

How Adaptive Aggregate Contextual Recommender Benefits IP-based TV Services

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ABSTRACT

Nowadays, for achieving personalized content offering, IP-based TV services make use of recommendation systems to automatically suggest programs for users. In such recommenders, to avoid filter bubbles, the research focus is recently transferred to diversity and novelty after many years of pursuing accuracy and personalization. Despite that many approaches have been proved effective to increase the diversity and novelty in recommenders, their defects as unexplainable results and non-interactivity make them not so friendly to users. On the other hand, contextual factors such as timing, location, company by other people etc., which possess quite clear context meanings are proved influential on IP-based TV services' users' choices. Such contextual factors were often integrated in recommenders though, to my best knowledge, their roles of reasonably increasing diversity and novelty haven't been detailed studied yet. In this Ph.D. work, I plan to realize an "Adaptive Aggregate Contextual Recommender" for IP-based TV services, which makes uses of multiple contextual factors in an adaptive way to resolve the issues of interpretability and interactivity when increasing diversity and novelty in recommenders.

Author Keywords

Diversity and novelty; contextual factors; adaptive recommender; IP-based TV services

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

INTRODUCTION

It is now a consensus that high accuracy or precision rate on a specific data set is not a satisfiable goal for recommenders any more, while diversity and novelty are recognized more valuable to present the essence of a recommender: initially inspiring users in the area he/she might have ignored rather than passively guessing what users will choose [14]. If you have

ever experienced the annoyance of always being involved in a filter bubble thus missing niche content in IP-based TV services, it verifies your desire of diversity and novelty from recommenders. Nevertheless, achieving diversity and novelty in recommenders does not mean casually selecting any items with the range as broad as possible, users' personal preference should also be the premise, otherwise they would be bothered rather than eased.

To trade off between these two knotty issues, many approaches have been investigated these years. Lathia et al. pointed that multiple algorithms, including Singular Value Decomposition (SVD), k-Nearest Neighbors (kNN) Collaborative Filtering (CF) and baseline, temporally switching can be used to increase results' diversity while maintaining a relatively low Root Mean Square Error (RMSE) [7]. Hybrid algorithm which integrated content-based method into kNN CF was also proved effective especially for newly coming items [4]. In [1], experiments with respect of both loss of precision and diversity gain proved that re-ranking techniques can improve aggregate recommendations as well. In addition, novel similarity calculation and neighbors selection mechanism were turned out to be constructive in balancing accuracy and average diversity in [8]. In spite of the effects these solutions brought considering off-line metrics, their defects of lacking interpretability and interactivity are unavoidable due to models' complexity. Without reasonable explanations, unclear understanding of recommended content may result in weakened users' interaction with the recommender.

Targeting increasing interpretability and interactivity along with taking diversity and novelty into account in recommenders of IP-based TV services, which involves not only IPTV through set-top boxes, but also WebTV and web-based Mobile Apps, I plan to make use of contextual factors to settle the issues. Actually, many IP-based TV services have taken contextual factors into consideration in recommenders for the sake of raising accuracy or precision rate [12, 5, 3]. Yet actually, both single context situation dynamically changing and multi context merging can bring about diversity and novelty as well [9]. Besides, these specific context meanings can make the recommended results more intuitive and understandable, so that users can better interact with the system. Therefore, I intend to realize an "Adaptive Aggregate Contextual Recommender" (AACR) for IP-based TV services, in which contextual factors of timing, location, company by other people and breaking news, which are proved influential

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on users' choices in [13, 2, 6], will be adaptively aggregated. In this paper, the preliminary frame work and evaluation design of this recommender will be introduced in detail.

The rest of the paper is organized as follows: Section 2 introduces the design concept of this proposed "Adaptive Aggregate Contextual Recommender" Framework. Innovations and challenges of this framework are listed in Section 3. Section 4 consequently draws the conclusion and future picture.

