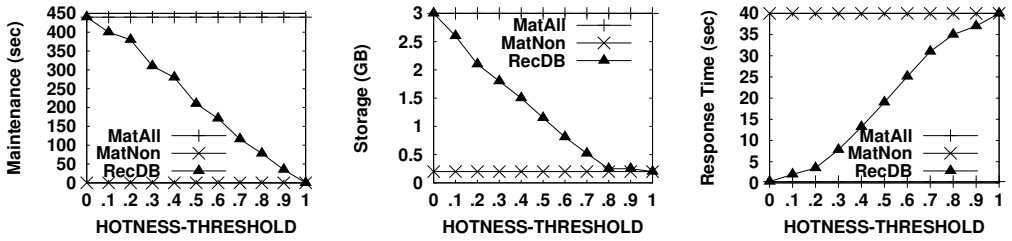


(a) ItemCosCF (b) UserPearCF (c) SVD

Fig. 5.11: Ranking: Varying Limit (k) Size (MovieLens)

about an order of magnitude better than `Join` for all recommendation algorithms. The main reason is that JoinRecommend efficiently calculates the predicted score only for filtered items. In the meantime, the bigger the data size, the worse the query execution performance for both `Join` and `JoinRec`, since more data are joined. That happens for all recommendation algorithms, except for *SVD*.

Varying Selectivity. In these experiments, we vary the selectivity of the joined table with the input recommender. We generate a workload of 100 random join queries of the same selectivity, and execute such queries for each recommendation algorithm. We simulate the selectivity change in terms of the ratio of output tuples (filtered by a selection predicate) over the original number of tuples in the joined table *rel*. Figure 5.9 shows that *JoinRec* exhibits more than an order of magnitude better performance than *Join* for high selectivity (small % of *rel*). However, when the selectivity decreases (% of *rel* increases), *JoinRec* performance becomes closer to *Join* since *JoinRec* has to compute the predicted score for more items.



(a) Maintenance (b) Storage (c) Query Processing

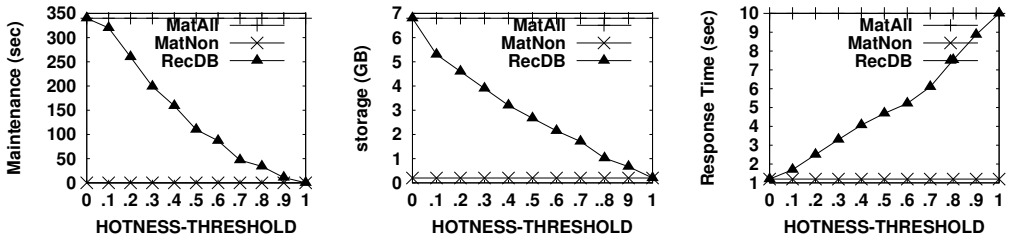
Fig. 5.12: Scalability Vs. Queries (SVD) (MovieLens)

Ranking (Top-k) (Query 9)

This section studies the performance of top-k recommendation queries. Unless mentioned otherwise, k is set to 1000 and the data size is 1M ratings.

Varying data size. Figure 5.10 depicts the effect of data size on top-k recommendation query performance. As given in the figure, *IndRec* exhibits more than an order of magnitude performance over *Rec*. That is justified by the fact that *IndRec* leverages the pre-computed recommendation scores, created for active users, in the *RecScoreIndex* to retrieve items in sorted order. Hence, the limit operator terminates early when the required number of items is retrieved. On the other hand, *Rec* has to first calculate recommendation scores, then sort items based on their score, and finally pick the top-k items. Note that the query response time in *Rec* increases as the data gets bigger (except for *SVD*) because *Rec* takes more time accessing bigger models. However, the response time in *IndRec* slightly increases since *IndRec* retrieve pre-computed recommendation scored in sorted order.

Varying k. Figure 5.11 gives the impact of k on top-k recommendation query performance. We vary k from 100 to 1000, generate a workload of 100 top-k recommendation queries, and measure the response time for *ItemCosCF*, *UserPearCF*, and *SVD* algorithms. In all algorithms, *IndRec* achieves more than an order of magnitude better performance than *Rec* for all values of k. Moreover, *Rec* performance is constant for different k values, which is explained by the fact that sorting in *Rec* is dominating the query execution performance. On the other side, the response time in *IndRec* slightly increases for larger k values as more items are accessed in *RecScoreIndex*.



(a) Maintenance (b) Storage (c) Query Processing

Fig. 5.13: Scalability Vs. Queries (ItemCosCF) (MovieLens)

5.4.2 Recommender Storage and Maintenance

In this section, we evaluate the tradeoff between system scalability in terms of storage/maintenance overhead and query processing performance. We vary the value of `HOTNESS-THRESHOLD` from 0 to 1 (with an increment of 0.1) and measure the maintenance overhead (Figure 5.12(a) and 5.13(a)), storage cost (Figure 5.12(b) and 5.13(a)), and query processing performance (Figure 5.12(c) and 5.13(c)). We randomly generate a 80:20, 50:50, 20:80 query:update workload. We compare RecQuEx with two basic approaches: (1) *MatAll*: that maintains all *RecScoreIndex* entries, and (2) *MatNon*: that does not maintain *RecScoreIndex* at all. For all approaches, we measure the aggregate maintenance cost (in Seconds), storage overhead (in GBytes), and query response time for both SVD and ItemCosCF algorithms.

As it turns out from Figures 5.12(a) and 5.13(a), *MatAll* incurs the highest maintenance overhead due to the fact that *MatAll* maintains all *RecScoreIndex* entries. *MatNon* has the lowest maintenance overhead as it maintains no *RecScoreIndex* entries. As `HOTNESS-THRESHOLD` increases, RecQuEx maintains more *RecScoreIndex* entries and hence leads to higher maintenance cost. Figure 5.12(b) and 5.13(a) show that *MatAll* occupies the highest storage space since it maintains all *RecScoreIndex* entries. *MatNon* occupies the least storage space due to the fact that it does not maintain *RecScoreIndex* at all. On the other hand, RecQuEx stores more recommendation models for higher `HOTNESS-THRESHOLD` values. In Figure 5.12(c) and 5.13(c), *MatAll* achieves the best query execution performance since all *RecScoreIndex* entries are available at query time whereas the total opposite happens for the *MatNon* approach. RecQuEx achieves better query performance as `HOTNESS-THRESHOLD` decreases.

Chapter 6

RecDB Support for Context Pre-filtering Recommenders

Classical recommender systems answer traditional *context-free recommendation* queries like, *Recommend me 10 movies*, where recommendation is generated to the querying user regardless of the context (e.g., user age, job, gender, and location). On the other side, a context-aware recommender would consider contextual information in producing recommendation to end-users. For instance, a *Context Post-Filtering Recommender* would build a recommendation model M using all users' opinions history and then filter the produced recommendation (calculated using $PredictRating(u, i)$) based on a set of attributes to answer context-aware recommendation queries like: *Recommend me 10 Restaurants that are near by my location.* Also, a *Context Pre-filtering Recommender* trains the recommendation model M only based on a subset of the users' opinions that correspond to specific (filtered) attributes' range and hence would be able to support *context-aware* recommendations queries such as: *Recommend me 10 movies that people my age would like*, or *Recommend me 5 movies that people that live in my city would like.* From a modeling perspective, it has been shown that such context-aware recommenders would exhibit higher accuracy than context-free recommendations [34, 35, 56, 57, 58, 59, 60]. Chapter 5 shows how to to generate context post-filtering recommendation by incorporating the recommendation functionality inside the database system query

processor. This chapter explains an extension of RecDB that supports context pre-filtering recommender.

6.1 Context Pre-Filtering Recommender

This section describes how RecDB users creates and query a context pre-filtering recommender.

6.1.1 Creating a Recommender

To allow creating a new recommender, RecDB employs a new SQL statement, called `CREATE RECOMMENDER`, as follows:

```
CREATE RECOMMENDER [Recommender Name] ON [Ratings Table]
USERS FROM [Users ID Column]
ITEMS FROM [Items ID Column]
RATINGS FROM [Ratings Value Column]
ATTRIBUTES [Attributes Set]
USING [Recommendation algorithm]
```

The recommender creation SQL is extended to accept the `ATTRIBUTES` parameter which represents a set of dimensions that the recommender will be built on (e.g., age). Examples are given below:

Recommender 4 AgeRec*: an age-aware context-prefiltering recommender created on the input data stored in the Ratings table of Figure 3.2, using the ItemCosCF recommendation algorithm:*

```
Create Recommender AgeRec On Ratings
Users From uid Item From iid Ratings From ratingval
Attributes age Using ItemCosCF
```

With this SQL, a new recommender, named *AgeRec*, is added to the database system, and can be queried later to return a set of recommended movies based on the user age, e.g., *recommend me five movies that people in my age like.*

Recommender 5 AgeCityGenderRec*: an (age, city, gender)-aware recommender created on the input ratings table, using the SVD recommendation algorithm:*

```
Create Recommender AgeCityGenderRec On Ratings
Users From uid Item From iid Ratings From ratingval
Attributes age, city, gender Using SVD
```

With this SQL clause, RecDB creates a new recommender, named *AgeCityGenderRec*, that is added it to the database system. This recommender can be queried later to return to a querying users a set of recommended movies based on the user age, city, and gender, e.g., *recommend me five movies that people in my age, living in my city, and of my gender, would like.*

Notice that in the above two examples, if we had no `ATTRIBUTES` clause, we would create a traditional recommender that can be queried to recommend a set of movies for a certain user, regardless of the user attributes, e.g., *recommend me five movies.*

6.1.2 Querying a Recommender

Once a recommender is created and registered in RecDB using the `CREATE RECOMMENDER` statement, users can issue SQL queries that harnesses the initialized context pre-filtering recommender to produce recommendation to end-users, as follows:

```
SELECT    <Select Clause>
FROM  <CFILTER(Ratings Table, Attributes)>
RECOMMEND <UserID> TO <ItemID> ON <RatingVal>
USING     <Recommendation Algorithm>
WHERE     <Where Clause>
```

Query Semantics. To access a context pre-filtering recommender, the application developer has to invoke the `CFILTER()` function. `CFILTER` takes the `Ratings` table and designated contextual attributes as input and returns a view which consists of tuples in the ratings table that satisfy the given contextual attributes. An example of a query is given below:

Query 11 *Return the top-10 recommended items to user with ID 1, based on the user age, city, and gender.*

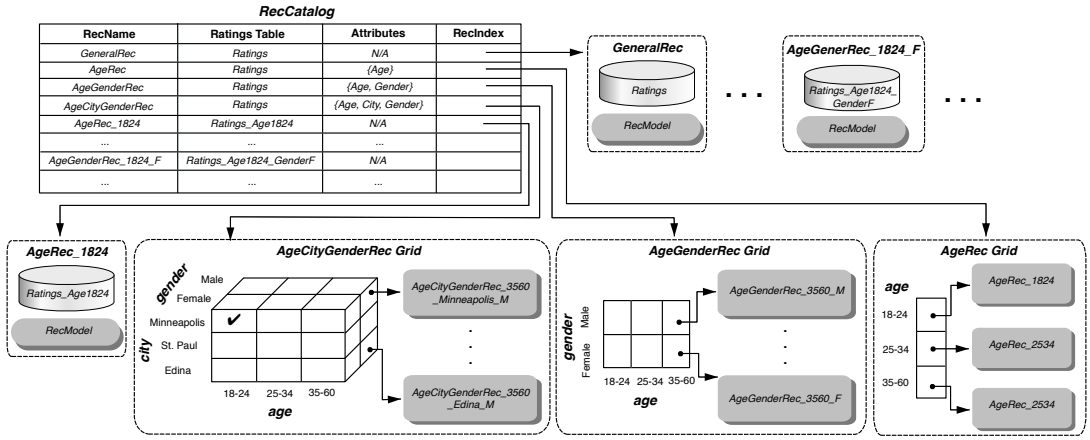


Fig. 6.1: Recommender Grid data structure

```
Select R.uid, R.iid, R.ratingval
From CFilter(Ratings,age='18-25',city='Minneapolis',gender=F) as R
Recommend R.iid To R.uid On R.ratingVal Using ItemCosCF
Where R.uid=1 Order By R.ratingVal Desc Limit 10
```

In this case, RecDB uses the `AgeCityGenderRec`, which was created before using `CREATE RECOMMENDER`. Since this recommender was created based on the age attribute, Query 11 will predict the ratings based on the values of the age attribute value passed to the `CFilter` function. The query finally returns the Top-10 movies to user 1 in a descending order of the predicted rating value (`ratingval`).

6.2 Data Structure

After creating a context pre-filtering recommender, a main challenge is how to internally represent, store, and maintain the underlying recommendation models in a scalable manner. To address this issue, we introduce the following data structures to represent user-created multidimensional recommenders: (1) We maintain one global structure, namely *RecCatalog*, for all created recommenders (section 6.2.1). (2) For each recommender, we maintain one multidimensional grid and we explain how we reduce both storage and maintenance overhead to achieve scalability (section 6.2.2).

6.2.1 Recommender Catalog

RecDB maintains a relational table, termed *RecCatalog*, that includes metadata about all created recommenders, and is stored as part of the main database catalog that includes information about tables, index structures, etc. A row in *RecCatalog* has seven attributes: (1) *RecName*; the recommender name, (2) *Users*; the input users table, (3) *Items*; the input items table, (4) *Ratings*; the input ratings table, (5) *Attributes*; a vector where each element corresponds to an attribute in the *users* table that contributes to the recommender model, (6) *Algorithm*; the algorithm used to generate predicted scores, and (7) *RecIndex*; a pointer to the multi-dimensional grid index for this particular recommender. A new row is added/deleted to/from *RecCatalog* with each successful `CREATE RECOMMENDER` / `DROP RECOMMENDER` SQL statement. Figure 6.1 gives an example of *RecCatalog*, where it has four entries for four recommenders, *AgeRec*, *AgeGenderRec*, *AgeCityGenderRec*, and *GeneralRec*. With each recommender, the corresponding attributes are listed. Notice that in the case of *GeneralRec*, *Attributes* is empty, which corresponds to a general recommender system regardless of any attributes.

6.2.2 Recommender Grid

For each recommender, RecDB maintains a *Multi-dimensional Grid G*, where each dimension corresponds to one of the recommender attributes. A grid cell C in G represents a subdomain of the space created by the multiple attributes. The subdomain could be a certain value for categorical attributes or range of values for continuous domain attributes. For example, as *AgeRec* recommender in Figure 6.1 is defined based on only one attribute (*age*), its index is a one-dimensional grid based on the age attribute. As this is a continuous domain attribute, each cell represents a range of age values, i.e., [18-24], [25-34], and [35-60]. In the meantime, the *AgeCityGenderRec* recommender index is a three-dimensional grid based on three attributes (*age*, *city*, and *gender*). The *age* dimension is divided into three categories based on range of values. The *city* attribute has three values as {Minneapolis, St. Paul, Edina}, while the *gender* attribute is divided into two categorical values as {Male, Female}. The top left outer cell (check marked in Figure 6.1) in *AgeCityGenderRec* represents the values ⟨18-24, Minneapolis, Female⟩ that correspond to its values of the ⟨*age*, *city*, *gender*⟩ dimensions.

