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A Comprehensive Survey on Comparisons across Contextual Pre-filtering, Contextual Post-filtering and Contextual Modelling Approaches

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Abstract

Recently, there has been growing interest in recommender systems (RS) and particularly in context-aware RS. Methods for generating context-aware recommendations are classified into pre-filtering, post-filtering and contextual modelling approaches. In this paper, we present the several novel approaches of the different variant of each of these three contextualization paradigms and present a complete survey on the state-of-the-art comparisons across them. We then identify the significant challenges that require being addressed by the current RS researchers, which will help academicians and practitioners in comparing these three approaches to select the best alternative according to their strategies.

Keywords*: contextual pre-filtering, contextual post-filtering, contextual modelling, comparisons, contextualization paradigms context-aware recommender system*

1. Introduction

With the help of the internet, users can now deliver, access and retrieve whatever web resources they wish at any time and in anywhere according to their interest. However, the excessive availability of web resources leads to the problem of information overload [2, 3], in which users can easily be lost over the Cyber Ocean of information [4, 5]. Recommender systems (RS) that personalise suggestions of various items and services to users emerged in the mid of 1990s to remediate the problem of information overload [6-9]. At its emergence, traditional 2D RS were predominantly used to predict users' preferences. These approaches utilised the items and users as the set of entities to predict the ratings that are either implicitly deduced by the system [10] or are expressly provided by the users [11, 12].

In the early 2000s, researchers extend the research in recommender systems to leverage contexts in the recommendation process [13, 14]. Context is an all-around concept [15], that has been studied across numerous disciplines, such as linguistics, philosophy, and cognitive and organisational science. In the late 1980s, computer science as a discipline adopts the concept of context primarily in ubiquitous computing and AI [16].

Context has been researched across numerous disciplines [17], in which every discipline tends to proffer its idiosyncratic view [18]. A hundred and fifty different views of context from different fields of research have been presented and examined in [19]. The authors concluded that it would be very much difficult to find a single definition of context that is unanimously satisfying all research disciplines. However, the most reported view of the context in the field of computer science is that of [20], which viewed context as:

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"Any information that can be used to characterise the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and application themselves".

Context has additionally been classified in several ways. However, the foremost reported categorisation within the field of computing is that of [21] that considers context to be representational and interactional views. The interactional view assumes context to be some specific factors that induced user behaviour and which may not necessarily be observable, while representational view assumes context to be some specific factors that are priori identified, and which are defined by some contextual factors with known hierarchical structures and which do not change considerably over time. In the early work of [20, 22], the context was classified into computing, user, and physical.

Most of the previous researchers focused on the representational view of context [23]. Authors in [15, 24] have further extended the view of representational context to include contextual pre-filtering, contextual post-filtering and contextual modelling approaches as shown in Figure 1. Then, they challenged researchers within the area of recommendation systems to examine those strategies further and to compare them in numerous experimental settings and with considering various recommendation factors to determine which approach is superior to the others and under what situation. The comparison is essential not only to the researchers but also to the practitioners [1].

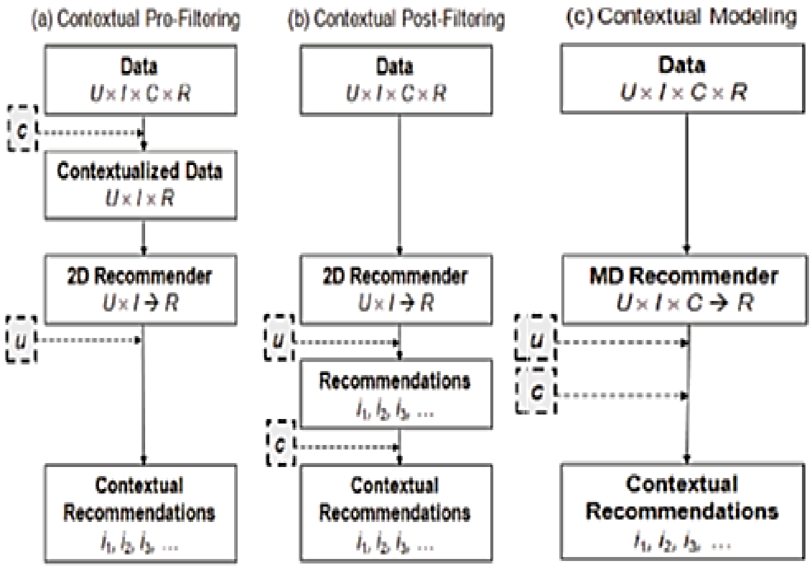

Figure 1. Contextualization Paradigms (Figure from [12])