FRAMEWORK ACCR

In this section, I firstly elaborate the framework of "Adaptive Aggregate Contextual Recommender" (AACR), after which aims and objectives are presented. Then concrete approaches designed so far are listed, and the work has been done is hereafter mentioned in the end.

Proposed Framework

As shown in Figure 1, in this AACR, there will be four branch recommended lists, each regarding a specific contextual factor, and the final main list will be the aggregation of those four lists. In front of users, only the final aggregated list will persist showing as the main list while the four branch lists will be hidden in a shrinkable panel, which only shows as supplementary of the main list in the light of users' demands. For each recommended item, its contextual type and description will be offered in a hidden div, which can be the reference when users choose from these candidates.

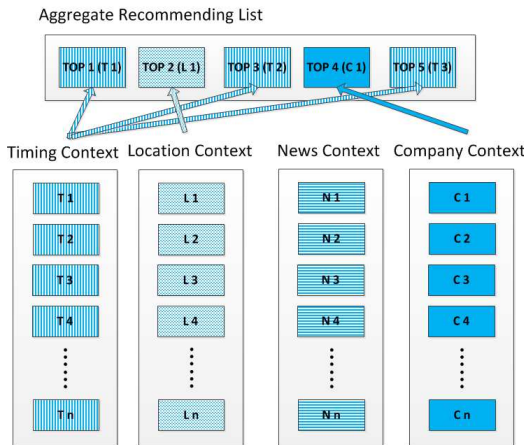


Figure 1. Framework of Adaptive Aggregate Contextual Recommender

For the concept of "Adaptive Aggregate Contextual Recommender", I will explain it from back to front literally. First, as to *Contextual*, although various contextual factors as timing, location, devices condition etc. have been directly applied in many recommenders [5, 2, 8], we made our own survey [13] to investigate the role of context information plays in recommenders from the perspective of users' opinions in connection with IP-based TV services. The result of this survey tells us that timing, location, company by other people and breaking news are influential factors when users using IP-based TV services. In addition, these factors are independently existing and users' dependencies on them are individually different and dynamically altering. Thence I would like to pick these

four contextual factors when building this AACR. Second, *Aggregate* conveys my backing of dealing with each contextual factor respectively and then aggregating the results instead of directly modeling them together as in [6, 10]. In this way, the explanation for each item in the final aggregated list would be feasible by signing each recommended item with its context condition, due to which the item is recommended. Thus the purpose of diversity and novelty can be reached by considering different contextual factors, meanwhile the interpretability can be realized by this aggregating approach. Third, *Adaptive* means that the way different contextual models aggregate will be adaptive to users' inclination altering. That is to say, recommender will adjust the weight assignment in model selection procedure according to users' feedback, so that it can interact with users by automatically calibrating the weights of models accordingly.

System adaptivity is actually a by-product when dealing users' interaction with recommenders. As presented in Figure 2, once the models for each contextual factor are determined, users' any behavior (clicking, watching duration or bookmarking) on the recommended list could kind of reveal their inclinations among these contextual factors. Hence their selections can be treated as a feedback to the recommender system, which helps fine-tune the assignment of the weight of contextual factor. What is attractive here is that user's behavior is used not only for evaluation metrics but also for recommender's self-tune.

