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Adaptive Aggregation of Recommender Systems

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***Abstract*—Modern recommender systems combine multiple standard recommenders in order to leverage disjoint patterns in available data. These aggregations are done on a generalized level by estimating weights that result in an optimal combination. However, we posit these systems have an important weakness. There exists an underlying, misplaced subjectivity to relevance prediction. In an aggregation of different recommenders, each chosen algorithm reflects one view of how each user and item *should* be modeled. We believe this selection should be adaptively and automatically chosen based on how accurate each prediction is likely to be for each user and item. This paper presents a novel method for prediction aggregation, called *adaptive recommenders*. Multiple recommender systems are combined on a per-user and per-item basis by estimating how accurate each recommender will be for the current user and item. This is done by creating a set of secondary error estimating recommenders. As far as we know, this type of adaptive prediction aggregation has not been done before.**

1. Introduction

Information is a curious thing: having too much can be as harmful as having no information at all. While lacking information is an obvious problem, too much leads to information overload, where relevant content drowns in irrelevant noise. This is a common problem: whenever we have enough information, any extra data only leads to confusion. Our ability to make informed decisions is often the first thing to go [15, p1].

However, while people struggle with excessive information, algorithms in *artificial intelligence* (AI) can not get enough. [17, p1] calls this the "unreasonable effectiveness of data": perhaps surprisingly, more data often trumps more efficient algorithms. For example, [5, p3] show how common algorithms in AI can be substantially improved by giving them a lot more data to work with. As much as researchers chase elegant algorithms, finding more data to work with may be time better spent.

Few places is this difference of users and computers more apparent than in *recommender systems*. A recommender system is a technique in user modeling to estimate the relevance of an item to a user. An item can be just about anything: documents, websites, movies, events or other users. These systems use data such as search query logs, ratings from similar users, social connections and much more to predict unknown relevance, as we shall soon see. Recommender systems are especially prolific on the Web: wherever there is personalized recommendations of news, books, movies, articles, social connections, search results, et cetera, recommender systems are working behind the scenes.

Modern recommendation approaches often embrace the unreasonable effectiveness of data, by combining multiple recommender systems, that each predict relevance in various ways. By considering different aspects of users and items when making predictions, the methods provide quite complex predictions that rely on much evidence. For example, [7, p1] took this to its logical conclusion by combining 107 different recommender systems when winning the Netflix movie recommender challenge (see [8]).

While the name might seem constraining, recommender systems are incredibly powerful tools. If we can accurately predict how each user will react to each item, we will have come a long way towards solving information overload.

However, despite their apparent power, recommender systems are often confined to simple tasks like creating small lists of recommended items or suggesting similar items to the ones being considered by a user. Common examples are lists of recommended items based on the one being viewed, recommending new social connections, or suggesting news articles based on previous reading. Seldom are their full potential reached by creating completely adaptive content systems, that work hard to mitigate any signs of information overload.

We posit that traditional recommender systems have an important weakness. There exists an underlying, misplaced subjectivity to relevance prediction. We believe this fundamental weakness hinders the full adoption of these systems. There is a mismatch between how

recommender systems perform predictions, and how each user and item wants these predictions to be made.

Consider this: when an algorithm is selected for use in a recommender system, there is a concious decision of which predictive data pattern to use. Before any user modeling is performed, the researcher or developer selects one or more methods that is thought to best model every user and item in the system. While the methods themselves may perform well, their selection reflects how whoever created the system assumes how each user can and *should* be modeled. This underlying subjectivity is not desirable. We call this the *latent subjectivity problem* (see [10, p33]).

Examples are not hard to come by. For instance, while one user might appreciate social influence in their search results, another user might not. While one user might find frequency of communication maps well to relevance, another might not. One user might feel the similarity of movie titles are a good predictor, while another might be more influenced by production year. Some users may favor items rated highly on a global scale, while others are more interested in what users similar to themselves have to say. The same problem exists for items: while one item might best be judged by its content, another might be better described by previous ratings from other users. One item's relevance may be closely tied to when it was created, while other items may be timeless. The exact differences are not important — what is important is that they exist.

Another way of explaining the latent subjectivity problem is that *user modeling methods are dependent on the subjective assumptions of their creators*. In other words, a modeling method use some aspect of available data to make predictions, and this aspect is chosen by whoever creates the system.

Aggregate modeling methods face the same problem of misplaced subjectivity: Aggregation is done on a generalized, global level, where each user and item is expected to place the same importance on each modeling method (e.g. [4], [14], [7], [13], [27]). While the aggregation is of course selected to minimize some error over a testing set, the subjective nature remains: the compiled aggregation is a generalization, treating all users the same — hardly a goal of user modeling.