Each cell in the multi-dimensional grid points to a table, *RecModel*, that maintains auxiliary precomputed information to speed up the generation of the recommendation query result. The precomputed information may have different schema based on the underlying recommendation algorithm. For example, for the Item-Item collaborative filtering algorithm, *RecModel* represents an items similarity list with the schema (*ItemID1*, *ItemID2*, *SimScore*), where *SimScore* is computed.

Initialization. The multi-dimensional grid G is initialized upon issuing a `CREATE RECOMMENDER` statement, through two main steps: (1) *Grid Construction*, where we allocate the memory space for the grid, and decide on each cell size in terms of the values it represents. In case of categorical attributes (e.g., Gender, Job, and City), we allocate one cell per attribute. For continuous domain attributes (e.g., age and salary), we divide the space into N parts, where parts have almost equal number of ratings. More sophisticated techniques can be used to divide the space. Yet, we opt for a simple division here as a proof of concept for RecDB functionality. (2) *RecModel Building*, where the *RecModel* table for each cell C in G is built by running the specified recommender algorithm in the `CREATE RECOMMENDER` statement on the set of users U whose attributes correspond to the subdomain covered by C. For instance, in case of *ItemCosCF* recommendation algorithm, we scan the *ratings* table and run a nested loop algorithm over all items to calculate the cosine similarity score between every item pair in each cell C. After the initialization procedure successfully terminates, a pointer to the newly created grid structure G is added to the *RecIndex* field corresponding to the appropriate recommender entry in *RecCatalog*.

6.2.3 The CFilter Function

`CFILTER` is a database function that takes as input a ratings table (see Figure 3.2) and a set of contextual attributes. By specifying the `CFILTER` in the `FROM` clause, RecDB looks into *RecCatalog* to find an existing context pre-filtering recommender created on the specified ratings table and contextual attributes. Therefore, `CFILTER` follows the index pointer of the *RecCatalog* entry to fetch the multi-dimensional recommender grid index, and returns as output the local recommender that matches the specified contextual attributes. An example is given below:

Algorithm 6 CFilter (*Ratings R*, *AttributesAttr*)

1: $Cat \leftarrow$ *RecCatalog* entry that corresponds to recommender R
2: $G \leftarrow Cat.RecIndex$ (The Multi-dimensional Grid Index)
3: $Attr \leftarrow$ The set of attributes in $Cat.Attributes$
4: $AttrV \leftarrow$ Values of attributes $Attr$ in table $Cat.Users$ for uid
5: $C \leftarrow$ The cell in G that corresponds to $AttrV$
6: **return** $C.ratingView$

Query 12 *Predict the rating that system users would give to unseen items based on the user age, city, and gender.*

```
Select R.uid,R.iid, R.ratingval
From CFilter(Ratings,age='18-25,city='Minneapolis',gender='Female') as R
Recommend R.iid To R.uid On R.ratingval Using ItemCosCF
```

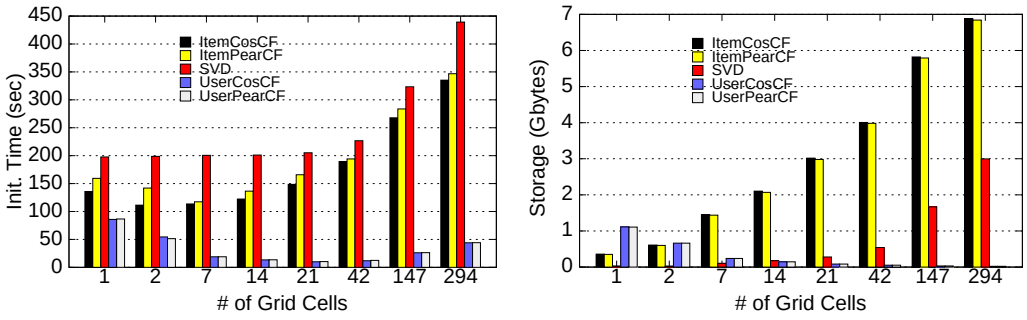
The `CFilter` finds that the *AgeCityGenderRec* recommender, registered in the *RecCatalog*, matches the input contextual attributes, i.e., age, gender, and city. RecDB thus follows the index pointer of the *RecCatalog* entry to the three-dimensional recommender grid index, and retrieves the local recommender grid cell that corresponds to the specified contextual attributes (18-25 age, Female gender, and 'Minneapolis' city). `CFilter` finally returns the name of the ratings view R that consists of all ratings residing in the local recommender cell, and the query is re-written as follows:

```
Select R.uid,R.iid, R.ratingval
From ratings_1825_Minneapolis_Female as R
Recommend R.iid To R.uid On R.ratingval Using ItemCosCF
```

After applying the `CFilter` function, RecDB executes the above (re-written) query using the Recommend operator as described before in Section 5.1.

6.3 Experimental Evaluation

We evaluate the context pre-filtering recommender creation and initialization process performance using the following two metrics: (1) *Recommender Initialization Time*: the total runtime (in seconds) taken by the system to process a `CREATE RECOMMENDER`



(a) Initialization Time (b) Storage Overhead

Fig. 6.2: Initialization Time and Storage Overhead.

statement, and (2) *Recommender Storage Overhead*: the amount of storage (in Gbytes) occupied by the multidimensional grid and recommendation models created upon recommender creation. We run our experiments for the following five popular recommendation algorithms, all supported and built into RecDB :

1. **ItemCosCF**: Item-Item collaborative filtering with cosine distance used to measure similarity among items.
2. **ItemPearCF**: Item-Item Collaborative filtering with Pearson correlation used to measure similarity among items.
3. **UserCosCF**: User-User Collaborative Filtering with cosine distance used to measure similarity among users.
4. **UserPearCF**: User-User Collaborative Filtering with Pearson correlation used to measure similarity among users.
5. **SVD**: Regularized Gradient Descent Singular Value Decomposition.

Figure 6.2 gives the effect of varying the number of grid cells for the multidimensional grid structure on the context-aware recommender initialization time and storage overhead. Since we have three contextual attributes, *age*, *gender*, and *job*, we have the possibility of eight context-aware recommenders with 1, 2, 7, 14, 21, 42, 147, and 294 three-dimensional grid cells. A context-aware recommender with one grid cell corresponds to context-free recommenders that do not take care of any attributes. On the other side, a context-aware recommender of 294 cells corresponds to the combination of three attributes: *age*, *gender*, and *job*. The number 294 is the product of 21,

7, and 2, as the number of categories of *job*, *age*, and *gender* attributes, respectively. Similarly, 147 grid cells correspond to an ⟨*age*, *job*⟩-aware recommender, and so on.

Figure 6.2 shows that the higher the number of grid cells, the higher the initialization time and storage overhead for the *ItemCosCF*, *ItemPearCF*, and *SVD* recommendation algorithms. The main reason is that more grid cells lead to building more recommendation models, as we build one recommendation model per grid cell. This consumes both storage and computation time. However, the opposite scenario happens for *UserCosCF* and *UserPearCF* algorithms. This counter intuitive behavior is mainly because these two recommender algorithms partition the user ratings based on the user attributes and hence, the number of users is small in each cell and building a user similarity list for several small cells is faster (and requires less storage) than building the user similarity list for one fat cell. Overall, for all recommender algorithms and number of grid cells, RecDB is able to provide a reasonable computational and storage overhead.

Comparing various recommender algorithms to each other shows that *UserCosCF* and *UserPearCF* are mostly faster and occupy less storage on disk than *ItemCosCF* and *ItemPearCF*. That happens due to the fact that the number of ratings per user in the dataset is less than the number of ratings per item. For all created recommenders, *SVD* consistently takes more time than other algorithms since *SVD* is an iterative algorithm that takes several iterations to build the recommendation model.

Chapter 7

Handling Location-Aware Recommendation Scenarios

Currently, myriad applications can produce *location-based ratings* that embed user and/or item locations. For example, location-based social networks (e.g., Foursquare [61] and Facebook Places [62]) allow users to "check-in" at spatial destinations (e.g., restaurants) and rate their visit, thus are capable of associating both user and item locations with ratings. Such ratings motivate an interesting new paradigm of *location-aware recommendations*, whereby the recommender system exploits the spatial aspect of ratings when producing recommendations. Existing recommendation techniques [6] assume ratings are represented by the (*user*, *rating*, *item*) triple, thus are ill-equipped to produce location-aware recommendations.

In this Chapter, we propose LARS, a novel location-aware recommender system built specifically to produce high-quality location-based recommendations in an efficient manner. LARS produces recommendations using a taxonomy of *three* types of location-based ratings within a single framework: (1) Spatial user ratings for non-spatial items, represented as a four-tuple (*user*, *ulocation*, *rating*, *item*), where *ulocation* represents a user location; (2) non-spatial user ratings for spatial items, represented as a four-tuple (*user*, *rating*, *item*, *ilocation*), where *ilocation* represents an item location, for example, a user with unknown location rating a restaurant; (3) spatial user ratings for spatial items, represented as a five-tuple (*user*, *ulocation*, *rating*, *item*, *ilocation*), for example, a

U.S. State	Top Movie Genres	Avg. Rating
Minnesota	Film-Noir	3.8
	War	3.7
	Drama	3.6
	Documentary	3.6
Wisconsin	War	4.0
	Film-Noir	4.0
	Mystery	3.9
	Romance	3.8
Florida	Fantansy	4.3
	Animation	4.1
	War	4.0
	Musical	4.0

(a) Movielens preference locality

Users from:	Visited venues in:	% Visits
Edina, MN	Minneapolis , MN	37 %
	Edina , MN	59 %
	Eden Prarie , MN	5 %
Robbinsdale, MN	Brooklyn Park, MN	32 %
	Robbinsdale, MN	20 %
	Minneapolis, MN	15 %
Falcon Heights, MN	St. Paul, MN	17 %
	Minneapolis, MN	13 %
	Roseville, MN	10 %

(b) Foursquare preference locality

Fig. 7.1: Preference locality in location-based ratings.

user at his/her office rating a restaurant visited for lunch. Traditional rating triples can be classified as non-spatial ratings for non-spatial items and do not fit this taxonomy.

7.1 A Study of Location-Based Ratings

The motivation for our work comes from analysis of two real-world location-based rating datasets: (1) a subset of the well-known MovieLens dataset [50] containing approximately 87K movie ratings associated with user zip codes (i.e., spatial user ratings for non-spatial items) and (2) data from the Foursquare [61] location-based social network containing user visit data for 1M users to 643K venues across the United States (i.e., spatial ratings for spatial items).

Preference locality. Preference locality suggests users from a spatial region (e.g., neighborhood) prefer items (e.g., movies, destinations) that are manifestly different than items preferred by users from other, even adjacent, regions. Figure 7.1(a) lists the top-4 movie genres using average MovieLens ratings of users from different U.S. states. While each list is different, the top genres from Florida differ vastly from the others. Florida's list contains three genres ("Fantasy", "Animation", "Musical") not in the other lists. This difference implies movie preferences are unique to specific spatial regions, and confirms previous work from the New York Times [27] that analyzed Netflix user queues across U.S. zip codes and found similar differences. Meanwhile, Figure 7.1(b) summarizes our observation of preference locality in Foursquare by depicting the visit

destinations for users from three *adjacent* Minnesota cities. Each sample exhibits diverse behavior: users from Falcon Heights, MN favor venues in St. Paul, MN (17% of visits) Minneapolis (13%), and Roseville, MN (10%), while users from Robbinsdale, MN prefer venues in Brooklyn Park, MN (32%) and Robbinsdale (20%). Preference locality suggests that recommendations should be influenced by location-based ratings *spatially close* to the user. The intuition is that localization influences recommendation using the unique preferences found within the spatial region containing the user.

Travel locality. Our second observation is that, when recommended items are spatial, users tend to travel a limited distance when visiting these venues. We refer to this property as "travel locality." In our analysis of Foursquare data, we observed that 45% of users travel 10 miles or less, while 75% travel 50 miles or less. This observation suggests that spatial items closer in travel distance to a user should be given precedence as recommendation candidates. In other words, a recommendation loses efficacy the further a querying user must travel to visit the destination. Existing recommendation techniques do not consider travel locality, thus may recommend users destinations with burdensome travel distances (e.g., a user in Chicago receiving restaurant recommendations in Seattle).

7.2 Non-Spatial User Ratings for Non-Spatial Items

The traditional item-based collaborative filtering (CF) method is a special case of LARS*. CF takes as input the classical rating triplet (*user*, *rating*, *item*) such that neither the user location nor the item location are specified. In such case, LARS directly employs the traditional model building phase (Phase-I in section **??**) to calculate the similarity scores between all items. Moreover, recommendations are produced to the users using the recommendation generation phase (Phase-II in section **??**). During the rest of the paper, we explain how LARS* incorporates either the user spatial location or the item spatial location to serve location-aware recommendations to the system users.

7.3 Spatial User Ratings for Non-Spatial Items

This section describes how LARS produces recommendations using spatial ratings for non-spatial items represented by the tuple (*user*, *ulocation*, *rating*, *item*). The idea is to exploit *preference locality*, i.e., the observation that user opinions are spatially unique. We identify three requirements for producing recommendations using spatial ratings for non-spatial items: (1) *Locality*: recommendations should be influenced by those ratings with user locations spatially close to the querying user location (i.e., in a spatial neighborhood); (2) *Scalability*: the recommendation procedure and data structure should scale up to large number of users; (3) *Influence*: system users should have the ability to control the size of the spatial neighborhood (e.g., city block, zip code, or county) that influences their recommendations.

LARS achieves its requirements by employing a *user partitioning* technique that maintains an adaptive pyramid structure, where the shape of the adaptive pyramid is driven by the three goals of *locality*, *scalability*, and *influence*. The idea is to adaptively partition the rating tuples (*user*, *ulocation*, *rating*, *item*) into spatial regions based on the *ulocation* attribute. Then, LARS produces recommendations using any existing collaborative filtering method (we use item-based CF) over the remaining three attributes (*user*, *rating*, *item*) of *only* the ratings within the spatial region containing the querying user. We note that ratings can come from users with varying tastes, and that our method only forces collaborative filtering to produce personalized user recommendations based only on ratings restricted to a specific spatial region. In this section, we describe the pyramid structure in Section 7.3.1, query processing in Section 7.3.2, and finally data structure maintenance in Section 7.3.3.