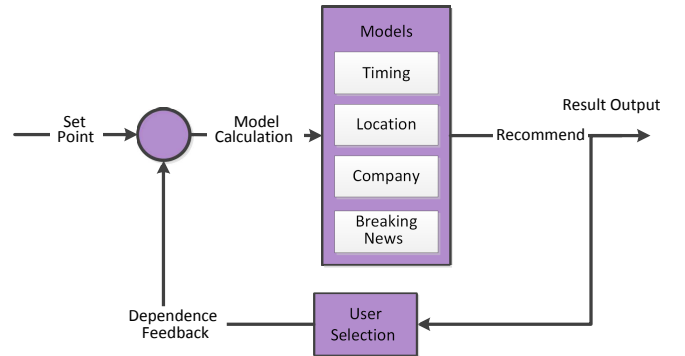


Figure 2. Adaptive System: a Feedback Mechanism

Aims and Objectives

Since in AACR, each contextual factor will be dealt with separately, the basic goal of accuracy should be guaranteed in such separated model primarily. As Table 1 describes, normalized Discounted Cumulative Gain ($nDCG_n = \frac{DCG_n}{IDCG_n}$, in which $DCG_n = \sum_{i=1}^n \frac{2^{rel_i} - 1}{\log_2(i+1)}$ and $IDCG_n = \sum_{i=1}^n \frac{1}{\log_2(i+1)}$), Click Through Rate ($CTR = \frac{Clicks}{Impressions} \times 100\%$, where *Impressions* means the recommended times on a specific item while *Clicks* denotes users' total clicks after seeing these recommendations) and Mean Average Precision ($MAP(N) = \frac{\sum_{u=1}^U AveP_u(N)}{|\{U\}|}$, where $AveP(N) = \frac{\sum_{n=1}^N (P(n) \times rel(n))}{|\{Hitte\} Items\}|}$), can be used as optimization objectives in these independent models [11]. When comes to the indicators for the final integrated list, Average Diversity ($diversity(L_i, L_j, N) = \frac{|L_j \setminus L_i|}{N}$, where $L_j \setminus L_i = x \in L_j \setminus x \notin L_i$

	Contextual Models Accuracy				Other Global Indicators			
	Timing	Location	Breaking news	Social Company	Diversity	Novelty	Interpretability	Interactivity
Evaluation /Objective	nDCG	CTR	MAP	nDCG	Average Diversity	Average Novelty	Five-likert scale rating	Five-likert scale rating
Off-line	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Candidate Dataset	TV1/TV2	LDOS-CoMoDa	EPG data from SMA	Douban Social	Data of our SMA	Data of our SMA	Data of our SMA	Data of our SMA
Approach	Tensor	Tensor	LDA	MF	AACR	AACR	AACR	AACR

Table 1. Proposed Objectives and Approaches

and N denotes the length of every result list L) and Average Novelty ($novelty(L_i, N) = \frac{|L_i \setminus A_t|}{N}$, in which A_t represents the number of all items that has been recommended to date t) will be targeted at measuring diversity and novelty for Top-N results respectively [7]. For interpretability and interactivity, which are quite relevant with user's personal experience, it's better to invite users to play around with the recommender and express their feelings on these two indicators by rating through Five-likert scale questionnaire on line. So it's obvious that excepting the last two ones, all the metrics mentioned above can be evaluated by off-line method.

Approaches

Due to the current status as lacking users, our IPTV service, Smart Media Assistance (SMA), needs some external datasets to build several models at first. Given the concrete purpose of each procedure, as can be seen in Table1, I propose following candidate datasets for training and testing. When considering the timing factor, since TV1 and TV2 datasets¹, which have been collected by two IP-television providers in Europe, keep records of timestamps of every viewing, their usefulness of involving timing factor is quite clear. As to location context, I found that LDOS-CoMoDa dataset² acquires users' ratings on movies along with their concrete contextual conditions, including daytype, mood, location etc.. LDOS-CoMoDa only holds ratings on movies rather than all TV programs though, the location information it pertains is quite valuable because seldom dataset takes this contextual factor into account. As to breaking news, Electronic Program Guide (EPG) extracted by our own SMA can be directly used to train the model for hot topic matching. For social company factor, Douban Social dataset³, which possesses users' friendship information and their ratings on movies, is quite suitable for social company model building. When it comes to the rest global indicators, which should be actually judged by a unified dataset for the aggregated list, I would suggest to collect our own dataset from system SMA to tell the effect.