Should it not be up to each user to implicitly decide which method best describes their preferences? And, considering the vast scope of items we can come by, will the selected methods really perform optimally for every item? We believe the priority of each algorithm should be implicitly and automatically based on how well they have previously worked for each user and item. Without this adaptability, it may be hard for recommender systems to gain traction in scenarios with widely differing users and items. The scope of users and items is simply too great for any one or generalized combination of methods to capture the nuanced nature of relevance prediction.

We propose a novel method called *adaptive recommenders*, where these decisions are left to each user and item, providing an extra level of abstraction and personalization. The decisions are implicit, and happens in the background, without any extra interaction required. This leaves the subjective nature of selecting ways to model users and items where it should be: in the hands of each individual user, and dependent on each specific item, without any extraneous effort. If each method of relevance prediction is *only used* based on how well it performs for each element, any possibly applicable recommender system suddenly becomes a worthy addition to the system.

As far as we know, such adaptive prediction aggregation has not been done before. Can a system where each user and item implicitly decides how they should be modeled outperform traditional approaches? *That is the main research question of this paper*.

2. Related Work

[4] describes a number of simple approaches to prediction aggregation. Min, max and sum models combine the individual predictions in some way, or select one or more of the results as the final prediction. Other models use the average, or log-average of the different methods. The linear combination model trains weights for each predictor, and weighs predictions accordingly. At slightly more complex approach is to train a logistic regression model [4, p3] over a training set, in an effort to find the combination that gives the lowest possible error. This last method improved on the top-scoring predictor by almost 11% [4, p3], showing that even fairly simple combinations have merit.

Early approaches in recommender systems dabbled in aggregating content-based and collaborative approaches. [14] combined the two approaches in an effort to thwart problems with each method. Collaborative filtering (CF) methods have problems rating items for new users, radically different users or when dealing with very sparse data. Content-based (CB) methods do not have the same problems, but are less effective than CF in the long run, as CB does not tap into the knowledge of other users in the system — knowledge that out-performs simple content analysis. In [14], the two types of recommenders were used to create a simple weighted result.

Generally, methods for aggregating predictions in the field of machine learning is called *ensemble methods* (EM) [16, p1]. While most often used to combine classifiers that classify items with discrete labels, these methods are also used for aggregating numerical values (see the numerical parts of [12]). Approaches include *bootstrap aggregation* (bagging) and *boosting* for selecting proper training and testing sets, and creating a *mixture of experts* for combining the predictors [24, p27].

[7] took method aggregation to its logical conclusion when winning the Netflix Challenge, by combining 107 individual results from different recommenders: "We strongly believe that the success of an ensemble approach depends on the ability of its various predictors to expose different, complementing aspects of the data. Experience shows that this is very different from optimizing the accuracy of each individual predictor. Quite frequently we have found that the more accurate predictors are less useful within the full blend." [7, p6]

See [10] for more background theory and related work.

3. Adaptive Recommenders

Adaptive Recommenders (AR) is a technique for combining recommender systems in an effort to answer two important questions. Given that we wish to predict the relevance of an item to a user, using many methods that consider disjoint data patterns,

1) What rating does each method predict?
2) How accurate will each of these predictions be?

User modeling methods and recommender systems traditionally only care about the first question: a single method is used to predict an unknown rating. Modern aggregation techniques goes one step further, and combines many methods using a generic (often weighted) combination (e.g. [6], [19]). However, we wish to make the aggregation *adaptive*, so that the aggregation itself depends on which user and which item we are considering.

Formally, we define adaptive recommenders as *adapting a set of recommender systems with another complementary set of recommender systems* (see Figure 1). The first set creates standard prediction scores, and answers the first question. The second set predicts how accurate each method will be for the current user and item, answering the second question. The interesting bit is that AR can use recommender systems for both these tasks, as we shall soon see. A system for adaptive recommenders is specified by a 6-tuple, $\mathrm{AR} = (I, U, R, F, M, A)$.

We have sets of $Users$ (U) and $Items$ (I), and a set of $Ratings$ (R): each user $u \in U$ can produce a rating $r \in R$ of an item $i \in I$. Items can be just about anything: documents, websites, movies, events, or indeed, other users. The ratings can be explicitly provided by users, for example by rating movies, or they can be mined from existing data, for example by mining query logs. We use the term "rating" loosely — equivalent terms include *relevance*, *utility*, *score* or *connection strength*. In other words, this is a measure of what a user thinks of an item in the current domain language. However, since *rating* matches the data in our experiment, that is what we shall use.

The $Framework$ (F) variable specifies how the data is represented. The two canonical ways of representing users, items and ratings are graphs and matrices (see [22]). We shall use a matrix, where the first dimension corresponds to users, the second to items, and each populated cell is an explicit or implicit rating:

$$R_{u,i} = \begin{pmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,i} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,i} \\ \vdots & \vdots & \ddots & \vdots \\ r_{u,1} & r_{u,2} & \cdots & r_{u,i} \end{pmatrix}.$$

As we wish to leverage disjoint data patterns, we have a set of modeling $Methods$, each with their own way of estimating unknown ratings. Each model $m \in M$ is used to compute independent and hopefully complimentary predictions. In our case, these methods are recommender systems.