7.3.1 Data Structure

LARS employs a partial pyramid structure [63] (equivalent to a partial quad-tree [64]) as depicted in Figure 7.2. The pyramid decomposes the space into H levels (i.e., pyramid height). For a given level h, the space is partitioned into 4^h equal area grid cells. For example, at the pyramid root (level 0), one grid cell represents the entire geographic area, level 1 partitions space into four equi-area cells, and so forth. We represent each cell with a unique identifier *cid*. In each cell, we store an item-based collaborative

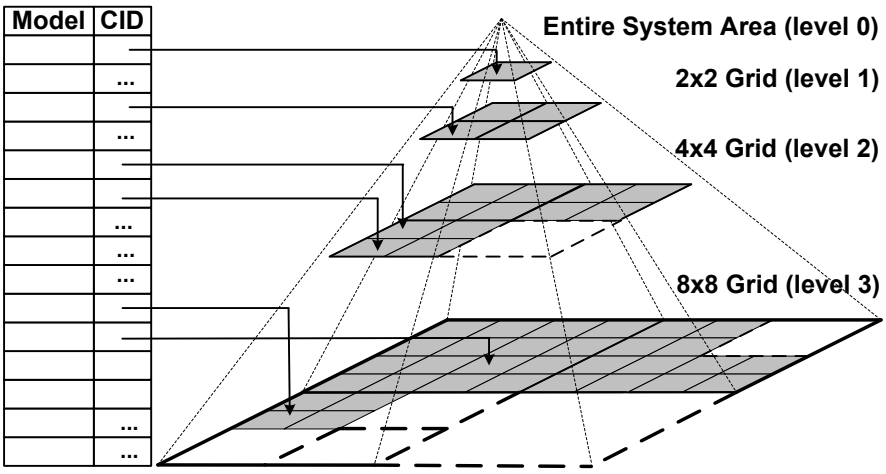


Fig. 7.2: Partial pyramid data structure.

filtering model built using *only* the spatial ratings with user locations contained in the cell's spatial region. A rating may contribute to up to H collaborative filtering models: one per each pyramid level starting from the lowest maintained grid cell containing the embedded user location up to the root level. Note that the root cell (level 0) of the pyramid represents a "traditional" (i.e., non-spatial) item-based collaborative filtering model. Levels in the pyramid can be incomplete, as LARS will periodically merge or split cells based on trade-offs of locality and scalability (discussed in Section 7.3.3). For example, in Figure 7.2, the four cells in the upper right corner of level 3 are not maintained (depicted as blank white squares).

We chose to employ a pyramid as it is a "space-partitioning" structure that is guaranteed to completely cover a given space. For our purposes, "data-partitioning" structures (e.g., R-trees) are less ideal, as they index data points and are not guaranteed to completely cover a given space.

7.3.2 Query Processing

Given a recommendation query with user location L and a limit K, LARS performs two query processing steps: (1) The user location L is used to find the lowest maintained cell C in the adaptive pyramid that contains L. This is done by hashing the user location to retrieve the cell at the lowest level of the pyramid. If this cell is not maintained,

we return the nearest maintained ancestor cell. (2) The top-k recommended items are generated using the item-based collaborative filtering technique using the model stored at C. As mentioned earlier, the model in C is built using *only* the spatial ratings associated with user locations within C.

In addition to traditional recommendation queries (i.e., snapshot queries), LARS also supports continuous queries and can account for the *influence* requirement for each user as follows.

Continuous queries. LARS evaluates a continuous query in full once it is issued, and sends recommendations back to a user U as an initial answer. LARS then monitors the movement of U using her location updates. As long as U does not cross the boundary of her current grid cell, LARS does nothing as the initial answer is still valid. Once U crosses a cell boundary, LARS reevaluates the recommendation query for the new cell and only sends incremental updates [65] to the last reported answer. Like snapshot queries, if a cell at level h is not maintained, the query is temporarily transferred higher in the pyramid to the nearest maintained ancestor cell. Note that since higher-level cells maintain larger spatial regions, the continuous query will cross spatial boundaries less often, reducing the amount of required recommendation updates.

Influence level. LARS addresses the *influence* requirement by allowing querying users to specify an optional *influence level* (in addition to location L and limit K) that controls the size of the spatial neighborhood used to influence their recommendations. An influence level I maps to a pyramid level and acts much like a "zoom" level in Google or Bing maps (e.g., city block, neighborhood, entire city). The level I instructs LARS to process the recommendation query starting from the grid cell containing the querying user location at level I, instead of the lowest maintained grid cell (the default). An influence level of zero forces LARS to use the root cell of the pyramid, and thus act as a traditional (non-spatial) collaborative filtering recommender system.

7.3.3 Data Structure Maintenance

This section describes building and maintaining the pyramid data structure. Initially, to build the pyramid, all location-based ratings currently in the system are used to build a *complete pyramid* of height H, such that all cells in all H levels are present and contain a collaborative filtering model. The initial height H is chosen according to the

level of *locality* desired, where the cells in the lowest pyramid level represent the most localized regions. After this initial build, we invoke a *merging* step that scans all cells starting from the lowest level h and merges quadrants (i.e., four cells with a common parent) into their parent at level $h-1$ if it is determined that a tolerated amount of locality will not be lost (merging is discussed in Section 7.4.3). We note that while the original partial pyramid [63] was concerned with spatial queries over static data, it did not address pyramid maintenance.

As time goes by, new users, ratings, and items will be added to the system. This new data will both increase the size of the collaborative filtering models maintained in the pyramid cells, as well as alter recommendations produced from each cell. To account for these changes, LARS performs maintenance on a cell-by-cell basis. Maintenance is triggered for a cell C once it receives $N\%$ new ratings; the percentage is computed from the number of existing ratings in C. We do this because an appealing quality of collaborative filtering is that as a model matures (i.e., more data is used to build the model), more updates are needed to significantly change the top-k recommendations produced from it [17]. Thus, maintenance is needed less often. Algorithm 8 provides the pseudocode for the LARS maintenance algorithm. The algorithm takes as input a pyramid cell C and level h, and includes two main steps: *model rebuild* and *merge/split maintenance*.

Step I: Model Rebuild. The first step is to rebuild the item-based collaborative filtering (CF) model for a cell C (line 7). Rebuilding the CF model is necessary to allow the model to "evolve" as new location-based ratings enter the system (e.g., accounting for new items, ratings, or users). Given the cost of building the CF model is $O(\frac{R^2}{U})$, the cost of the model rebuild for a cell C at level h is $\frac{(R/4^h)^2}{(U/4^h)}=\frac{R^2}{4^hU}$, assuming ratings and users are uniformly distributed.

Step II: Merging/Split Maintenance. After rebuilding the CF model for cell C, LARS invokes a merge/split maintenance step that may decide to merge or split cells based on trade-offs in *scalability* and *locality*. The algorithm first checks if C has a child quadrant q maintained at level $h+1$ (line 9), and that none of the four cells in q have maintained children of their own (line 11). If both cases hold, LARS considers quadrant q as a candidate to merge into its parent cell C (calling function *CheckDoMerge* on line 10). We provide details of merging in Section 7.4.3. On the other hand, if C

Algorithm 7 Pyramid maintenance algorithm

```
/* Called after cell C receives N% new ratings */
Function PyramidMaintenance(Cell C, Level h)
/*Step I: Model Rebuild */
Rebuild item-based collaborative filtering model for cell C
/*Step II: Merge/Split Maintenance */
if (C has children quadrant q maintained at level h + 1) then
  if (All cells in q have no maintained children) then
    CheckDoMerge(q,C) /* Merge covered in Section 7.4.3 */
else
  CheckDoSplit(C) /* Split covered in Section 7.4.3 */
return
```

does *not* have a child quadrant maintained at level $h + 1$ (line 13), LARS considers splitting C into four child cells at level $h + 1$ (calling function *CheckDoSplit* on line 14). The split operation is covered in Section 7.4.3. Merging and splitting are performed completely in quadrants (i.e., four equi-area cells with the same parent). We made this decision for simplicity in maintaining the partial pyramid. However, we also discuss (in Section 7.3.4) relaxing this constraint by merging and splitting at a finer granularity than a quadrant.

We note the following features of pyramid maintenance: (1) Maintenance can be performed completely offline, i.e., LARS can continue to produce recommendations using the "old" pyramid cells while part of the pyramid is being updated; (2) maintenance does not entail rebuilding the whole pyramid at once, instead, only one cell is rebuilt at a time; (3) maintenance is performed only after $N\%$ new ratings are added to a pyramid cell, meaning maintenance will be amortized over many operations.

Cell Merging

Merging entails discarding an entire quadrant of cells at level h with a common parent at level $h - 1$. Merging improves scalability (i.e., storage and computational overhead) of LARS, as it reduces storage by discarding the item-based collaborative filtering (CF) models of the merged cells. Furthermore, merging improves computational overhead in two ways: (a) *less maintenance computation*, since less CF models are periodically rebuilt, and (b) *less continuous query processing computation*, as merged cells represent

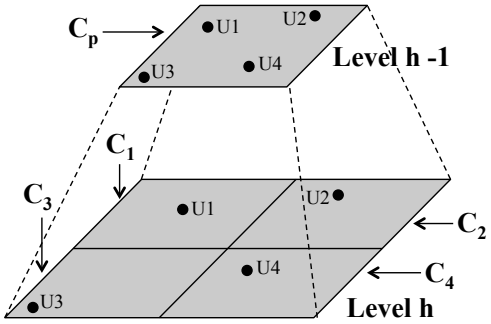
a larger spatial region, hence, users will cross cell boundaries less often triggering less recommendation updates. Merging hurts locality, since merged cells capture community opinions from a wider spatial region, causing less unique (i.e., "local") recommendations than smaller cells.

To determine whether to merge a quadrant q into its parent cell C_P (i.e., function *CheckDoMerge* on line 10 in Algorithm 8), we calculate two percentage values: (1) *locality_loss*, the amount of locality lost by (potentially) merging, and (2) *scalability_gain*, the amount of scalability gained by (potentially) merging. Details of calculating these percentages are covered next. When deciding to merge, we define a system parameter $\mathcal{M}$, a real number in the range [0,1] that defines a tradeoff between scalability gain and locality loss. LARS merges (i.e., discards quadrant q) if:

$$(1 - \mathcal{M}) * scalability\_gain > \mathcal{M} * locality\_loss \tag{7.1}$$

A smaller $\mathcal{M}$ value implies gaining scalability is important and the system is willing to lose a large amount of locality for small gains in scalability. Conversely, a larger $\mathcal{M}$ value implies scalability is not a concern, and the amount of locality lost must be small in order to merge. At the extremes, setting $\mathcal{M}$=0 (i.e., always merge) implies LARS will function as a traditional CF recommender system, while setting $\mathcal{M}$=1 causes LARS to never merge, i.e., LARS will employ a complete pyramid structure maintaining all cells at all levels.

Calculating Locality Loss. We calculate locality loss by observing the loss of recommendation uniqueness when discarding a cell quadrant q and using its parent cell C_P to produce recommendations in its place. We perform this calculation in three steps. (1) *Sample*. We take a sample of diverse system users $\mathcal{U}$ that have at least one rating within C_P (and by definition one of the more localized cells $C_u \in q$). Due to space, we do not discuss user sampling in detail, however, the intuition is to select a set of users with *diverse* tastes by comparing each user's rating history. We measure diversity using the Cosine distance between users in the same manner as Equation 2.1, except we employ user vectors in the calculation (instead of item vectors). (2) *Compare*. For each user $u \in \mathcal{U}$, we measure the potential loss of recommendation uniqueness by comparing the list of top-k recommendations R_P produced from the merged cell C_P (i.e., the parent) with the list of recommendations R_u that the user receives from the



User	Recommendation		Locality Loss
	C_u	C_p	
U_1	I_1, I_2, I_5, I_6	I_1, I_2, I_5, I_7	25%
U_2	I_1, I_2, I_3, I_4	I_1, I_2, I_3, I_5	25%
U_3	I_3, I_4, I_5, I_6	I_3, I_4, I_5, I_6	0%
U_4	I_3, I_4, I_6, I_8	I_3, I_4, I_5, I_7	50%
Average Locality Loss			25%

Fig. 7.3: Merge and split example

more localized cell $C_u \in q$. Formally, the loss of uniqueness can be computed as the ratio $\frac{|R_u - R_P|}{k}$, which indicates the number of recommended items that appear in R_u but not in the parent recommendation R_P, normalized to the total number of recommended objects k. (3) *Average*. We calculate the average loss of uniqueness over all users in $\mathcal{U}$ to produce a single percentage value, termed *locality_loss*.

Calculating scalability gain. Scalability gain is measured in storage and computation savings. We measure scalability gain by summing the model sizes for each of the merged (i.e., child) cells (abbr. $size_m$), and divide this value by the sum of $size_m$ and the size of the parent cell. We refer to this percentage as the *storage_gain*. We also quantify *computation* savings using storage gain as a surrogate measurement, as computation is considered a direct function of the amount of data in the system.

Cost. The cost of *CheckDoMerge* is $|\mathcal{U}|(2(\frac{n|\mathcal{I}|}{4^h}) + k)$, where $|\mathcal{U}|$ is the size of the user sample, $|\mathcal{I}|$ is the number of items in the model stored within a cell, n is the model size, and k is the cost of comparing two recommendation lists. We note that this cost is less than the model re-build step.

Example. Figure 7.3 depicts four merge candidate cells C_1 to C_4 at level h merging into their parent C_P at level $h-1$, along with four sampled users u_1 to u_4. Each user location is shown twice: once within one of the cells C_u and then at the parent cell C_P. The recommendations produced for each user from cell C_u and C_P are provided in the table in Figure 7.3, along with the locality loss for each user. For example, for user u_1, cell C_1 produces recommendations R_{u_1}=$\{I_1, I_2, I_5, I_6\}$, while C_P produces recommendations R_P=$\{I_1, I_2, I_5, I_7\}$. Thus, the loss of locality for u_1 is 25% as only

one item out of four (I_6) will be lost if merging occurs. Given locality loss for the four users u_1 to u_4 as 25%, 25%, 0%, and 50%, the final *locality loss* value is the average 25%. To calculate scalability gain, assume the sum of the model sizes for cells C_1 to C_4 and C_P is 4GB, and the sum of the model sizes for cells C_1 to C_4 is 2GB. Then, the *scalability gain* is $\frac{2}{4}$=50%. Assuming $\mathcal{M}$=0.7, then (0.3 * 50) < (0.7 * 25), meaning that LARS will not merge cells C_1, C_2, C_3, C_4 into C_P.

Splitting

Splitting entails creating a new cell quadrant at pyramid level h under a cell at level $h-1$. Splitting improves locality in LARS, as newly split cells represent more granular spatial regions capable of producing recommendations unique to the smaller, more "local", spatial regions. On the other hand, splitting hurts scalability by requiring storage and maintenance of more item-based collaborative filtering models. Splitting also negatively affects continuous query processing, since it creates more granular cells causing user locations to cross cell boundaries more often, triggering recommendation updates.

To determine whether to split a cell C_P into four child cells (i.e., function *CheckDoSplit* on line 14 of Algorithm 8), we perform a *speculative split* that creates a temporary child quadrant q_s for C_P. Using C_P and q_s, two percentages are calculated: *locality_gain* and *scalability_loss*. These values are the opposite of those calculated for the merge operation. LARS splits C_P only if the following condition holds:

$$\mathcal{M} * locality\_gain > (1 - \mathcal{M}) * scalability\_loss \tag{7.2}$$

This equation represents the opposite criteria of that presented for merging in Equation 7.1. We will next describe how to perform speculative splitting, followed by a description of how to calculate *locality gain* and *scalability loss*.

Speculative splitting. In order to evaluate *locality gain* and *scalability loss*, we must build, from scratch, the collaborative filtering (CF) models of the four cells that potentially result from the split, as they do not exist in the partial pyramid. As building CF models is non-trivial due to its high cost, we perform a cheaper *speculative split* that builds each model using a random sample of only 50% of the ratings from the spatial region of each potentially split cell. LARS uses these models to measure *locality_gain* and *scalability_loss*. If LARS decides to split, it builds the *complete* model for the

newly split cells using all of the ratings. Speculative splitting is sufficient for calculating *locality_gain* and *scalability_loss* using the item-based CF technique, as experiments on real data and workloads have shown that using 50% of the ratings for model-building results in loss of only 3% of recommendation accuracy [21], assuming sufficiently high number of ratings (i.e., order of thousands). Thus, we *only* speculatively split if we have more than 1,000 ratings for the potentially split cell, otherwise, the model for the cell is built using all of R.