In this paper, we determined to provide a complete survey of the state-of-the-art comparisons between these three approaches. This is followed after the several novel approaches of each of the pre-filtering, post-filtering and contextual modelling approaches are presented. We then raised the significant challenges that require being addressed by the present RS researchers. This paper is supposed to assist researchers in developing a deeper understanding of those contextualisation paradigms, and their trade-offs and practitioners will use it to decide on the most effective possibility of keeping with their market strategy. In summary, the contributions of this paper are:

a. The paper presents the concept of context and also the three-contextualization paradigms for incorporating contextual data in the recommendation process.
b. The paper provides a comprehensive summary of the many novel approaches of pre-filtering, post-filtering, and contextual modelling approaches.
c. The paper presents state-of-the-art comparisons between pre-filtering, post-filtering and contextual modelling approaches.

d. The paper also presents outstanding challenges that are not entirely addressed within the literature and suggests available opportunities for future research directions.

The remaining sections of the paper are organised as follows. Section 2 presents the adopted methodology for extracting the literature. Section 3 presents the three-contextualisation paradigms, and the several novels approach for incorporating contexts in the recommendation process. The comparisons between pre-filtering, post-filtering, and contextual modelling approaches are presented in section 4. We then present outstanding challenges and suggest possible opportunities for future research directions in section 5, and finally conclude the paper in section 6.

2. Methodology

As defined by [25, 26], a review is a rigorous way of identifying, appraising, selecting, synthesising, evaluating and interpreting all available researches relevant to particular research questions of particular interest. It aims at critically making an appraisal on the previous contributions based on specific research questions to draw attention to research gaps that need to be addressed. In this paper, we target to provide a complete survey of the state-of-the-art comparisons between pre-filtering, post-filtering, and contextual modelling approaches.

To perform a comprehensive search, we identified the bibliographic databases that cover the majority of journals and conference proceedings papers published in the field of computer science. These databases are ScienceDirect, ACM Digital Library, SpringerLink, Web of Science, IEEE Xplore, Scopus, Dblp computer science bibliography, and Google Scholar Portal.

The searching process was performed based on the Boolean search criteria. We extracted all of the papers that mentioned any of the following words/phrase in the paper title; Recommender system, context-aware, pre-filtering, post-filtering, contextual modelling. We then reviewed all of the selected papers and included all papers that either compare any of the contextualization paradigms or proposed a new variant of the three approaches.

In order to retrieve the highest number of publications, we followed the list of references of each of the chosen papers and compared with our databases to search out any missing paper that might satisfy our inclusion criteria. We also searched each of the selected papers in scholar.google.com and had a brief overview over the title of all the papers in 'cited by', 'related articles' and 'all versions'.

3. Contextualization Paradigms in Recommender Systems

As shown in Figure 1, three different algorithmic paradigms exist for incorporating contexts in the recommendation process. The approaches are based on when the contextual information is considered to be significant in conjunction with the classical two-dimensional approaches. These approaches are pre-filtering, post-filtering, and contextual modelling approaches. Since the challenge raised by [27], a substantial number of researchers have proposed and compared novel ways of incorporating contexts in the recommender systems. In this section, we described each of the paradigms and presented its corresponding novel approaches from the literature.

3.1. Contextual Pre-Filtering

A pre-filtering approach depicted in Figure 1a is an approach that applies a context-dependent criterion, which selects only items that are appropriate to a specific context. In contextual pre-filtering, only the filtered items are considered for recommendations. One advantage of this approach is its ability to employ any of the many classical recommendation techniques. That is to say, all the approaches on traditional recommender system can be applied to the reduced data. In what follows, we briefly described each of the several novel contextual pre-filtering approaches proposed from the literature.