As demonstrated in [1], [23], [25], [26], there are many different recommendation algorithms, that consider different aspects in the data: users, items and ratings, as well as sources such as intra-user connections in social networks or intra-item connections in information retrieval systems. Examples of such recommender systems include Slope One predictions [20], SVD factorization (e.g. [9, p5], [28] and [7]) and Nearest Neighbor weighted predictions [26, p11]. These methods predict unknown connections between users and items based on some pattern in the data, for example user profile similarity, rating correlations or social connections. As previously explained, to achieve the best possible combined result, we wish to use methods that look at disjoint patterns, i.e. complementary predictive parts of the data (as described by [6, p1]).

The $Adapters$ (A) part of our 6-tuple refers to the second level of user modeling methods. In traditional prediction aggregation this is a simple linear function for combining the different predictions, for example by pre-computing a set of weights, one for each method. As found by [7, p6] the accuracy of the combined predictor is more dependent on the ability of the various predictors to expose different aspects of the data, than on the individual accuracy of each predictor. Multiple prediction results are normally combined into a final singular result, based on a generalized combination found by minimizing some error across all users.

With adaptive recommenders, the $Adapters$ are themselves user modeling methods. However, instead of modeling users, we wish to model each recommender system. More specifically, we wish to model the *accuracy* of each recommender system. Methods in this second layer are used to predict how accurate each of their corresponding basic recommenders will be. It is these methods that will allow us to do adaptive aggregation based on the current user and item. In other words, we have two distinct layers of user modeling (see Figure 1):

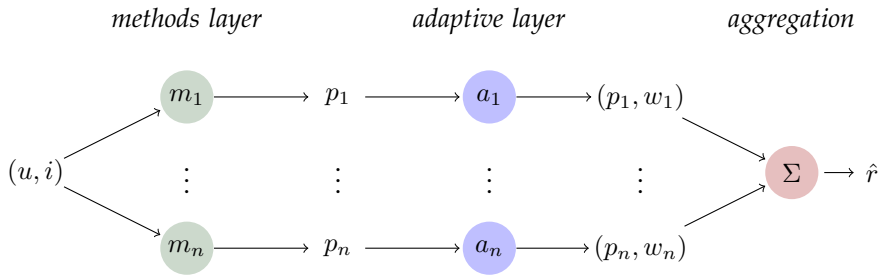

Fig. 1: Layers of recommenders: The method layer consists of ordinary modeling methods, each predicting the rating between a user and an item. This produces a set of predicted ratings (p). The adaptive layer estimates how well each modeling method will perform for the current user and item, and weighs the predictions accordingly. This produces a set of predictions and weights $[(p, w)]$. The aggregation weighs the predictions into a final score $\hat{r}$.

3.1. Adaptive Aggregation

To perform adaptive aggregation, we need the *Adapters* to be actual recommender systems. The simplest generalized way of prediction aggregation is to take the average of all predictions made by the different methods (e.g. [4, p3]). However, many aggregators attempt to weigh each method differently (e.g. [14]):

$$\hat{r}_{u,i} = \sum_{m \in M} w_m \times p(m, u, i).$$

Here, w_m is the weight applied to modeling method m. These weights fall in the range $[0, 1]$ and sum up to 1. The weights can be estimated through different machine learning methods. However, as discussed in Section 1, this is still a generalized result, averaged across every prediction. The system assumes that the best average result is the best result for each individual user and item. Even with method-specific weights we are still hindered by the latent subjectivity problem.

In order to leverage as many patterns as possible while sidestepping the latent subjectivity, we need *adaptive weights* that are computed specifically for each combination of a user and an item. However, if we wish each weight to be combination-specific, pre-computing each weight for each method becomes unfeasible — we would have to compute a weight for each method for each possible rating. In other words, these adaptive weights also have to be estimated, just as the ratings themselves:

$$\hat{r}_{u,i} = \sum_{m \in M} p_w(m, u, i) \times p_r(m, u, i).$$

Here, $p_w(m, u, i)$ is the predicted optimal weight for method m when applied to user u and item i. We have reduced our mission of adaptive prediction aggregation to creating this function.

We wish to use standard recommender systems for predicting optimal adaptive weights. To do this, we need to create a matrix (or graph) that stores known values of how accurate some of the rating predictions will be.