Calculating locality gain. After speculatively splitting a cell at level h into four child cells at level $h+1$, evaluating locality gain is performed exactly the same as for merging, where we compute the ratio of recommendations that will appear in R_u but not in R_P, where R_u and R_P are the list of top-k recommendations generated by the speculatively split cells C_1 to C_4 and the existing parent cell C_P, respectively. Like the merging case, we average locality gain over all sampled users. One caveat here is that if *any* of the speculatively split cells do not contain ratings for enough unique items (say less than ten unique items), we immediately set the locality gain to 0, which disqualifies splitting. We do this to prevent *recommendation starvation*, i.e., not having enough diverse items to produce meaningful recommendations.

Calculating scalability loss. We calculate *scalability loss* by estimating the storage necessary to maintain the newly split cells. The maximum size of an item-based CF model is approximately $n|I|$, where n is the model size. We can multiply $n|I|$ by the number of bytes needed to store an item in a CF model to find an upper-bound storage size of each potentially split cell. The sum of these four estimated sizes (abbr. $size_s$) divided by the sum of the size of the existing parent cell and $size_s$ represents the *scalability loss* metric.

Cost. The cost of *CheckDoSplit* is the sum of two operations (1) the cost of speculatively building four CF models at level $h+1$ using 50% of the rating, which is $4\frac{(0.5R)^2}{4^{(h+1)}U}$ and (2) the cost of calculating locality gain and scalability loss, which is the same cost as *CheckDoMerge*.

Example. Consider the example used for merging in Figure 7.3, but now assume we have *only* a cell C_P, and are trying to determine whether to split C_P into four new cells C_1 to C_4. *Locality gain* will be computed as in the table in Figure 7.3 to be 25%. Further, assume that we estimate the extra storage overhead for splitting (i.e.,

storage loss) to be 50%. Assuming $\mathcal{M}$=0.7, then (0.7 * 25) > (0.3 * 50), meaning that LARS will decide to split C_P into four cells as *locality gain* is significantly higher than *scalability loss*.

7.3.4 Partial Merging and Splitting

So far, we have assumed cells are merged and split in complete quadrants. We now relax this constraint by discussing the changes to LARS necessary to support *partial* merging and splitting of pyramid cells.

Partial Merging

It may be beneficial to *partially* merge at a more granular level in order to sacrifice *less* locality while still gaining scalability. For example, in Figure 7.3 we may only want to merge cells C_1 and C_2 while leaving cells C_3 and C_4 intact, meaning three child cells would be maintained under the example parent C_P. To support partial merging, all techniques described in Section 7.4.3 remain the same, with two exceptions: (1) The resulting merged candidate cell (e.g., C_1 merged with C_2, abbreviated C_{12}) plays the role of the "parent" cell in evaluating locality loss; (2) When calculating storage gain, we must subtract the size of the resulting merge candidate cell (e.g., C_{12}) from the sum of the sizes of cells that will merge (e.g., C_1 and C_2), since we no longer discard the merged cells completely, i.e., the resulting merged cell now replaces the individual cells.

Partial merging involves extra overhead (compared to merging complete quadrants) since we must build, from scratch, the CF model for the candidate merge result cell (e.g., C_{12}) in order to calculate locality loss. In order to perform the build efficiently, we perform a *speculative merge* that builds the CF model using only 50% of the rating data. This is the *same* method used in *speculative splitting* (Section 7.4.3), except applied to the case of merging.

Partial Splitting

To support *partial splitting*, all techniques discussed in Section 7.4.3 remain the same. There are, however, two distinguishable cases of partial splitting: (1) A "parent" at level h splitting into less than four cells at level $h + 1$. This case requires speculative

splitting to be aware of which "partial" child cells to create. (2) A cell at level h is split into two or three separate cells that remain at level h, i.e., cells at level $h+1$ are not created. This case requires that a previous partial merge took place that originally reduced a cell quadrant to two or three cells.

7.4 Optimized Spatial User Ratings for Non-Spatial Items

In this section, we present LARS*, an extension to LARS that employs a partial *in-memory* pyramid structure [63] (equivalent to a partial quad-tree [64]) as depicted in Figure 7.2. The pyramid decomposes the space into H levels (i.e., pyramid height). For a given level h, the space is partitioned into 4^h equal area grid cells. For example, at the pyramid root (level 0), one grid cell represents the entire geographic area, level 1 partitions space into four equi-area cells, and so forth.

To provide a tradeoff between recommendation locality and system scalability, the pyramid data structure maintains three types of cells (see figure 7.2): (1) Recommendation Model Cell (α-Cell), (2) Statistics Cell (β-Cell), and (3) Empty Cell (γ-Cell), explained as follows:

Recommendation Model Cell (α-Cell). Each α-Cell stores an item-based collaborative filtering model built using *only* the spatial ratings with user locations contained in the cell's spatial region. Note that the root cell (level 0) of the pyramid is an α-Cell and represents a "traditional" (i.e., non-spatial) item-based collaborative filtering model. Moreover, each α-Cell maintains statistics about all the ratings located within the spatial extents of the cell. Each α-Cell C_p maintains a hash table that indexes all items (by their IDs) that have been rated in this cell, named *Items Ratings Statistics Table*. For each indexed item i in the *Items Ratings Statistics Table*, we maintain four parameters; each parameter represent the *number of user ratings* to item i in each of the four children cells (i.e., C_1, C_2, C_3, and C_4) of cell C_p. An example of the maintained parameters is given in Figure 7.4. Assume that cell C_p contains ratings for three items I_1, I_2, and I_3. Figure 7.4 shows the maintained statistics for each item in cell C_p. For example, for item I_1, the number of user ratings located in child cell C_1, C_2, C_3, and C_4 is equal to 109, 3200, 14, and 54, respectively. Similarly, the number of user ratings is calculated for items I_2 and I_3.

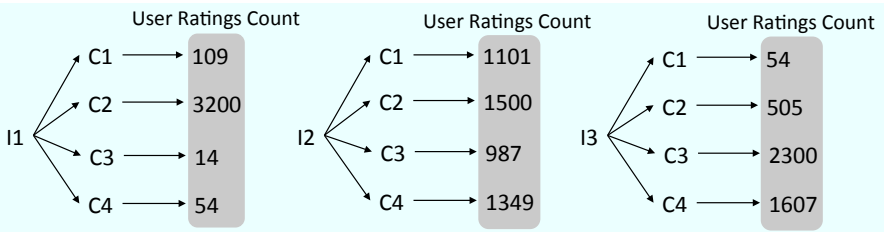


Fig. 7.4: Example of *Items Ratings Statistics Table*

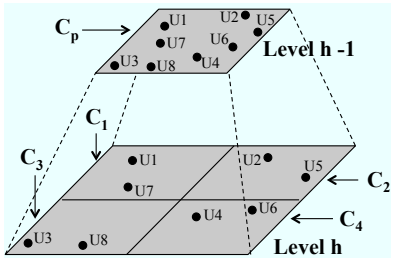


Fig. 7.5: Two-Levels Pyramid

Statistics Cell (β-Cell). Like an α-Cell, a β-Cell maintains statistics (i.e., *items ratings Statistics Table*) about the user/item ratings that are located within the spatial range of the cell. The only difference between an α-Cell and a β-Cell is that a β-Cell does not maintain a collaborative filtering (CF) model for the user/item ratings lying in its boundaries. In consequence, a β-Cell is a light weight cell such that it incurs less storage than an α-Cell. In favor of system scalability, LARS* prefers a β-Cell over an α-Cell to reduce the total system storage.

Empty Cell (γ-Cell). a γ-Cell is a cell that maintains neither the statistics nor the recommendation model for the ratings lying within its boundaries. a γ-Cell is the most light weight cell among all cell types as it almost incurs no storage overhead. Note that an α-Cell can have α-Cells, β-Cells, or γ-Cells children. Also, a β-Cell can have α-Cells, β-Cells, or γ-Cells children. However, a γ-Cell cannot have any children.

7.4.1 Pyramid structure intuition

An α-Cell requires the highest storage and maintenance overhead because it maintains a CF model as well as the user/item ratings statistics. On the other hand, an α-Cell (as opposed to β-Cell and γ-Cell) is the only cell that can be leveraged to answer

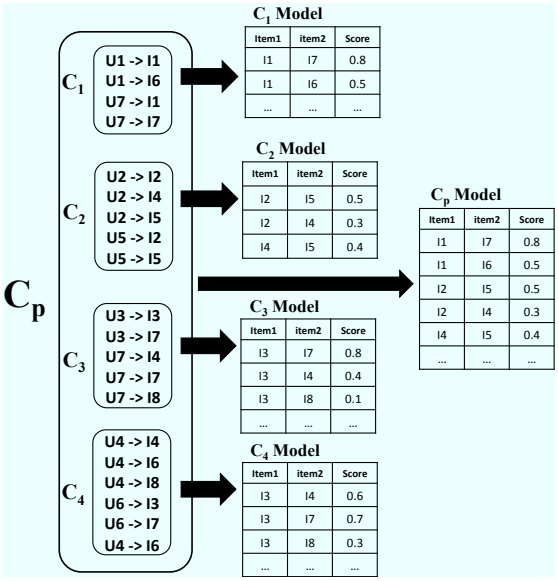


Fig. 7.6: Ratings Distribution and Recommendation Models

recommendation queries. A pyramid structure that only contains α-Cells achieves the highest recommendation locality, and this is why an α-Cell is considered the highly ranked cell type in LARS*. a β-Cell is the secondly ranked cell type as it only maintains statistics about the user/item ratings. The storage and maintenance overhead incurred by a β-Cell is less expensive than an α-Cell. The statistics maintained at a β-Cell determines whether the children of that cell needs to be maintained as α-Cells to serve more localized recommendation. Finally, a γ-Cell (lowest ranked cell type) has the least maintenance cost, as neither a CF model nor statistics are maintained for that cell. Moreover, a γ-Cell is a leaf cell in the pyramid.

LARS* upgrades (downgrades) a cell to a higher (lower) cell rank, based on trade-offs between recommendation locality and system scalability (discussed in Section 7.3.3). If recommendation locality is preferred over scalability, more α-Cells are maintained in the pyramid. On the other hand, if scalability is favored over locality, more γ-Cells exist in the pyramid. β-Cells comes as an intermediary stage between α-Cells and γ-Cells to further increase the recommendation locality whereas the system scalability is not quite affected.

Item	$\|RP_{C,i}\|$	$\|RS_{C,i}\|$	$LG_{C,i}$
I1	1	0	0.0
I2	1	0	0.0
I3	1	1	1.0
I4	3	3	1.0
I5	1	0	0.0
I6	3	2	0.666
I7	6	2	0.166
I8	1	1	1.0
Cell Locality Gain ($LG_{C,i}$)			0.48

Fig. 7.7: Locality Loss/Gain at C_p]

We chose to employ a pyramid as it is a "space-partitioning" structure that is guaranteed to completely cover a given space. For our purposes, "data-partitioning" structures (e.g., R-trees) are less ideal than a "space-partitioning" structure for two main reasons: (1) "data-partitioning" structures index data points, and hence covers only locations that are inserted in them. In other words, "data-partitioning" structures are not guaranteed to completely cover a given space, which is not suitable for queries issued in arbitrary spatial locations. (2) In contrast to "data-partitioning" structures (e.g., R-trees [66]), "space partitioning" structures show better performance for dynamic memory resident data [67, 68, 65].

7.4.2 LARS* versus LARS

Table 7.1 compares LARS* against LARS. Like LARS*, LARS [69] employs a partial pyramid data structure to support spatial user ratings for non-spatial items. LARS is different from LARS* in the following aspects: (1) As shown in Table 7.1, LARS* maintains α-Cells, β-Cells, and γ-Cells, whereas LARS only maintains α-Cells and γ-Cells. In other words, LARS either merges or splits a pyramid cell based on a tradeoff between scalability and recommendation locality. LARS* employs the same tradeoff and further increases the recommendation locality by allowing for more α-Cells to be maintained at lower pyramid levels. (2) As opposed to LARS, LARS* does not perform a speculative splitting operation to decide whether to maintain more localized CF models. However, LARS maintains extra statistics at each α-Cell and β-Cell that helps in quickly

	LARS	**LARS***
	Supported Features	
α-Cell	Yes	Yes
β-Cell	No	Yes
γ-Cell	Yes	Yes
Speculative Split	Yes	No
Rating Statistics	No	Yes
	Performance Factors	
Locality	-	$\approx$26% higher than LARS
Storage	$\approx$5% lower than LARS*	-
Maintenance	-	$\approx$38% lower than LARS

Table 7.1: Comparison between LARS and LARS*

deciding wether a CF model needs to be maintained at a child cell. (3) As it turns out from Table 7.1, LARS* achieves higher recommendation locality than LARS. That is due to the fact that LARS maintains a CF recommendation model in a cell at pyramid level h if and only if a CF model, at its parent cell at level $h-1$, is also maintained. However, LARS* may maintain an α-Cell at level h even though its parent cell, at level $h-1$, does not maintain a CF model, i.e., the parent cell is a β-Cell. In LARS*, the role of a β-Cell is to keep the *user/item ratings statistics* that are used to quickly decide whether the child cells needs to be γ-Cells or α-Cells. (4) As given in Table 7.1, LARS* incurs more storage overhead than LARS which is explained by the fact that LARS* maintains additional type of cell, i.e., β-Cells, whereas LARS only maintains α-Cells and γ-Cells. In addition, LARS* may also maintain more α-Cells than LARS does in order to increase the recommendation locality. (5) Even LARS* may maintain more α-Cells than LARS besides the extra statistics maintained at β-Cells, nonetheless LARS* incurs less maintenance cost. That is due to the fact that LARS* also reduces the maintenance overhead by avoiding the expensive speculative splitting operation employed by LARS maintenance algorithm. Instead, LARS* employs the *user/item ratings statistics* maintained at either a β-Cell or an α-Cell to quickly decide whether the cell children need to maintain a CF model (i.e., upgraded to α-Cells), just needs to maintain the statistics (i.e., become β-Cells), or perhaps downgraded to γ-Cells.

7.4.3 Pyramid Maintenance

This section describes building and maintaining the pyramid data structure. Initially, to build the pyramid, all location-based ratings currently in the system are used to build a *complete pyramid* of height H, such that all cells in all H levels are α-Cells and contain ratings statistics and a collaborative filtering model. The initial height H is chosen according to the level of *locality* desired, where the cells in the lowest pyramid level represent the most localized regions. After this initial build, we invoke a *cell type maintenance* step that scans all cells starting from the lowest level h and downgrades cell types to either (β-Cell or γ-Cell) if necessary (cell type switching is discussed in Section 7.4.3). We note that while the original partial pyramid [63] was concerned with spatial queries over static data, it did not address pyramid maintenance.

Main idea. As time goes by, new users, ratings, and items will be added to the system. This new data will both increase the size of the collaborative filtering models maintained in the pyramid cells, as well as alter recommendations produced from each cell. To account for these changes, LARS* performs maintenance on a cell-by-cell basis. Maintenance is triggered for a cell C once it receives $N\%$ new ratings; the percentage is computed from the number of existing ratings in C. We do this because an appealing quality of collaborative filtering is that as a model matures (i.e., more data is used to build the model), more updates are needed to significantly change the top-k recommendations produced from it [17]. Thus, maintenance is needed less often.