3.1.1. Item Splitting

Item splitting is a pre-filtering technique that tries to find a contextual condition on which to split items. The approach was introduced in [28-30] and compared with a reduction-based approach presented in [31]. In this approach, items are split based on the perceived context and items with similar context are combined and processed together. This approach assumes that the analysis of some certain items might result in a distinct outcome in several contextual settings. A more comprehensive evaluation of these approaches has been presented in [32].

3.1.2. Micro Profiling

Micro profiling is a bit more similar to item splitting which was proposed by [33]. While item splitting splits items, micro profiling split users instead. In this technique, user profiles are split into numerous sub-profiles known as micro-profiles, each representing users in a selected context. These micro-profiles are then used to make recommendations.

3.1.3. Distributional-Semantics Pre-Filtering (DSPF)

Distributional-semantic pre-filtering (DSPF) is an approach that aims at handling the well-known data-sparsity problem of CARS. The novel method was presented in [11] to take advantage of the distributional semantics of contextual conditions to build a context-aware rating prediction model. DSPF is a reduction-based method that employs a situation-to-situation similarity feature to select the right level of contextualisation for given information. Given a target contextual situation, the ratings tagged with the contextual situations are used to construct a predictive model primarily based on matrix factorisation. The model is then used to compute the rating predictions and identify recommendations that are specific to the target contextual situation.

3.1.4. Exact and Generalized Pre-Filtering

Exact and generalised pre-filtering are two forms of contextual pre-filtering proposed by [34]. Exact pre-filtering (EPF) selects all the information mentioned the correctly given context within the recommendation process, whereas generalised pre-filtering selects all the information that mentioned a particular context which supports the generalisation of the contextual information [24].

3.2. Contextual Post-Filtering

A contextual post-filtering approach depicted in Figure 1b is similar to contextual pre-filtering approach only that it applies the filtering process after recommendations have been computed. In other words, contextual post-filtering approach disregards the contextual information in the input data when generating the list of the top-N recommendations. The list of the top-N will then be refined by either filtering out recommendations with a smaller probability of relevance or by adjusting the ranking of recommendations by weighting the predicted rating score with the probability of relevance. Similar to contextual pre-filtering, contextual post-filtering also allows using any of the numerous traditional recommendation techniques. In what follows, we briefly described each of the several novel contextual post-filtering approaches proposed from the literature.

3.2.1. Weight PoF and Filter PoF

Weight PoF and Filter PoF are two kinds of the post-filtering technique proposed by [34]. In Weight PoF, the suggested items from 2D recommendations are re-ordered and weighted based on the rating probability of relevance in the given context. While, in Filter PoF, the suggested items with little probability relevance from the 2D recommendations process are filtered out from the recommendation list. The two approaches differ in how the recommendations are contextualised; Filter PoF filters the traditional 2D ratings out based on a threshold value P.

$$Rating_k(i,j) = \begin{cases} Rating(i,j) & if\ (P_k(i,j) \geq P) \\ 0 & if\ (P_k < P) \end{cases} \tag{1}$$

Whereas Weight PoF multiplies each of the traditional 2D ratings by $P_k(i,j)$

$$Rating_k(i,j) = Rating(i,j) * P_k(i,j) \tag{2}$$

Where P is the threshold value.

3.2.2. Context-RS

Context Recommender System (Context-RS) is a generic contextual post-filtering technique proposed by [35] by mining association rules between contextual knowledge and item characteristics to find their useful correlations. Context-RS combines traditional 2D recommender systems, contextual knowledge and association rules to enhance the quality of top-N recommendations.

3.3. Contextual Modelling

Contextual modelling approach depicted in Figure 1c takes contextual considerations into the recommendation algorithm itself. That is to say, the contextual information that is considered relevant is employed directly within the classical RS modelling method as part of the recommendation process. In other words, the contextual information is employed directly within the recommendation function as an explicit predictor of a user's rating score for an item. In what follows, we briefly described each of the several novel contextual modelling approaches proposed from the literature.

3.3.1. Graph-Based Relevance Measure (CGR)

Graph-based relevance measure (CGR) is a contextual modelling approach proposed by [36]. The approach aimed to model and incorporate contexts within the recommendation method by assessing the potential relevance of a target user with the set of items for a better recommendation.