This can be done my modeling the errors of each method. By modeling the errors with standard recommender systems, we can in turn predict errors for untested combinations. If we predict the error of a recommender system for a user and an item, we have also predicted its accuracy. To achieve this, we can create an *error matrix*:

$$E_{u,i} = \begin{pmatrix} e_{1,1} & e_{1,2} & \cdots & e_{1,i} \\ e_{2,1} & e_{2,2} & \cdots & e_{2,i} \\ \vdots & \vdots & \ddots & \vdots \\ e_{u,1} & e_{u,2} & \cdots & e_{u,i} \end{pmatrix}$$

Creating an error matrix for each modeling method is quite simple: by splitting the ratings data in two, the first set can be used for the actual training, and the second can be used to populate each error matrix.

Each standard modeling method gets an error matrix where some cells have values: each value corresponds to the prediction error for a combination of a user and an item. Each modeling method is trained with a part of the ratings data. The error matrix is populated from the rest of the data, by computing the error of each known rating the method was not trained for:

$$\forall (u, i, r) \in (d_e - d_m) : E(m)_{u,i} = |r - p(m, u, i)|.$$

Here, D is the current dataset, and d_m and d_e are subsets of D. m is a modeling method trained with the subset d_m. To populate the error matrix for this method, we take each rating which have not been used to train the method and calculate the error of the method on this combination. The result is a sparse error matrix we can use to predict unknown errors. Notice how similar this matrix is to the previously introduced ratings matrix. This similarity is what will allow us using standard recommender systems to perform adaptive aggregation.

3.2. Modeling Phase

Whenever we wish to train a new modeling method, *the modeling phase*, we apply the following algorithm:

1) Split the ratings data into two sets for training and error estimation.
2) Train the modeling method in its specific way with the first training set.
3) Use the error estimation data set to create the error matrix.
4) Train an error model based on the error matrix.

Constructing the subsets of the available data is a common task in ensemble learning [24, p7]. We use *bootstrap aggregation*, also known as *bagging* (introduced by [12]). Originally, bagging is used by ensemble learning classification methods, where multiple classifiers are trained by uniformly sampling a subset of the available training data. Each model is then trained on one of these subsets, and the models are aggregated by averaging their individual predictions.

Bagging suits our needs perfectly, for a few reasons: First, the method helps create disjoint predictors, since each predictor is only trained (or specialized for) a subset of the available data. Second, it allows us to easily train the underlying modeling methods without any complex partitioning of the data. Our partitioning strategy is now clear:

The error models are trained using standard recommender systems. After all, the mission is the same: we have two dimensions, with a sparse set of known connections, and wish to predict unknown connections from this data. The result is a set of modeling methods that can predict the error of a recommender system when its used on a particular user and item combination.

What will happen when we train a recommender system with the error matrix? First of all, the errors will be on the same scale as the initial ratings. Second, just as the ratings matrix will include noise (ratings that do not contribute to any underlying pattern), this will be true for the error matrix as well.

For example, one method might have a large error for a particular user and item combination, yet still work well for both these elements. Luckily, this is just the kind of noise recommender systems are good at pruning away. What we are interested in are situations where a method has stable and significant errors for many ratings from a user, or many ratings of an item. In this case, there is a pattern where this method does not work well for the element in question. This is exactly the kind of pattern recommender systems are good at identifying.

In other words, the same capabilities that makes recommender systems work well on the ratings matrix, will also make them work well on the error matrix. The properties we need for predicting ratings are the same as those needed to predict accuracy.

Of course, some recommender systems will work better than others for the adaptive layer. Most often we are seeking global patterns in the data. We are looking for groups of users or items (or both) that suite some recommenders especially well, or that some recommenders will not work for. SVD-based recommenders is one type of RS that can be used for this purpose. By reducing the method-error space into an "error category space", we can identify how well a set of groups suite each available method. We will get back to this when testing the performance of our approach in Section 4.

3.3. Prediction Phase

When we have an error model for each modeling method, we can use these errors to estimate each weight. Whenever we wish to create an adaptive aggregate prediction, *the prediction phase*, we apply the following algorithm:

1) Collect predictions from each modeling method for (u, i).
2) Collect estimated errors for each method for (u, i).
3) Compute weights for each method based on their relative predicted errors.
4) Sum the weighted predictions to get the adaptively predicted rating.

The next section will explain these steps in detail. We can now express the prediction phase of adaptive recommenders as an equation. Each rating/relevance prediction is weighted by its predicted accuracy, conditioned on the current user and item, as seen in Equation 1.

In Equation 1, each recommender method has two corresponding models: m_r is the ratings model, used to predict ratings, and m_e is the error model, used to predict errors. $p(m, u, i)$ is the prediction of the model m (a recommender system) for the relevance of item i to user u. Each method is weighted by its predicted accuracy. The weights are computed by taking the opposite of each methods predicted error. The errors are normalized across each user and item by $errors(u, i)$, which is the sum of the errors of each method for the current combination. This gives us weights in the range $[0, 1]$ ensuring final rating predictions on the same scale as that returned by the basic recommenders.