We note the following features of pyramid maintenance: (1) Maintenance can be performed completely offline, i.e., LARS* can continue to produce recommendations using the "old" pyramid cells while part of the pyramid is being updated; (2) maintenance does not entail rebuilding the whole pyramid at once, instead, only one cell is rebuilt at a time; (3) maintenance is performed only after $N\%$ new ratings are added to a pyramid cell, meaning maintenance will be amortized over many operations.

Maintenance Algorithm. Algorithm 8 provides the pseudocode for the LARS* maintenance algorithm. The algorithm takes as input a pyramid cell C and level h, and includes three main steps: *Statistics Maintenance*, *Model Rebuild* and *Cell Child Quadrant Maintenance*, explained below.

Step I: Statistics Maintenance. The first step (line 4) is to maintain the *Items Ratings Statistics Table*. The maintained statistics are necessary for cell type switching

Algorithm 8 Pyramid maintenance algorithm

```
/* Called after cell C receives N% new ratings */
Function PyramidMaintenance(Cell C, Level h)
/* Step I: Statistics Maintenance*/
Maintain cell C statistics
/*Step II: Model Rebuild */
if (Cell C is an α-Cell) then
  Rebuild item-based collaborative filtering model for cell C
/*Step III: Cell Child Quadrant Maintenance */
if (C children quadrant q cells are α-Cells) then
  CheckDownGradeToSCells(q,C) /* covered in Section 7.4.3 */
else if (C children quadrant q cells are γ-Cells) then
  CheckUpGradeToSCells(q,C)
else
  isSwitchedToMcells ← CheckUpGradeToMCells(q,C) /* covered in Section 7.4.3 */
  if (isSwitchedToMcells is False) then
    CheckDownGradeToECells(q,C)
return
```

decision, especially when new location-based ratings enter the system. As the *items ratings statistics table* is implemented using a hash table, then it can be queried and maintained in $O(1))$ time, requiring $O(|I_C|)$ space such that I_C is the set of all items rated at cell C and $|I_C|$ is the total number of items in I_C.

Step II: Model Rebuild. The second step is to rebuild the item-based collaborative filtering (CF) model for a cell C (line 7). The model is rebuilt at cell C only if cell C is an α-Cell, otherwise (β-Cell or γ-Cell) no CF recommendation model is maintained, and hence the model rebuild step does not apply Rebuilding the CF model is necessary to allow the model to "evolve" as new location-based ratings enter the system (e.g., accounting for new items, ratings, or users).

Step III: Cell Child Quadrant Maintenance. LARS* invokes a maintenance step that may decide whether cell C child quadrant need to be switched to a different cell type based on trade-offs between *scalability* and *locality*. The algorithm first checks if cell C child quadrant q at level $h + 1$ is of type α-Cell (line 9). If that case holds, LARS* considers quadrant q cells as candidates to be downgraded to β-Cells (calling function *CheckDownGradeToSCells* on line 10). We provide details of the *Downgrade α-Cells to β-Cells* operation in Section 7.4.3. On the other hand, if C have a child

quadrant of type γ-Cells at level $h+1$ (line 11), LARS* considers upgrading cell C four children cells at level $h+1$ to β-Cells (calling function *CheckUpGradeToSCells* on line 12). The *Updgrade From E to β-Cells* operation is covered in Section 7.4.3. However, if C have a child quadrant of type β-Cells at level $h+1$ (line 11), LARS* first considers upgrading cell C four children cells at level $h+1$ from β-Cells to α-Cells (calling function *CheckUpGradeToMCells* on line 14). If the children cells are not switched to α-Cells, LARS* then considers downgrading them to γ-Cells (calling function *CheckDownGradeToECells* on line 16). Cell Type switching operations are performed completely in quadrants (i.e., four equi-area cells with the same parent). We made this decision for simplicity in maintaining the partial pyramid.

Recommendation Locality

In this section, we explain the notion of locality in recommendation that is essential to understand the cell type switching (upgrade/downgrade) operations highlighted in the PyramidMaintenance algorithm (algorithm 8). We use the following example to give the intuition behind recommendation locality.

Running Example. Figure 7.5 depicts a two-levels pyramid in which C_p is the root cell and its children cells are C_1, C_2, C_3, and C_4. In the example, we assume eight users (U_1, U_2, ..., and U_8) have rated eight different items (I_1, I_2, ..., and I_8). Figure 7.6 gives the spatial distributions of users U_1, U_2, U_3, U_4, U_5, U_6, U_7, and U_8 as well as the items that each user rated.

Intuition. Consider the example given in Figure 7.5. In cell C_p, users U_2 and U_5 that belongs to the child cell C_2 have both rated items I_2 and I_5. In that case, the similarity score between items I_2 and I_5 in the item-based collaborative filtering CF model built at cell C_2 is exactly the same as the one in the CF model built at cell C_p. The last phenomenon happened because items (i.e., I_2 and I_5) have been rated by mostly users located in the same child cell, and hence the recommendation model at the parent cell will not be different from the model at the children cells. In this case, if the CF model at C_2 is not maintained, LARS* does not lose recommendation locality at all.

The opposite case happens when an item is rated by users located in different pyramid cells (spatially skewed). For example, item I_4 is rated by users U_2, U_4, and U_7 in three different cells (C_2, C_3, and C_4). In this case, U_2, U_4, and U_7 are spatially

Parameter	Description
$RP_{c,i}$	The set of user pairs that co-rated item i in cell c
$RS_{c,i}$	The set of user pairs that co-rated item i in cell c such that each pair of users $\langle u_1, u_2\rangle \in S_{c,i}$ are not located in the same child cell of c
$LG_{c,i}$	The degree of locality lost for item i from downgrading the four children of cell c to β-Cells, such that $0 \leq LG_{c,i} \leq 1$
LG_c	The amount of locality lost by downgrading cell c four children cells to β-Cells ($0 \leq LG_c \leq 1$)

Table 7.2: Summary of Mathematical Notations.

skewed. Hence, the similarity score between item I_4 and other items at the children cells is different from the similarity score calculated at the parent cell C_p because not all users that have rated item I_4 exist in the same child cell. Based on that, we observe the following:

Observation 1 *The more the user/item ratings in a parent cell C are geographically skewed, the higher the locality gained from building the item-based CF model at the four children cells.*

The amount of locality gained/lost by maintaining the child cells of a given pyramid cell depends on whether the CF models at the child cells are similar to the CF model built at the parent cell. In other words, LARS* loses locality if the child cells are not maintained even though the CF model at these cells produce different recommendations than the CF model at the parent cell. LARS* leverages Observation 1 to determine the amount of locality gained/lost due to maintaining an item-based CF model at the four children. LARS* calculates the locality loss/gain as follows:

Locality Loss/Gain. Table 7.2 gives the main mathematical notions used in calculating the recommendation locality loss/gain. First, the *Item Ratings Pairs Set* ($RP_{c,i}$) is defined as the set of all possible pairs of users that rated item i in cell c. For example, in figure 7.7 the item ratings pairs set for item I_7 in cell C_p (RP_{C_p,I_7}) has three elements (i.e., RP_{C_p,I_7}=$\{\langle U_3, U_6\rangle, \langle U_3, U_7\rangle, \langle U_6, U_7\rangle\}$) as only users U_1 and U_7 have rated item I_1. Similarly, RP_{C_p,I_2} is equal to $\{\langle U_6, U_7\rangle\}$ (i.e., Users U_2 and U_5 have rated item I_2).

For each item, we define the *Skewed Item Ratings Set ($RS_{c,i}$)* as the total number of user pairs in cell c that rated item i such that each pair of users $\in RS_{c,i}$ do not exist in the same child cell of c. For example, in Figure 7.7, the skewed item ratings set for item I_2 in cell C_p (RS_{C_P,I_2}) is $\emptyset$ as all users that rated I_2, i.e., U_2 and U_5 are collocated in the same child cell C_2. For I_4, the skewed item ratings set RS_{C_P,I_2}=$\{\langle U_2, U_7\rangle, \langle U_2, U_4\rangle, \langle U_4, U_7\rangle\}$ as all users that rated item I_2 are located in different child cells,i.e., U_2 at C_2, U_4 at C_4, and U_7 at C_3.

Given the aforementioned parameters, we calculate *Item Locality Loss ($LG_{c,i}$)* for each item, as follows:

Definition 1 Item Locality Loss ($LG_{c,i}$)
$LG_{c,i}$ is defined as the degree of locality lost for item i from downgrading the four children of cell c to β-Cells, such that $0 \leq LG_{c,i} \leq 1$.

$$LG_{c,i} = \frac{|RS_{c,i}|}{|RP_{c,i}|} \tag{7.3}$$

The value of both $|RS_{c,i}|$ and $|RP_{c,i}|$ can be easily extracted using the *items ratings statistics table*. Then, we use the $LG_{c,i}$ values calculated for all items in cell c in order to calculate the overall *Cell Locality loss (LG_c)* from downgrading the children cells of c to α-Cells.

Definition 2 Locality Loss (LG_c)
LG_c is defined as the total locality lost by downgrading cell c four children cells to β-Cells ($0 \leq LG_c \leq 1$). It is calculated as the the sum of all items locality loss normalized by the total number of items $|I_c|$ in cell c.

$$LG_c = \frac{\sum_{i \in I_c} LG_{c,i}}{|I_c|} \tag{7.4}$$

The cell locality loss (or gain) is harnessed by LARS* to determine whether the cell children need to be downgraded from α-Cell to β-Cell rank, upgraded from the γ-Cell to β-Cell rank, or downgraded from β-Cell to γ-Cell rank. During the rest of section 7.3, we explain the cell rank upgrade/downgrade operations.

Downgrade α-Cells to β-Cells

That operation entails downgrading an entire quadrant of cells from M-Cells to β-Cells at level h with a common parent at level $h-1$. Downgrading α-Cells to β-Cells improves

scalability (i.e., storage and computational overhead) of LARS*, as it reduces storage by discarding the item-based collaborative filtering (CF) models of the the four children cells. Furthermore, downgrading α-Cells to β-Cells leads to the following performance improvements: (a) *less maintenance cost*, since less CF models are periodically rebuilt, and (b) *less continuous query processing computation*, as β-Cells does not maintain a CF model and if many β-Cells cover a large spatial region, hence, for users crossing β-Cells boundaries, we do not need to update the recommendation query answer. Downgrading children cells from α-Cells to β-Cells might hurt recommendation locality, since no CF models are maintained at the granularity of the child cells anymore.

At cell C_p, in order to determine whether to downgrade a quadrant q cells to β-Cells (i.e., function *CheckDownGradeToSCells* on line 10 in Algorithm 8), we calculate two percentage values: (1) *locality_loss* (see equation 7.4), the amount of locality lost by (potentially) downgrading the children cells to β-Cells, and (2) *scalability_gain*, the amount of scalability gained by (potentially) downgrading the children cells to β-Cells. Details of calculating these percentages are covered next. When deciding to downgrade cells to β-Cells, we define a system parameter $\mathcal{M}$, a real number in the range [0,1] that defines a tradeoff between scalability gain and locality loss. LARS* downgrades a quadrant q cells to β-Cells (i.e., discards quadrant q) if Equation 7.1 holds true:
A smaller $\mathcal{M}$ value implies gaining scalability is important and the system is willing to lose a large amount of locality for small gains in scalability. Conversely, a larger $\mathcal{M}$ value implies scalability is not a concern, and the amount of locality lost must be small in order to allow for β-Cells downgrade. At the extremes, setting $\mathcal{M}$=0 (i.e., always switch to β-Cell) implies LARS* will function as a traditional CF recommender system, while setting $\mathcal{M}$=1 causes LARS* pyramid cells to all be α-Cells, i.e., LARS* will employ a complete pyramid structure maintaining a recommendation model at all cells at all levels.

Calculating Locality Loss. To calculate the locality loss at a cell C_p, LARS* leverages the *Item Ratings Statistics Table* maintained in that cell. First, LARS* calculates the item locality loss $LG_{C_p,i}$ for each item i in the cell C_p. Therefore, LARS* aggregates the item locality loss values calculated for each item $i \in C_p$, to finally deduce the global cell locality loss LG_{C_p}.

Calculating scalability gain. Scalability gain is measured in storage and computation savings. We measure scalability gain by summing the recommendation model sizes for each of the downgraded (i.e., child) cells (abbr. $size_m$), and divide this value by the sum of $size_m$ and the recommendation model size of the parent cell. We refer to this percentage as the *storage_gain*. We also quantify *computation* savings using storage gain as a surrogate measurement, as computation is considered a direct function of the amount of data in the system.

Cost. using the *Items Ratings Statistics Table* maintained at cell C_p, the locality loss at cell C_p can be calculated in $O(|I_{C_p}|)$ time such that $|I_{C_p}|$ represents the total number of items in C_p. As scalability gain can be calculated in $O(1)$ time, then the total time cost of the *Downgrade To β-Cells* operation is $O(|I_{C_p}|)$.

Example. For the example given in Figure 7.7, the locality loss of downgrading cell C_p four children cells $\{C_1, C_2, C_3, C_4\}$ to β-Cells is calculated as follows: First, we retrieve the locality loss $LG_{C_p,i}$ for each item $i \in \{I_1, I_2, I_3, I_4, I_5, I_6, I_7, I_8\}$, from the maintained statistics at cell C_p. As given in figure 7.7, LG_{C_p,I_1}, LG_{C_p,I_2}, LG_{C_p,I_3}, LG_{C_p,I_4}, LG_{C_p,I_5}, LG_{C_p,I_6}, LG_{C_p,I_7}, and LG_{C_p,I_8} are equal to 0.0, 0.0, 1.0, 1.0, 0.0, 0.666, 0.166, and 1.0, respectively. Then, we calculate the overall locality loss at C_p (using equation 7.4), LG_{C_p} by summing all the locality loss values of all items and dividing the sum by the total number of items. Hence, the scalability loss is equal to $(\frac{0.0+0.0+1.0+1.0+0.0+1.0+0.666+1.0}{8}) = 0.48 = 48\%$. To calculate scalability gain, assume the sum of the model sizes for cells C_1 to C_4 and C_P is 4GB, and the sum of the model sizes for cells C_1 to C_4 is 2GB. Then, the *scalability gain* is $\frac{2}{4}$=50%. Assuming $\mathcal{M}$=0.7, then $(0.3 \times 50) < (0.7 \times 48)$, meaning that LARS* will not downgrade cells C_1, C_2, C_3, C_4 to β-Cells.

Upgrade β-Cells to α-Cells

Upgrading β-Cells to α-Cells operation entails upgrading the cell type of a cell child quadrant at pyramid level h under a cell at level $h-1$, to α-Cells. *Upgrading β-Cells to α-Cells* operation improves locality in LARS*, as it leads to maintaining a CF model at the children cells that represent more granular spatial regions capable of producing recommendations unique to the smaller, more "local", spatial regions. On the other hand, upgrading cells to α-Cells hurts scalability by requiring storage and maintenance

of more item-based collaborative filtering models. The upgrade to α-Cells operation also negatively affects continuous query processing, since it creates more granular α-Cells causing user locations to cross α-Cell boundaries more often, triggering recommendation updates.