Further more, for each dataset, I have tentatively chosen the approach considering corresponding objectives. As to contextual factors of timing and location, tensor factorization, which is nowadays frequently used in recommenders, can be

a good choice. Yet for breaking news, which is more associated with text description (EPG data), topic model Latent Dirichlet Allocation (LDA) can help solving problems in topic matching. As to social company, users' two dimensional friendships can be directly represented by an adjacency matrix and analyzed by Matrix Factorization (MF), and the social recommendation decision will be made according to such friendship analysis. When these four models are built, proposed weighted linear combination will aggregate them into the final list. Such AACR approach will be then assessed by the evaluation methods we mentioned before.

Work Done So Far

For the proposed AACR, the work done so far includes two parts. The first one is an "IP-based TV Service Usage Questionnaire", which investigated users' opinions on the role contextual factors play when they watch programs in IP-based TV services. Summarized from results in this questionnaire, I made the decision of choosing those four contextual factors for AACR. The second part is the progress of the branch-model associated with "breaking news". I'm now dealing with EPG data extracted from SMA by building topic model LDA on it, and try to make hot topics be filtered out from EPG data more easily.

INNOVATIONS AND CHALLENGES

It is encouraging to see the feasibility and potential benefits of the proposed framework from the above analysis. In this section, I will further illustrate innovations and challenges of it from technical perspective.

Innovations

Innovations of this newly proposed recommender can be summarized from five aspects. As Figure 3 shows, these five aspects are: 1) multi-contextual factors rather than only a single one considered in the recommender; 2) as for improving diversity, conventional ideas as algorithm hybrid is converted to contextual factor hybrid here; 3) different from context-aware approach which considering users' dependencies on contextual factor as a constant variable, the adaptive thought endues users' with a dynamic inclination towards contextual factors; 4)it broadens the range of personalization objectives from items or categories to context inclinations; 5) F-measure will probably find its new usage: harmonic mean of diversity/novelty and accuracy. With these innovations, users in IP-based TV services could understand the reason why programs are recommended and better interact with the system.

¹<http://home.deib.polimi.it/cremones/memo/?Datasets>

²<http://212.235.187.145/spletnastran/raziskave/um/comoda/comoda.php>

³<https://www.cse.cuhk.edu.hk/irwin.king/pub/data/douban>

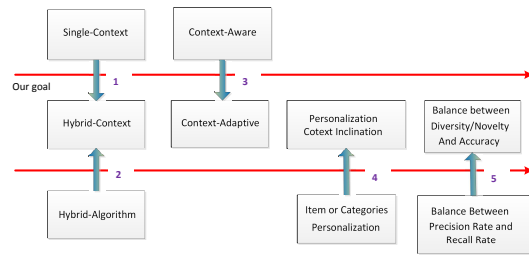


Figure 3. Innovations of the Framework

Challenges

Innovations must be accompanied with challenges, and it is not exceptional for the proposed framework. The foreseeable challenges are listed as follows: 1) due to the difference among ranking approaches for respective context-based recommended list, the compatibility to aggregate the final list should be seriously taken into account; 2) how to deal with each model's evaluation and the final F-measure fine tune demands more careful verification; 3) a dynamic combination of several different models is a non-trivial work, updating interval and updating condition among different models need to be carefully considered. Though these challenges exist, it deserves our effort on account of altering recommender's role from prediction-purposed to guiding-oriented, which is really attractive and exciting.

CONCLUSION AND FUTURE PLAN

In this paper, I elaborated my tentative ideas about an "Adaptive Aggregate Contextual Recommender" in IP-based TV services, and analyzed the benefits as diversity, novelty, interpretability and interactivity such recommender can bring about. The framework design, evaluation approaches and detailed approaches illustrated the feasibility and applicability of this system. Innovations and challenges analysis also helped clear the emphasis and directions for the next steps. Given the plans in this paper, my future aim is to build the recommending models regarding each contextual factor one by one, and to ultimately aggregate them together in an adaptive way as I proposed.

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