Notice that the *only* difference between m_e and m_r is how they are created. m_r is trained with the standard ratings matrix, and m_e is trained using the error matrix. This means we can use *any* standard recommender system to perform adaptive aggregation. Hence, the name *adaptive recommenders*: a set of secondary recommenders is used to adapt a set of standard recommenders to each user and item.

It is also important to note that the types of recommenders used for the adaptive layer is independent of

$$\hat{r}_{u,i} = \sum_{(m_e,m_r)\in M} (1 - \frac{p(m_e,u,i)}{error(u,i)}) \times p(m_r,u,i) \quad \text{where} \quad error(u,i) = \sum_{m_e \in M} p(m_e,u,i) \tag{1}$$

the basic recommenders. Each adaptive recommender need only predicted ratings from each basic recommender, and does not care which algorithm it employs. When making predictions, the calculations in the methods layer and adaptive layer are independent of each other, as both use pre-computed models: the method layer use the ratings matrix, or their own models created during training, while the adaptive layers use the error matrices for each basic method.

The result of this is a system that does not only aggregate a number of predictions for each unknown combination of users and items, but that also combines these methods based on how accurate each prediction is likely to be. Now that we have our model, it is time to see how it performs.

4. Experiments & Results

We chose the MovieLens dataset[1] to test the performance of our system. This dataset is often used to test the performance of recommender systems (as described in [3, p9], [20, p4], [1, p1] and [18, p2]). It consists of a set of users, a set of movies, and a set of movie ratings from users, on the scale 1 through 5. We chose a subset of the entire MovieLens collection, with 100,000 ratings from 943 users on 1,682 movies. The dataset was split into disjoint sets ($D = \{d_1, ..., d_5\}$) to perform five-fold cross-validation.

To evaluate how our model performs during prediction aggregation, we need a measure for computing the total error across a large number of predictions. The canonical measure for estimating the error of a recommender system is the *Root mean squared error* (RMSE) measure (for example in [18, p17], [1, p13] and [7, p6]). We shall use this measure to estimate the performance of our adaptive prediction aggregation algorithms. The RMSE of a set of estimations $\hat{R}$, compared the correct rating values R, is defined as

$$\text{RMSE}(\hat{R}, R) = \sqrt{\text{E}((\hat{R} - R)^2)} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{R}_i - R_i)^2}{n}},$$

where n is the total number of predictions. The RMSE combines a set of errors into one single combined error. A beneficial feature of the RMSE is that the resulting error will be on the same scale as the estimations. For example, if we are predicting values on the scale $1-5$, the computed error will be on this scale as well. In this case, an error of 1 would then say that we are on average 1 point away from the true ratings on our $1-5$ scale.

[1]See http://www.grouplens.org/node/73 — accessed 10.05.2011

TABLE I: adaptive modeling methods: A short overview of each of the recommender methods used in our experiment. Each recommender is used in every experiment.

	method	algorithm	description
S	svd1	SVD	ALSWR factorizer, 10 features.
S	svd2	SVD	ALSWR factorizer, 20 features.
S	svd3	SVD	EM factorizer, 10 features.
S	svd4	SVD	EM factorizer, 20 features.
S	slope_one	Slope One	Rating delta computations.
S	item_avg	Baseline	Item averages.
S	baseline	Baseline	User and item averages.
S	cosine	Cosine sim.	From similar items.
S	knn	Pearson Corr.	From similar users.
A	median	Aggregation	Median aggregate rating.
A	average	Aggregation	Average aggregate rating.
A	adaptive	Adaptive agg.	Our approach.

In addition to the dataset, we need a collection of recommender systems. Standard recommenders will be used for both the basic predictions, and the accuracy estimations, as described in Section 3.

Naturally, we need a large number of different recommenders, preferably ones that consider disjoint patterns in the data. Table I gives a short overview of the recommender systems we shall employ. Each experiment will use every recommender in this table. This section only gives a short introduction to each recommender.

4.1. Basic Recommenders

As seen in Table I, we have two types of recommenders: First, we have the basic recommenders, denoted by *S* in the table. These recommenders each look at the data in different ways to arrive at predicted ratings. We chose this wide range of recommenders for just this reason: as previously explained, the performance of aggregate recommenders are more dependent on the dissimilarity of the basic recommenders than their individual performance.

Let us briefly explain how each basic recommender works. In recommender systems, SVD is used to compress the ratings space into what is sometimes called a *taste space*, where users are mapped to higher-level "taste" categories (e.g. [2, p5], [11, p4] or [21, p2]). The factorizers refers to algorithms used to factorize the ratings matrix (e.g. the ALSWR factorizer [29]).

The Slope One and baseline algorithms look at average ratings for items and from users, and use these to predict

ratings. These are simple algorithms that often perform as well as more complex approaches.