To determine whether to upgrade a cell C_P (quadrant q) four children cells to α-Cells (i.e., function *CheckUpGradeToMCells* on line 14 of Algorithm 8). Two percentages are calculated: *locality_gain* and *scalability_loss*. These values are the opposite of those calculated for the *Upgrade to β-Cells* operation. LARS* change cell C_P child quadrant q to α-Cells only if the condition in Equation 7.2 holds.
This equation represents the opposite criteria of that presented for *Upgrade to β-Cells* operation in Equation 7.1.

Calculating locality gain. To calculate the locality gain, LARS* does not need to speculatively build the CF model at the four children cells. The locality gain is calculated the same way the locality loss is calculated in equation 7.4.

Calculating scalability loss. We calculate *scalability loss* the same way we calculated scalability gain in Section 7.4.3

Cost. Similar to the *CheckDownGradeToSCells* operation, scalability loss is calculate in $O(1)$ and locality gain can be calculated in $O(|I_{C_p}|)$ time. Then, the total time cost of the *CheckUpGradeToMCells* operation is $O(|I_{C_p}|)$.

Example. Consider the example given in Figure 7.7. Assume the cell C_p is an α-Cell and its four children C_1, C_2, C_3, and C_4 are β-Cells. The *locality gain* (LG_{C_p}) is calculated using equation 7.4 to be 0.48 (i.e., 48%) as depicted in the table in Figure 7.7. Further, assume that we estimate the extra storage overhead for upgradinging the children cells to α-Cells (i.e., *storage loss*) to be 50%. Assuming $\mathcal{M}$=0.7, then $(0.7 \times 48) > (0.3 \times 50)$, meaning that LARS* will decide to upgrade C_P four children cells to α-Cells as *locality gain* is significantly higher than *scalability loss*.

Downgrade β-Cells to γ-Cells and Vice Versa

Downgrading β-Cells to γ-Cells operation entails downgrading the cell type of a cell child quadrant at pyramid level h under a cell at level $h-1$, to γ-Cells (i.e., empty cells). Downgrading the child quadrant type to γ-Cells means that the maintained statistics are no more maintained in the children cell, which definitely reduces the overhead of

maintaining the *Item Ratings Statistics Table* at these cells. Even though γ-Cells incurs no maintenance overhead, however they reduce the amount of recommendation locality that LARS* provides.

The decision of downgrading from β-Cells to γ-Cells is taken based on a system parameter, named *MAX_SLEVELS*. It is defined as the maximum number of consecutive pyramid levels in which descendant cells can be β-Cells. *MAX_SLEVELS* can take any value between zero and the total height of the pyramid. A high value of *MAX_SLEVELS* results in maintaining more β-Cells and less γ-Cells in the pyramid. For example, in Figure 7.2, *MAX_SLEVELS* is set to two, and this is why if two consecutive pyramid levels are β-Cells, the third level β-Cells are autotmatically downgraded to γ-Cells. For each β-Cell C, a counter, called *S-Levels Counter*, is maintained. The S-Levels Counter stores of the total number of consecutive levels in the direct ancestry of cell C such that all these levels contains β-Cells.

At a β-Cell C, if the cell children are β-Cells, then we compare the *S-Levels Counter* at the child cells with the *MAX_SLEVELS* parameter. Note that the counter counts only the consecutive S-Levels, so if some levels in the chain are α-Cells the counter is reset to zero at the α-Cells levels. If *S-Levels Counter* is greater than or equal to *MAX_SLEVELS*, then the children cells of C are downgraded to γ-Cells. Otherwise, cell C children cells are not downgraded to γ-Cells. Similarly, LARS* also makes use of the same *S-Levels Counter* to decide whether to upgrade γ-Cells to β-Cells.

7.5 Non-Spatial User Ratings for Spatial Items

This section describes how LARS produces recommendations using non-spatial ratings for spatial items represented by the tuple (*user*, *rating*, *item*, *ilocation*). The idea is to exploit *travel locality*, i.e., the observation that users limit their choice of spatial venues based on travel distance (based on analysis in Section 7.1). Traditional (non-spatial) recommendation techniques may produces recommendations with burdensome travel distances (e.g., hundreds of miles away). LARS produces recommendations within reasonable travel distances by using *travel penalty*, a technique that penalizes the recommendation rank of items the further in travel distance they are from a querying user. *Travel penalty* may incur expensive computational overhead by calculating travel

distance to each item. Thus, LARS employs an efficient query processing technique capable of *early termination* to produce the recommendations without calculating the travel distance to all items. Section 7.5.1 describes the query processing framework while Section 7.5.2 describes travel distance computation.

7.5.1 Query Processing

Query processing for spatial items using the *travel penalty* technique employs a single system-wide item-based collaborative filtering model to generate the top-k recommendations by ranking each spatial item i for a querying user u based on $RecScore(u, i)$, computed as:

$$RecScore(u, i) = P(u, i) - TravelPenalty(u, i) \tag{7.5}$$

$P(u, i)$ is the standard item-based CF predicted rating of item i for user u. $TravelPenalty(u, i)$ is the road network travel distance between u and i normalized to the same value range as the rating scale (e.g., [0, 5]).

When processing recommendations, we aim to avoid calculating Equation 7.5 for *all* candidate items to find the top-k recommendations, which can become quite expensive given the need to compute travel distances. To avoid such computation, we evaluate items in monotonically increasing order of travel penalty (i.e., travel distance), enabling us to use early termination principles from top-k query processing [70, 71, 72]. We now present the main idea of our query processing algorithm and in the next section discuss how to compute travel penalties in an increasing order of travel distance.

Algorithm 9 provides the pseudo code of our query processing algorithm that takes a querying user id U, a location L, and a limit K as input, and returns the list R of top-k recommended items. The algorithm starts by running a k-nearest-neighbor algorithm to populate the list R with k items with lowest travel penalty; R is sorted by the recommendation score computed using Equation 7.5. This initial part is concluded by setting the lowest recommendation score value (*LowestRecScore*) as the *RecScore* of the k^{th} item in R (Lines 3 to 7). Then, the algorithm starts to retrieve items one by one in the order of their penalty score. This can be done using an *incremental* k-nearest-neighbor algorithm, as will be described in the next section. For each item i, we calculate the *maximum possible* recommendation score that i can have by subtracting

Algorithm 9 Travel Penalty Algorithm for Spatial Items

```
Function LARS_SpatialItems(User U, Location L, Limit K)
/* Populate a list R with a set of K items*/
R ← φ
for (K iterations) do
  i ← Retrieve the item with the next lowest travel penalty (Section 7.5.2)
  Insert i into R ordered by RecScore(U, i) computed by Equation 7.5
LowestRecScore ← RecScore of the k^th object in R
/*Retrieve items one by one in order of their penalty value */
while there are more items to process do
  i ← Retrieve the next item in order of penalty score (Section 7.5.2)
  MaxPossibleScore ← MAX_RATING - i.penalty
  if MaxPossibleScore ≤ LowestRecScore then
    return R /* early termination - end query processing */
  RecScore(U, i) ← P(U, i) - i.penalty /* Equation 7.5 */
  if RecScore(U, i) > LowestRecScore then
    Insert i into R ordered by RecScore(U, i)
    LowestRecScore ← RecScore of the k^th object in R
return R
```

the travel penalty of i from *MAX_RATING*, the maximum possible rating value in the system, e.g., 5 (Line 11). If i cannot make it into the list of top-k recommended items with this maximum possible score, we immediately terminate the algorithm by returning R as the top-k recommendations without computing the recommendation score (and travel distance) for more items (Lines 12 to 13). The rationale here is that since we are retrieving items in increasing order of their penalty and calculating the maximum score that any remaining item can have, then there is no chance that any unprocessed item can beat the lowest recommendation score in R. If the early termination case does not arise, we continue to compute the score for each item i using Equation 7.5, insert i into R sorted by its score (removing the k^{th} item if necessary), and adjust the lowest recommendation value accordingly (Lines 14 to 17).

Travel penalty requires very little maintenance. The only maintenance necessary is to occasionally rebuild the single system-wide item-based collaborative filtering model in order to account for new location-based ratings that enter the system. Following the reasoning discussed in Section 7.3.3, we rebuild the model after receiving $N\%$ new location-based ratings.

7.5.2 Incremental Travel Penalty Computation

This section gives an overview of two methods we implemented in LARS to incrementally retrieve items one by one ordered by their travel penalty. The two methods exhibit a trade-off between query processing efficiency and penalty accuracy: (1) an *online* method that provides exact travel penalties but is expensive to compute, and (2) an *offline* heuristic method that is less exact but efficient in penalty retrieval. Both methods can be employed interchangeably in Line 10 of Algorithm 9.

Incremental KNN: An Exact Online Method

To calculate an exact travel penalty for a user u to item i, we employ an incremental k-nearest-neighbor (KNN) technique [73, 74, 75]. Given a user location l, incremental KNN algorithms return, on each invocation, the next item i nearest to u with regard to travel distance d. In our case, we normalize distance d to the ratings scale to get the travel penalty in Equation 7.5. Incremental KNN techniques exist for both Euclidean distance [74] and (road) network distance [73, 75]. The advantage of using Incremental KNN techniques is that they provide an *exact* travel distances between a querying user's location and each recommendation candidate item. The disadvantage is that distances must be computed *online* at query runtime, which can be expensive. For instance, the runtime complexity of retrieving a single item using incremental KNN in Euclidean space is [74]: $O(k + logN)$, where N and k are the number of total items and items retrieved so far, respectively.

Penalty Grid: A Heuristic Offline Method

A more efficient, yet less accurate method to retrieve travel penalties incrementally is to use a pre-computed *penalty grid*. The idea is to partition space using an $n \times n$ grid. Each grid cell c is of equal size and contains all items whose location falls within the spatial region defined by c. Each cell c contains a *penalty list* that stores the pre-computed penalty values for traveling from anywhere within c to all other $n^2 - 1$ destination cells in the grid; this means all items within a destination grid cell share the *same* penalty value. The penalty list for c is sorted by penalty value and always stores c (itself) as the first item with a penalty of zero. To retrieve items incrementally, all items within

the cell containing the querying user are returned one-by-one (in any order) since they have no penalty. After these items are exhausted, items contained in the next cell in the penalty list are returned, and so forth until Algorithm 9 terminates early or processes all items.

To populate the penalty grid, we must calculate the penalty value for traveling from each cell to every other cell in the grid. We assume items and users are constrained to a road network, however, we can also use Euclidean space without consequence. To calculate the penalty from a single source cell c to a destination cell d, we first find the average distance to travel from anywhere within c to all item destinations within d. To do this, we generate an *anchor point* p within c that both (1) lies on the road network segment within c and (2) lies as close as possible to the center of c. With these criteria, p serves as an approximate average "starting point" for traveling from c to d. We then calculate the shortest path distance from p to *all* items contained in d on the road network (any shortest path algorithm can be used). Finally, we average all calculated shortest path distances from c to d. As a final step, we normalize the average distance from c to d to fall within the rating value range. Normalization is necessary as the rating domain is usually small (e.g., zero to five), while distance is measured in miles or kilometers and can have large values that heavily influence Equation 7.5. We repeat this entire process for each cell to all other cells to populate the entire penalty grid.

When new items are added to the system, their presence in a cell d can alter the average distance value used in penalty calculation for each source cell c. Thus, we recalculate penalty scores in the penalty grid after N new items enter the system. We assume spatial items are relatively static, e.g., restaurants do not change location often. Thus, it is unlikely *existing* items will change cell locations and in turn alter penalty scores.

7.6 Spatial User Ratings for Spatial Items

This section describes how LARS produces recommendations using spatial ratings for spatial items represented by the tuple (*user*, *ulocation*, *rating*, *item*, *ilocation*). A salient feature of LARS is that both the *user partitioning* and *travel penalty* techniques can be

used together with very little change to produce recommendations using spatial user ratings for spatial items. The data structures and maintenance techniques remain *exactly* the same as discussed in Sections 7.3 and 7.5; only the query processing framework requires a slight modification. Query processing uses Algorithm 9 to produce recommendations. However, the only difference is that the item-based collaborative filtering prediction score $P(u, i)$ used in the recommendation score calculation (Line 14 in Algorithm 9) is generated using the (localized) collaborative filtering model from the partial pyramid cell that contains the querying user, instead of the system-wide collaborative filtering model as was used in Section 7.5.

7.7 Experimental Evaluation

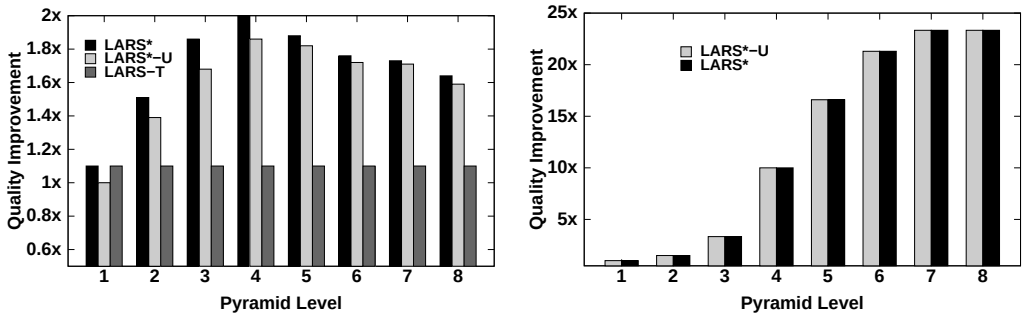
This section provides experimental evaluation of LARS* based on an actual system implementation using C++ and STL. We compare LARS* with the standard item-based collaborative filtering technique along with several variations of LARS*. We also compare LARS* to LARS [69]. Experiments are based on three data sets:

Foursquare: a real data set consisting of *spatial user ratings for spatial items* derived from Foursquare user histories. We crawled Foursquare and collected data for 1,010,192 users and 642,990 venues across the United States. Foursquare does not publish each "check-in" for a user, however, we were able to collect the following pieces of data: (1) user tips for a venue, (2) the venues for which the user is the mayor, and (3) the completed to-do list items for a user. In addition, we extracted each user's friend list.

Extracting location-based ratings. To extract spatial user ratings for spatial items from the Foursquare data (i.e., the five-tuple (*user*, *ulocation*, *rating*, *item*, *ilocation*)), we map each user visit to a single location-based rating. The *user* and *item* attributes are represented by the unique Foursquare user and venue identifier, respectively. We employ the user's home city in Foursquare as the *ulocation* attribute. Meanwhile, the *ilocation* attribute is the item's inherent location. We use a numeric *rating* value range of [1, 3], translated as follows: (a) 3 represents the user is the "mayor" of the venue, (b) 2 represents that the user left a "tip" at the venue, and (c) 1 represents the user visited the venue as a completed "to-do" list item. Using this scheme, a user may have multiple ratings for a venue, in this case we use the highest rating value.

Data properties. Our experimental data consisted of 22,390 location-based ratings for 4K users for 2K venues all from the state of Minnesota, USA. We used this reduced data set in order to focus our quality experiments on a *dense* rating sample. Use of *dense* ratings data has been shown to be a very important factor when testing and comparing recommendation quality [17], since use of *sparse* data (i.e., having users or items with very few ratings) tends to cause inaccuracies in recommendation techniques.
MovieLens: a real data set consisting of *spatial user ratings for non-spatial items* taken from the popular MovieLens recommender system [50]. The Foursquare and MovieLens data are used to test recommendation quality. The MovieLens data used in our experiments was real movie rating data taken from the popular MovieLens recommendation system at the University of Minnesota [50]. This data consisted of 87,025 ratings for 1,668 movies from 814 users. Each rating was associated with the zip code of the user who rated the movie, thus giving us a real data set of spatial user ratings for non-spatial items.
Synthetic: a synthetically generated data set consisting of spatial user ratings for spatial items for venues in the state of Minnesota, USA. The synthetic data set we use in our experiments is generated to contain 2000 users and 1000 items, and 500,000 ratings. Users and items locations are randomly generated over the state of Minnesota, USA. Users' ratings to items are assigned random values between zero and five. As this data set contains a number of ratings that is about twenty five times and five times larger than the foursquare data set and the Movielens data set, we use such synthetic data set to test scalability and query efficiency.

Unless mentioned otherwise, the default value of $\mathcal{M}$ is 0.3, k is 10, the number of pyramid levels is 8, the influence level is the lowest pyramid level, and MAX_SLEVELS is set to two. The rest of this section evaluates LARS* recommendation quality (Section 7.7.1), trade-offs between storage and locality (Section 7.7.4), scalability (Section 7.7.5), and query processing efficiency (Section 7.7.6). As the system stores its data structures in main memory, all reported time measurements represent the CPU time.



(a) Foursquare data (b) MovieLens data

Fig. 7.8: Quality experiments for varying locality

7.7.1 Recommendation Quality for Varying Pyramid Levels

These experiments test the recommendation quality improvement that LARS* achieves over the standard (non-spatial) item-based collaborative filtering method using both the Foursquare and MovieLens data. To test the effectiveness of our proposed techniques, we test the quality improvement of LARS* with only travel penalty enabled (abbr. LARS*-T), LARS* with only user partitioning enabled and M set to one (abbr. LARS*-U), and LARS* with both techniques enabled and M set to one (abbr. LARS*). Notice that LARS*-T represents the traditional item-based collaborative filtering augmented with the travel penalty technique (section 7.5) to take the distance between the querying user and the recommended items into account. We do not plot LARS with LARS* as both give the same result for M=1, and the quality experiments are meant to show how locality increases the recommendation quality.

Quality Metric. To measure quality, we build each recommendation method using 80% of the ratings from each data set. Each rating in the withheld 20% represents a Foursquare venue or MovieLens movie a user is known to like (i.e., rated highly). For each rating t in this 20%, we request a set of k ranked recommendations $\mathcal{S}$ by submitting the *user* and *ulocation* associated with t. We first calculate the quality as the weighted sum of the number of occurrences of the *item* associated with t (the higher the better) in $\mathcal{S}$. The weight of an item is a value between zero and one that determines how close the rank of this item from its real rank. The quality of each recommendation method is calculated and compared against the baseline, i.e., traditional item-based collaborative

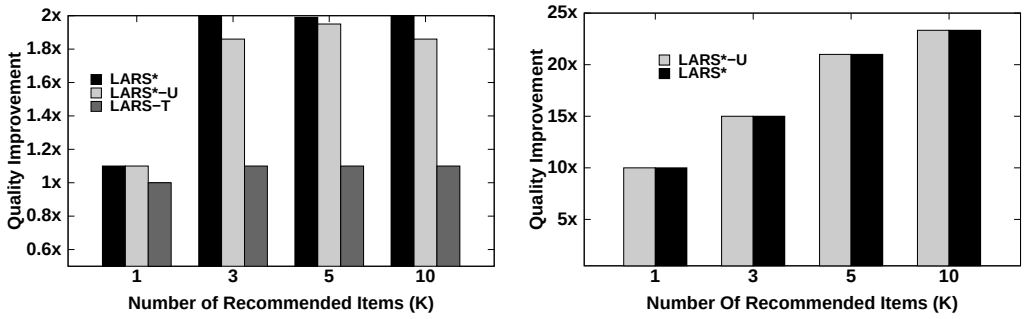
filtering. We finally report the ratio of improvement in quality each recommendation method achieves over the baseline. The rationale for this metric is that since each withheld rating represents a real visit to a venue (or movie a user liked), the technique that produces a large number of correctly ranked answers that contain venues (or movies) a user is known to like is considered of higher quality.

Figure 7.8(a) compares the quality improvement of each technique (over traditional collaborative filtering) for varying locality (i.e., different levels of the adaptive pyramid) using the Foursquare data. LARS*-T does not use the adaptive pyramid, thus has constant quality improvement. However, LARS*-T shows some quality improvement over traditional collaborative filtering. This quality boost is due to that fact that LARS*-T uses a *travel penalty* technique that recommends items within a feasible distance. Meanwhile, the quality of LARS* and LARS*-U increases as more localized pyramid cells are used to produce recommendation, which verifies that *user partitioning* is indeed beneficial and necessary for location-based ratings. Ultimately, LARS* has superior performance due to the additional use of *travel penalty*. While *travel penalty* produces moderate quality gain, it also enables more efficient query processing, which we observe later in Section 7.7.6.

Figure 7.8(b) compares the quality improvement of LARS*-U over CF (traditional collaborative filtering) for varying locality using the MovieLens data. Notice that LARS* gives the same quality improvement as LARS*-U because LARS*-T do not apply for this dataset since movies are not spatial. Compared to CF, the quality improvement achieved by LARS*-U (and LARS*) increases when it produces movie recommendations from more localized pyramid cells. This behavior further verifies that *user partitioning* is beneficial in providing quality recommendations localized to a querying user location, even when items are not spatial. Quality decreases (or levels off for MovieLens) for both LARS*-U and/or LARS* for lower levels of the adaptive pyramid. This is due to *recommendation starvation*, i.e., not having enough ratings to produce meaningful recommendations.

7.7.2 Recommendation Quality for Varying k

These experiments test recommendation quality improvement of LARS*, LARS*-U, and LARS*-T for different values of k (i.e., recommendation answer sizes). We do not plot



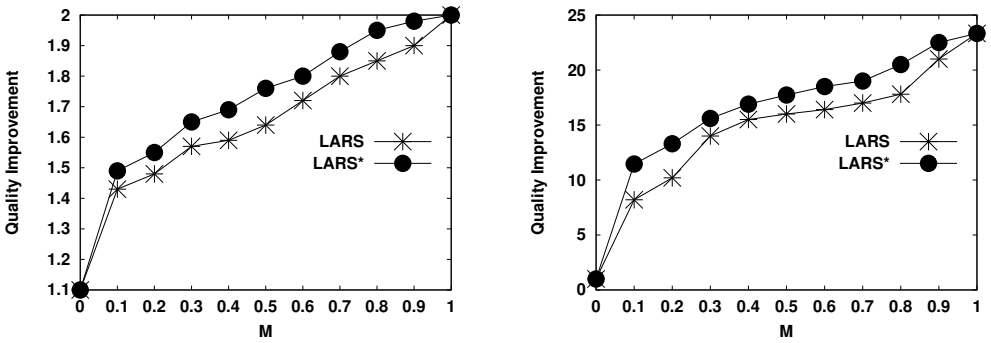
(a) Foursquare data (b) MovieLens data

Fig. 7.9: Quality experiments for varying answer sizes

LARS with LARS* as both gives the same result for M=1, and the quality experiments are meant to show how the degree of locality increases the recommendation quality. We perform experiments using both the Foursquare and MovieLens data. Our quality metric is exactly the same as presented previously in Section 7.7.1.

Figure 7.9(a) depicts the effect of the recommendation list size k on the quality of each technique using the Foursquare data set. We report quality numbers using the pyramid height of four (i.e., the level exhibiting the best quality from Section 7.7.1 in Figure 7.8(a)). For all sizes of k from one to ten, LARS* and LARS*-U consistently exhibit better quality. In fact, LARS* consistently achieves better quality over CF for all k. LARS*-T exhibits similar quality to CF for smaller k values, but does better for k values of three and larger.

Figure 7.9(b) depicts the effect of the recommendation list size k on the quality of improvement of LARS*-U (and LARS*) over CF using the MovieLens data. Notice that LARS* gives the same quality improvement as LARS*-U because LARS*-T do not apply for this dataset since movies are not spatial. This experiment was run using a pyramid hight of seven (i.e., the level exhibiting the best quality in Figure 7.8(b)). Again, LARS*-U (and LARS*) consistently exhibits better quality than CF for sizes of K from one to ten.



(a) Foursquare data (b) MovieLens data

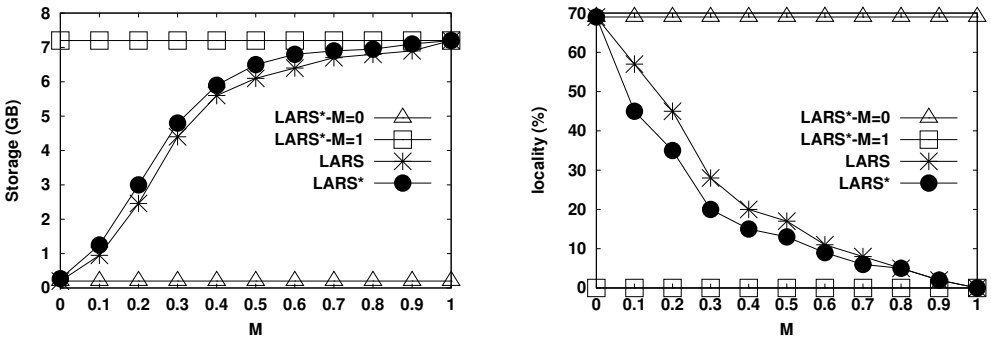
Fig. 7.10: Quality experiments for varying value of $\mathcal{M}$

7.7.3 Recommendation Quality for Varying $\mathcal{M}$

These experiments compares the quality improvement achieved by both LARS and LARS* for different values of $\mathcal{M}$. We perform experiments using both the Foursquare and MovieLens data. Our quality metric is exactly the same as presented previously in Section 7.7.1.

Figure 7.10(a) depicts the effect of $\mathcal{M}$ on the quality of both LARS and LARS* using the Foursquare data set. Notice that we enable both the user partitioning and travel penalty techniques for both LARS and LARS*. We report quality numbers using the pyramid height of four and the number of recommended items of ten. When $\mathcal{M}$ is equal to zero, both LARS and LARS* exhibit the same quality improvement as $\mathcal{M} = 0$ represents a traditional collaborative filtering with the travel penalty technique applied. Also, when $\mathcal{M}$ is set to one, both LARS and LARS* achieve the same quality improvement as a fully maintained pyramid is maintained in both cases. For $\mathcal{M}$ values between zero and one, the quality improvement of both LARS and LARS* increases for higher values of $\mathcal{M}$ due to the increase in recommendation locality. LARS* achieves better quality improvement over LARS because LARS* maintains α-Cells at lower levels of the pyramid.

Figure 7.10(b) depicts the effect of $\mathcal{M}$ on the quality of both LARS and LARS* using the Movilens data set. We report quality improvement over traditional collaborative filtering using the pyramid height of seven and the number of recommended items set to



(a) Storage (b) Locality

Fig. 7.11: Effect of $\mathcal{M}$ on storage and locality (Synthetic data)

ten. Similar to Foursquare data set, the quality improvement of both LARS and LARS* increases for higher values of $\mathcal{M}$ due to the increase in recommendation locality. For $\mathcal{M}$ values between zero and one, LARS* consistently achieves higher quality improvement over LARS as LARS* maintains more α-Cells at more granular levels of the pyramid structure.

7.7.4 Storage Vs. Locality

Figure 7.11 depicts the impact of varying $\mathcal{M}$ on both the storage and locality in LARS* using the synthetic data set. We plot LARS*-M=0 and LARS*-M=1 as constants to delineate the extreme values of $\mathcal{M}$, i.e., $\mathcal{M}$=0 mirrors traditional collaborative filtering, while $\mathcal{M}$=1 forces LARS* to employ a complete pyramid. Our metric for locality is *locality loss* (defined in Section 7.4.3) when compared to a complete pyramid (i.e., $\mathcal{M}$=1). LARS*-M=0 requires the lowest storage overhead, but exhibits the highest locality loss, while LARS*-M=1 exhibits no locality loss but requires the most storage. For LARS*, increasing $\mathcal{M}$ results in increased storage overhead since LARS* favors switching cells to α-Cells, requiring the maintenance of more pyramid cells each with its own collaborative filtering model. Each additional α-Cell incurs a high storage overhead over the original data size as an additional collaborative filtering model needs to be maintained. Meanwhile, increasing $\mathcal{M}$ results in smaller locality loss as LARS* merges less and maintains more localized cells. The most drastic drop in locality loss is between 0 and 0.3, which is why we chose $\mathcal{M}$=0.3 as a default. LARS* leads to smaller

locality loss (≈26% less) than LARS because LARS* maintains α-Cells below β-Cells which result in higher locality gain. On the other hand, LARS* exhibits slightly higher storage cost (≈5% more storage) than LARS due to the fact that LARS* stores the *Item Ratings Statistics Table* per each α-Cell and β-Cell.

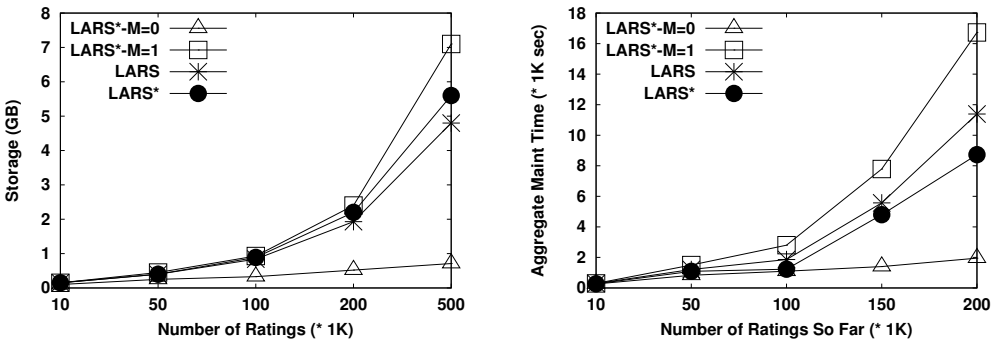
7.7.5 Scalability

Figure 7.12 depicts the storage and aggregate maintenance overhead required for an increasing number of ratings using the synthetic data set. We again plot LARS*-M=0 and LARS*-M=1 to indicate the extreme cases for LARS*. Figure 7.12(a) depicts the impact of increasing the number of ratings from 10K to 500K on storage overhead. LARS*-M=0 requires the lowest amount of storage since it only maintains a single collaborative filtering model. LARS*-M=1 requires the highest amount of storage since it requires storage of a collaborative filtering model for all cells (in all levels) of a complete pyramid. The storage requirement of LARS* is in between the two extremes since it merges cells to save storage. Figure 7.12(b) depicts the cumulative computational overhead necessary to maintain the adaptive pyramid initially populated with 100K ratings, then updated with 200K ratings (increments of 50K reported). The trend is similar to the storage experiment, where LARS* exhibits better performance than LARS*-M=1 due to switching some cells from α-Cells to β-Cells. Though LARS*-M=0 has the best performance in terms of maintenance and storage overhead, previous experiments show that it has unacceptable drawbacks in quality/locality. Compare to LARS, LARS* has less maintenance overhead (≈38% less) due to the fact that the maintenance algorithm in LARS* avoids the expensive speculative splitting used by LARS.