The cosine similarity algorithm looks for items that are rated similarly by the same users, and infers item similarity from this measure. New ratings are then predicted by taking known ratings of other items, weighted by their item's similarity to the new item.

The KNN algorithm employs yet another approach. This algorithm, similar in strategy to the cosine similarity algorithm, looks for users with similar rating patterns. The similarity is measured with the Pearson Correlation Coefficient. Predictions are created by collecting ratings from similar users of the item in question, weighted by their respective similarity. See [1], [23] or [25] for a more comprehensive exploration of different types of recommenders.

4.2. Aggregate Recommenders

The second type of recommenders are the aggregation methods, that combine the result of each of the basic recommender systems (the methods below the middle line in Table I, denoted "A"). The first two of these methods are simple aggregation approaches. The median aggregation method choses the median value of the predictions produced by the standard recommenders. Similarly, the average aggregation method takes the mean of the standard predictions. While not complex in nature, these methods will help us see how our method compares to simple, traditional aggregation techniques.

The last entry in Table I refers to our technique. This is the recommender outlined by Section 3, that create secondary accuracy estimating recommender systems, in order to adaptively weigh each basic recommender. All the aggregation approaches, including our technique, use every basic recommender system described so far.

As explained in Section 3, any basic recommender system can be used for the adaptive method. The only difference is how this method is trained: while the basic methods are trained using the ratings matrix, the adaptive methods are trained using the error model. In other words, we have as many possibilities for choosing the adaptive recommenders as the basic recommenders.

For our experiment, we went with SVD recommenders for each of the adaptive models. That is, each basic recommender method gets a secondary accuracy predicting recommender, which in this case is a standard SVD recommender. The SVD recommender is a natural choice in this case, since we wish to uncover latent patterns of accuracy for each model. Examples of these patterns include groups of items or users a specific recommender works well for.

It is important to note that the same configuration of recommenders was used for all three experiments. In other words, neither the basic nor the aggregate or adaptive recommenders were heavily tailored to each dataset. To be sure, higher performance could probably have been achieved by tailoring each recommender to each dataset. However, as our goal is to compare our finite set of methods, all we care about is how they perform compared to each other.

As with the basic recommenders, the same SVD recommender configuration was used for the adaptive layer in each Experiment. We chose to use en EM-factorizer to perform the actual decomposition, consisting of 20 features. The decomposition was performed by 20 iterations.

4.3. Results

Table II gives the resulting RMSE values when our algorithm is used with the MovieLens dataset. Each cell corresponds to the RMSE values for each dataset, for each recommender and aggregation approach. The bottom entry in this table refers to our adaptive recommenders method. As seen in this table, our approach outperforms both the standard recommenders and the aggregation approaches.

By outperform we mean that our model should have a lower mean RMSE score than the other singular methods. As we can see in Table II, our approach outperforms both the standard recommenders and simple generalized aggregation approaches. While we can not generalize too much on this basis, the fact that this dataset is a common testing ground for recommender systems, and that RMSE is the de facto measure for determining performance, we have grounds for some confidence in these results.

Statistics for each experiment are given in the last part of Table II. The statistical values are the minimum, maximum and mean values for each of the methods. We also include the standard deviation (σ) for each method, across each collection of subsets. This table confirms the results from the full results table: Our adaptive recommenders approach improves the mean performance of our system. The mean performance and the standard deviation are shown in Figure 2.

Let us take a look at the standard deviation measures from the different methods. As seen in Figure 2, most of the methods, including the adaptive models, exhibit quite a lot of variation in their results. If these variations occurred as a result of unstable predictions of the same dataset, this would be a substantial problem, resulting in unreliable predictions. However, the standard deviation is mostly caused by the differing performance across the varying datasets. As we see, the performance of each of the aggregation methods, as well as the best performing standard recommender, follow each other closely. At the same time, performance varies across the different datasets, which results in high values for σ.

There are two important limitations. First, our approach is much more complex than those we test it

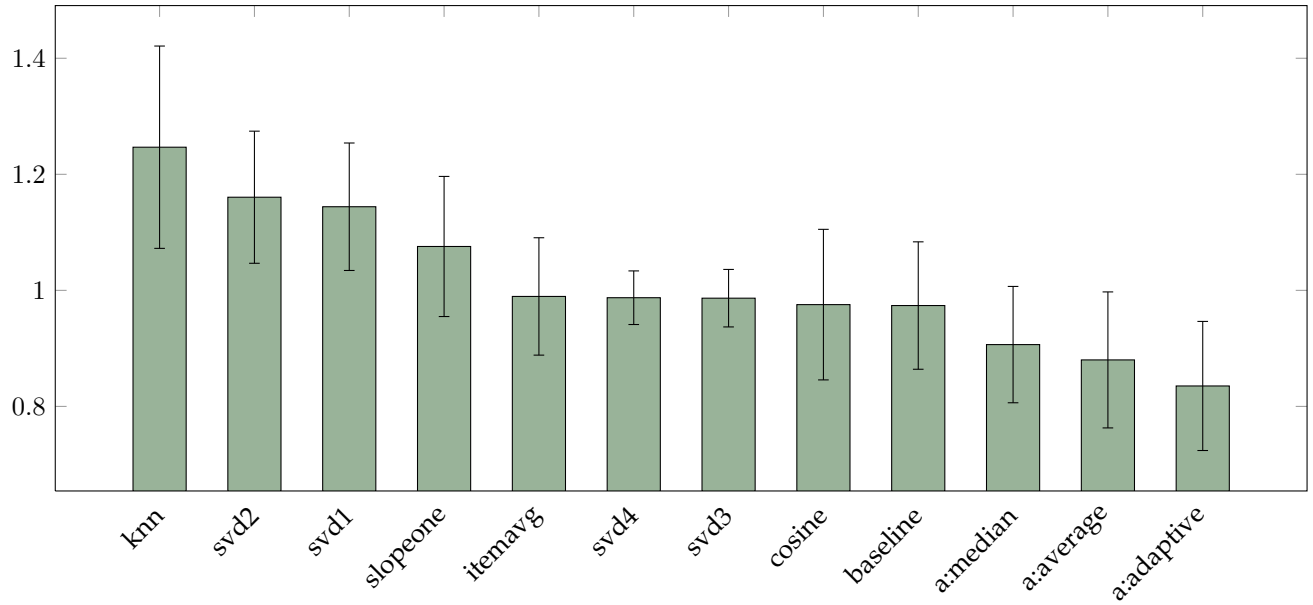

Fig. 2: Average RMSE plot: This plot shows the average RMSE for each method, and each aggregation method (denoted "a:"). The actual numbers are given in Table II. The error bars indicate the standard deviation of each method. Note the scale on the y-axis — the errors are not as pronounced as they might seem.

against. The question whether the methods performance is worth its extra complexity becomes important. Second, the generalized aggregation methods we chose to test our method with are simpler than the most powerful modern approaches to aggregate recommenders. This fundamentally limits how confident we can be that our system is indeed an improvement. We shall discuss this further in Section 5.

[10] performs more experiments with adaptive recommenders, including one where this approach is used to provide personalized search results.

5. Discussion

We have made two main contributions with this paper: (1) described the latent subjectivity problem and (2) developed the technique of adaptive recommenders.

(1) The latent subjectivity problem is one we think hinders standard recommender systems reaching their full potential. As far as we know, this problem has not been described in the context of recommender systems. The main choice for any such system is how to predict unknown ratings. To do this, a pattern in the available ratings data must be leveraged. These patterns are plentiful, and which works best is dependent on each user and item in the system. Modern aggregation recommenders utilize many patterns, but on a generalized level, where each user and item is treated the same. This underlying subjectivity leads to a mismatch between the notions of whoever developed the systems, and the users and items of the service.

Averaged or generalized weighted approaches will always chose the combination that performs best *on average*, with little concern to the uniqueness of items (and users). In other words, this is a comprehensive problem that may be discovered amongst many machine learning techniques.

(2) Adaptive recommenders is our attempt to solve the latent subjectivity problem. As far as we know, this type of adaptive prediction aggregation has not been done before. Section 4 showed that an aggregation that combines predictions based on estimated accuracy can outperform both standard recommenders and simple aggregation approaches. Our technique is strengthened by the fact that standard recommender algorithms are used for the accuracy estimations. This is the core insight of this paper: by creating error models for each recommender, we can use this to predict its accuracy for each user/item combination. These predictions can then be used to weigh each combined algorithm accordingly.

We believe there are greater opportunities in systems where there are even more diverging patterns to be leveraged. The prime examples of this are systems that may or may not use social connections between users, and systems which predict the relevance of widely varying items.

5.1. Limitations

There are some important general limitations to our research related to the (1) complexity of our method, (2) our choice of data and evaluation metrics, (3) the general usefulness of this approach, and (4) common issues with recommender systems.

TABLE II: Results from our experiment: Each cell gives an RMSE value, on the scale 1-5. The first table gives errors for each subset of the data (d_x). Lower values indicate better results. Bold values indicate the best result in each column. S refers to singular methods, and A to aggregation methods. σ refers to the standard deviation of each method across the subsets.