7.7.6 Query Processing Performance

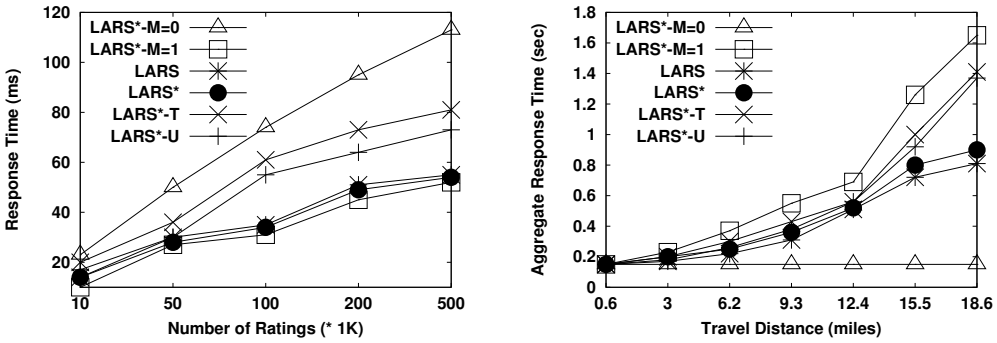
Figure 7.13 depicts snapshot and continuous query processing performance of LARS, LARS*, LARS*-U (LARS* with only *user partitioning*), LARS*-T (LARS* with only *travel penalty*), CF (traditional collaborative filtering), and LARS*-M=1 (LARS* with a complete pyramid), using the synthetic data set.

Snapshot queries. Figure 7.13(a) gives the effect of various number of ratings (10K to 500K) on the average snapshot query performance averaged over 500 queries posed



(a) Storage (b) Maintenance

Fig. 7.12: Scalability of the adaptive pyramid (Synthetic data)



(a) Snapshot Queries (b) Continuous Queries

Fig. 7.13: Query Processing Performance (Synthetic data).

at random locations. LARS* and LARS*-M=1 consistently outperform all other techniques; LARS*-M=1 is slightly better due to recommendations always being produced from the smallest (i.e., most localized) CF models. The performance gap between LARS* and LARS*-U (and CF and LARS*-T) shows that employing the *travel penalty* technique with early termination leads to better query response time. Similarly, the performance gap between LARS* and LARS*-T shows that employing *user partitioning* technique with its localized (i.e., smaller) collaborative filtering model also benefits query processing. LARS* performance is slightly better than LARS as LARS* sometimes maintains more localized CF models than LARS which incurs less query processing time.

Continuous queries. Figure 7.13(b) provides the continuous query processing performance of the LARS* variants by reporting the aggregate response time of 500 continuous queries. A continuous query is issued once by a user u to get an initial answer, then the answer is continuously updated as u moves. We report the aggregate response time when varying the travel distance of u from 1 to 30 miles using a random walk over the spatial area covered by the pyramid. CF has a constant query response time for all travel distances, as it requires no updates since only a single cell is present. However, since CF is unaware of user location change, the consequence is poor recommendation quality (per experiments from Section 7.7.1). LARS*-M=1 exhibits the worse performance, as it maintains all cells on all levels and updates the continuous query whenever the user crosses pyramid cell boundaries. LARS*-U has a lower response time than LARS*-M=1 due to switching cells from α-Cells to β-Cells: when a cell is not present on a given influence level, the query is transferred to its next highest ancestor in the pyramid. Since cells higher in the pyramid cover larger spatial regions, query updates occur less often. LARS*-T exhibits slightly higher query processing overhead compared to LARS*-U: even though LARS*-T employs the early termination algorithm, it uses a large (system-wide) collaborative filtering model to (re)generate recommendations once users cross boundaries in the penalty grid. LARS* exhibits a better aggregate response time since it employs the early termination algorithm using a localized (i.e., smaller) collaborative filtering model to produce results while also switching cells to β-Cells to reduce update frequency. LARS has a slightly better performance than LARS* as LARS tends to merge more cells at higher levels in the pyramid structure.

Chapter 8

Related Work

Related work spans various areas, which include recommender system architectures, context-aware recommendations, location-based services, location-aware recommender systems, database view management, and personalized databases.

Recommender System Architectures. Offline systems pre-compute recommendation offline for all users, store them on disk, and returns the pre-computed recommendation to a user when she logs on to the system. Such offline systems include: software libraries [45, 78] that perform the recommendation process in-memory, e.g., LensKit, as well as large-scale offline systems, e.g., Mahout [79], that are built on-top of Hadoop and run the recommendation generation process as a batch processing task. (II) Online systems: produce recommendation online for each user, when she logs on to the system, based on the recent snapshot of the user/item ratings data. Online architectures have the advantage of producing fresher recommendation than their offline counterparts. Moreover, online systems are capable of generating arbitrary recommendation to end-users. Such arbitrary recommendation queries require integrating the recommendation logic with other data access operations at query time which cannot be generated using Offline recommender systems since the recommendation is pre-computed and hence cannot be altered at query time. On the other side, online systems incur more recommendation generation latency from an end-user perspective, as opposed to offline systems that delivers the pre-computed recommendation fast to end-users at query time. In this thesis, we focus on online recommender systems.

Recommender systems in databases. Few, and recent, works have studied

the problem of integrating the recommender system functionality with database systems. This includes a framework for expressing flexible recommendation by separating the logical representation of a recommender system from its physical execution [80], algorithms for answering recommendation requests with complex constraints [81, 82], a query language for recommendation [83], and extensible frameworks to define new recommendation algorithms [45, 84], leveraging recommendation for database exploration [85, 86]. The aforementioned work lacks one or more of the following features: (1) Executing online arbitrary recommendation queries, (2) Efficiently initializing and maintaining multiple recommendation algorithms, (3) Native support for recommendation inside the database engine.

Contextual Recommendation. Existing context-aware recommendation algorithms [35] focus on leveraging contextual information to improve recommendation accuracy over classical recommendation techniques. Conceptual models for context-aware recommendation have also been proposed for better representation of multidimensional attributes in recommender systems [35]. Several frameworks have proposed defining context-aware recommendation services over the web using either client/server architecture [33], or by mimicking successful web development paradigms [36]. Such techniques, though they provide support for context-aware recommendation, do not consider system performance issues (e.g., efficiency and scalability). Location-aware recommender systems [55] present a special case of context-aware recommender systems, where efficiency and scalability are main concerns. However, the proposed techniques for location-aware recommender systems are strongly geared towards the spatial attribute, with no direct applicability to other attributes.

Location-based services. Current location-based services employ two main methods to provide interesting destinations to users. (1) KNN techniques [74] and variants (e.g., aggregate KNN [87]) simply retrieve the k objects nearest to a user and are completely removed from any notion of user *personalization*. (2) Preference methods such as skylines [88] (and spatial variants [89]) and location-based top-k methods [90] require users to express *explicit* preference constraints. Recent research has proposed the problem of hyper-local place ranking [91]. Given a user location and query string (e.g., "French restaurant"), hyper-local ranking provides a list of top-k points of interest influenced by previously logged directional queries (e.g., map direction searches from point

A to point B). Hyper-local ranking is fundamentally different from our work as it does *not personalize* answers to the querying user, i.e., two users issuing the same search term from the same location will receive exactly the same ranked answer set.

Location-aware recommenders. A wide array of techniques are capable of producing recommendations using non-spatial ratings for non-spatial items represented as the triple (*user*, *rating*, *item*) (see [6] for a comprehensive survey). We refer to these as "traditional" recommendation techniques. The closest these approaches come to considering location is by incorporating contextual attributes into statistical recommendation models (e.g., weather, traffic to a destination) [29]. Some existing commercial applications make cursory use of location when proposing interesting items to users. For instance, Netflix [92] displays a "local favorites" list containing popular movies for a user's given city. However, these movies are *not* personalized to each user (e.g., using recommendation techniques); rather, this list is built using aggregate rental data for a particular city [93].

The CityVoyager system [30] mines a user's personal GPS trajectory data to determine her preferred shopping sites, and provides recommendation based on where the system predicts the user is likely to go in the future. The spatial activity recommendation system [32] mines GPS trajectory data with embedded user-provided tags in order to detect interesting activities located in a city (e.g., art exhibits and dining near downtown). It uses this data to answer two query types: (a) given an activity type, return where in the city this activity is happening, and (b) given an explicit spatial region, provide the activities available in this region. This is a vastly different problem than we study in this thesis. Geo-measured friend-based collaborative filtering [31] produces recommendations by using only ratings that are from a querying user's social-network friends that live in the same city. This technique only addresses user location embedded in ratings.

Database Views. We can employ DBMS views as a solution to online collaborative filtering. Views are a fundamental topic within the data management research community, with a rich volume of research addressing various view aspects, including, but not limited to, view composition, materialized view maintenance, and query processing using views [94]. Views provide a *general* solution to a wide range of data management problems, including security (i.e., data access restriction), transparency from a physical

schema, and ease-of-use. In this thesis, we study the *specific* data management problem of online maintenance of recommender models, for which DBMS views incur serious efficiency drawbacks.

Personalization in databases. Adding personalization inside the database engine functionality has been well studied in the literature. Conceptual models for representing context-aware preferences in relational databases have been proposed in [95, 96, 97]. In [98], a SQL extension has been presented that allows for declaring contextual information inside a relational database. Systems for executing context and preference-aware queries have been proposed in [99, 100, 101]. Although the aforementioned techniques provide support for context-aware and preference-aware queries, none of them are adequate for executing recommendation queries.

Chapter 9

Conclusion and Discussion

9.1 Summary

This thesis bridges the gap between two areas: (1) Recommender Systems that aim at suggesting interesting items to users based on their history of preferences and content. (2) Data Management Systems that deal with storing and accessing data efficiently. Chapter 2 gave on overview of collaborative filtering recommender systems and introduced the straightforward approach to implementing the recommendation functionality using existing database systems technology. Chapter 3 introduced RecDB ; a recommendation engine built entirely inside a relational database system. RecDB provides an intuitive interface for application developers to build custom-made recommenders. Crafted inside a relational DBMS, the system is easily used and configured so that a novice application developer can declaratively define a variety of recommenders that fits the application needs in few lines of SQL code.

Chapter 4 presented RecStore , an extensible and adaptive DBMS storage engine module that provides *online* support for recommender queries. We fist presented the generic architecture of RecStore , and then described how RecStore supports online recommender model maintenance by enabling fast incremental updates to the model by implementing an intermediate and model store. We described how RecStore adapts to various system workloads, and provides load-shedding support for update-intense workloads. We then demonstrated the extensibility of RecStore by presenting a declarative model registration language, and provided case-studies showing

how RecStore accomodates various recommendation methods. Using a real recommender system workload and a system prototype of RecStore inside PostgreSQL, our experimental results show that RecStore provides superior performance to existing DBMS view approaches to support online recommender systems. Further, the experiments also confirm that RecStore is indeed adaptive to update-heavy or query-heavy recommender system workloads.

Chapter 5 introduced RecQuEx ; the query processing and optimization module in RecDB . RecQuEx adopts an *In-Database* approach that pushes the recommendation functionality inside a relational database engine to achieve the following properties: (1) *Seamless Integration*: The system is able to seamlessly integrate the recommendation functionality in the traditional `SPJ`, i.e., `SELECT`, `PROJECT`, `JOIN`, query pipeline to execute interactive recommendation queries. RecQuEx encapsulates the recommendation functionality into new query operators. Being a query operator allows the recommendation functionality to be a part of a larger query plan that includes other database query operators, e.g., selection,and join. It also means that the recommendation functionality will be treated as a first class citizen operation, allowing a myriad of query optimization techniques that can be integrated to speed up the online recommendation generation process. (2) *Efficiency and Scalability*: RecQuEx provides online recommendation to a high number of users over a large pool of items. It creates materialized views, that are leveraged by the query planner, to reduce the recommendation generation latency. RecQuEx partially materializes the predicted ratings to reduce the storage cost and maintenance overhead, and hence increase the overall system scalability.

Chapter 6 presented an extension to RecDB that supports Multi-Dimensional recommender systems. Chapter 7 described LARS; a Location-Aware Recommender System that tackles a problem untouched by traditional recommender systems by dealing with three types of location-based ratings: *spatial ratings for non-spatial items*, *non-spatial ratings for spatial items*, and *spatial ratings for spatial items*. LARS employs *user partitioning* and *travel penalty* techniques to support spatial ratings and spatial items, respectively. Both techniques can be applied separately or in concert to support the various types of location-based ratings. Experimental analysis using real and synthetic data sets show that LARS is efficient, scalable, and provides better quality recommendations than techniques used in traditional recommender systems.

9.2 Future Directions

Massive-Scale Recommender Systems. Recently, recommender systems data has become humongous in size, which stimulated using existing or even inventing novel big data platforms to perform the recommendation functionality at scale. It is quite essential to build a testbed that evaluates the scalability of existing recommender system architectures. The first challenge is to evaluate centralized (i.e., that run on a single machine) recommender system implementations. That includes RecDB as examples for In-Database system architecture. We plan to measure the run time, amount of memory, number of I/O operations used to build a recommender. The second challenge is to experimentally evaluate the scalability of popular recommendation algorithms over de facto big data platforms (i.e., Hadoop, GraphLab). The plan is to measure the speedup we achieve in building a recommender when increasing the number of machines. In summary, the main objective of this project is to evaluate the scalability of current recommender systems and provide a testbed to the community to evaluate new recommender systems implementations.

Content-based Recommender Systems. Social media (e.g., microblogs, shared photos, and videos) grabbed lots of attention in the past few years. In the context of microblogging for instance, users submit short messages (i.e., 140 characters in Twitter) featuring news, events, or any sort of information they would like to share with other users. Existing systems receive large amount of microblogging entries at very high rates and decides which entries are relevant to which users in a real time manner. In this future project, I plan to investigate how to extend content-based recommender systems to retrieve relevant data (e.g., Microblogs) to end-users based on the content. The main challenge is to generate real-time content-based recommendation to end-users whereas new data entries are streamed into the system.

Real-Time Recommender Systems. In the future, we plan to leverage data stream management systems to support the high arrival rates of modern recommendation applications (e.g., twitter, online news sites) that expect a stream of data entering the system. Implementing a real-time recommender system using a stream processing engine is beneficial for the following reasons: (1) Real-time incremental processing. Streaming systems are built for high throughput processing, where operators are tuned

for incremental evaluation, suitable for real-time recommendation generation. (2) Push-based Recommendation. Users can register recommendation requests, updated only when their recommendation list changes; this approach can be more scalable than on-demand systems that regenerate whole recommendations from scratch when the user logs-on to the system.

Recommender System in GeoSocial Networking Services. Location-based social networking systems yield three types of data: (1) Social Data: a social graph that represents the relationship between system users, (2) GeoSpatial Data: User GeoLocations, venues GeoLocations, and the information of users visiting venues, and (3) Users Opinions Data: Users expressing their opinions on visited venues. In this project, we propose building a recommender system that leverages both social proximity and spatial proximity to generate recommendations to end-users. In this case, the recommendation answer is influenced by the querying user location as well as the social ties of the querying user. In other words, the closer a venue v to a user u the higher the possibility user u would like to visit venue v. Moreover, the more user u friends liking a venue v the higher the possibility user u will also like venue v. The main challenge is to efficiently incorporate both the geospatial distance and social influence in the recommendation algorithm (e.g., collaborative filtering, content-based filtering).

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