RMSE values for the five disjoint subsets:

	method	d_1	d_2	d_3	d_4	d_5
S	svd1	1.2389	1.1260	1.1327	1.1045	1.1184
S	svd2	1.2630	1.1416	1.1260	1.1458	1.1260
S	svd3	1.0061	0.9825	0.9830	0.9815	0.9797
S	svd4	1.0040	0.9830	0.9849	0.9850	0.9798
S	slope_one	1.1919	1.0540	1.0476	1.0454	1.0393
S	item_avg	1.0713	0.9692	0.9662	0.9683	0.9725
S	baseline	1.0698	0.9557	0.9527	0.9415	0.9492
S	cosine	1.1101	0.9463	0.9412	0.9413	0.9382
S	knn	1.4850	1.1435	1.1872	1.2156	1.2022
A	median	0.9869	0.8886	0.8857	0.8857	0.8855
A	average	0.9900	0.8536	0.8525	0.8525	0.8519
A	adaptive	**0.9324**	**0.8015**	**0.7993**	**0.8238**	**0.8192**

Statistics for each method:

	method	min	max	mean	σ
S	svd1	1.1045	1.2389	1.1441	0.2197
S	svd2	1.1260	1.2630	1.1605	0.2277
S	svd3	0.9797	1.0061	0.9865	0.0991
S	svd4	0.9798	1.0040	0.9873	**0.0924**
S	slope_one	1.0393	1.1919	1.0756	0.2415
S	item_avg	0.9662	1.0713	0.9895	0.2023
S	baseline	0.9415	1.0698	0.9738	0.2196
S	cosine	0.9382	1.1101	0.9754	0.2595
S	knn	1.1435	1.4850	1.2467	0.3487
A	median	0.8855	0.9865	0.9065	0.2005
A	average	0.8519	0.9900	0.8801	0.2344
A	adaptive	**0.7993**	**0.9324**	**0.8352**	0.2225

(1) Complexity: As our approach is more complicated than standard recommenders, it is worth questioning if its gains are worth the extra complexity. This depends on the basic recommenders that are to be combined. If the system is made up by many different recommenders, that each user might place varying importance on, and that may have varying success with each item, adaptive recommenders may provide gains in accuracy.

On the other hand, if the recommenders are simple in nature, and look at similar patterns in the data, generalized aggregation methods might be more applicable. Clearly, the performance gains in our experiments are not substantial enough to declare anything without reservation. While we believe this technique has potential, without real-world success stories, it is hard to suggest that our method is particularly better than a simple standard recommender.

(2) Evaluation: we chose traditional datasets and evaluation metrics to validate the adaptive recommenders technique. While our initial results are promising, it is important to stress that this is only one test on one dataset. Considering the vast scope of applicable data, and the number of ways these results many be evaluated, the results must be seen for what they are: initial and preliminary explorations of a new technique that has yet to be proved useful in the real world.

(3) Usefulness: When considering the additional complexity of our approach, a natural response is whether or not current approaches to recommender systems are good enough. We do not think so: information overload is such a nuanced problem that the only solution lines in intelligent, adaptive systems. However, as most of today's recommender systems perform quite simple tasks, they may be more than good enough for their purpose.

This will always be a trade-off, between complexity and required accuracy. As in many other cases, each of the systems described in this paper have their use cases. In the end, the requirements of each system must decide which method best suit their needs.

(4) Common issues: The topic of recommenders and adaptive systems in general raise a number of questions which is outside the scope of this paper. For example, user privacy is a big issue. Whenever we have a system that tries to learn the tastes, habits and traits of its users, how each user will react to this must be considered. This is often a trade-off between adaptability and transparency. The most adaptive systems will not always be able to explain to the users what is going on and what it knows about each person, especially when dealing with emergent behavior based on numerical user models.

Another important issue is the usability of autonomous interfaces. While a thorough discussion of privacy and usability is outside our scope, they are both important limitations to considered when using a recommender system.

In addition to the general limitation, our experiment carries a few drawbacks.

Our method was only tested against a limited number of standard recommenders. The key word is standard: these recommenders were not heavily customized to fit the available data. As in all machine learning, achieving relatively good performance is quite simple. Any improvements above this standard requires deep domain knowledge, and methods customized to the problem at hand. In an actual system, the adaptive recommenders should be tested against carefully selected standard recommenders, optimized for the current domain.

Similarly, our method was only tested against simple aggregators. Many more complex aggregations are possible, for example by solving the problem of finding optimal generalized weights for each method. While our tests show the basic viability of our approach, more testing against complex aggregation functions is still required.

6. Conclusion

The information overload problem will always be present. No matter how elegant solutions one may find, the fact is that the overwhelming amount of available data quickly outgrows our ability to use it. We believe artificial intelligence is crucial to finding a solution. Only by creating intelligent systems that help us filter, sort and consume information can we hope to mitigate the overload.

As stated through the latent subjectivity problem, systems should not only tell users what has been predicted, but also allow flexible and adaptive usage of its internal algorithms. *After all, a system that insists on being adaptive in one particular way is not really adaptive at all.*

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