3.3.2. Contextual-neighbors

Contextual-neighbours are new types of contextual modelling approach proposed by [37], based on the notion of utilising contextual information to calculate the degree of the neighbourhood using a user-based collaborative filtering approach. The authors introduced four variant, in which each of the variants selects contextual neighbourhood differently (see [37]). We summarised each of these approaches in Table 1.

Table 1. Summary of Novel Approaches for Incorporating Contexts in the Recommendation Process

Research reference	Approach(es) proposed: Pre-filtering	Post-filtering	Contextual modelling
[23-25]	Item-Splitting		
[28]	Micro-Profiling		
[8]	Distributional semantic pre-filtering (DSPF)		
[29]	Exact Pre-Filtering (EPF), Generalized Pre-Filtering	Weight PoF, Filter PoF	
[30]		Context-RS	
[31]		Context-Aware Profiling	Graph-Based Contextual Modeling (CGR)
[33]			Context-Aware SVM
[32]			Contextual-neighbors CM (Mdl_1, Mdl_2, Mdl_3, Mdl_4)

4. Comparisons Across Contextual Pre-Filtering, Contextual Post-Filtering and Contextual Modelling Approaches

A number of researchers faced the challenge raised by [24] in comparing and proposing the several variants of pre-filtering, post-filtering, and contextual modelling approaches. To be specific, let us start with the work of [39], which undertake broad empirical experiments to study the significance of contextual information in predicting customer behaviour and how best it can be used when building customer models. The results from the experiments reveal that context does matter in modelling customers' behaviour and that user's contexts can be inferred from an existing data with acceptable accuracy. The results also show that contexts play an essential role in personalisation and companies can utilise the opportunity to enhance the predictive performance of customer's behaviour.

The authors in [40] target to identify the effect of contextual information on recommendation performance. In doing so, they utilised the collaborative recommender system to compare a pre-filtering method to a post-filtering approach. Based on their experimental results, the post-filtering approach has significantly outperformed the pre-filtering approach in all experimental setup. This is because pre-filtering approach suffers the problem of sparsity-homogeneity trade-off. To address the issues of homogeneity and sparsity, [41] studied the interaction between sparseness and homogeneity to understand how including context with a pre-filtering approach improves the performance of a recommender system using transactional data.

In [42], experimental analysis has also been carried out to investigate whether context-aware recommender systems (CARS) always surpass the classical RS. The authors assessed the performance of the classical RS with the three forms of CARS using two different recommendation tasks. The results from the experiments reveal that the type of recommendation task has a significant effect in the comparison between RS and CARS and that the primary conditions that affect the comparisons are the overall number of recommendable items, number of items in the recommendation list and the specific performance that has to be measured.

Also, [43] carried some series of experiments by varying market granularity, dependent variable and context granularity to understand whether including the contextual information in a predictive model reduces the misclassification costs and the conditions that trigger it to happen. The results reveal that context leads to a decrease in the misclassification cost, especially when the unit of analysis is a micro-segment.

To improve the target market, a conceptual framework has been proposed in [44]. The framework has the potential of incorporating contextual information, which can use by a segmentation model to construct a predictive model capable of identifying customers' behaviour in a segment.

A novel variant of contextual modelling approaches has been proposed in [45]. The approach called contextual neighbours is based on the notion of utilising contexts to calculate the degree of the neighbourhood in a collaborative filtering approach. In addition to introducing four variants of the approach, the authors also compared pre-filtering, post-filtering, the four variant and un-contextual recommendations between a wide range of experimental settings. The results show that contextual post-filtering approaches proved more significant than any other approach, but the comparison is time-consuming and laborious. On the other hand, contextual modelling approach proved to be second-best and therefore may be a good alternative.

The research presented in [34] compared the performance of two forms of post-filtering approaches weight PoF and filter PoF to be precise and exact pre-filtering. The comparison was to determine the circumstances in which one approach is preferable to others. Evaluation using predictive accuracy shows that the comparison depends mostly on the forms of post-filtering used. The comparison is extended further in [37] to include the different variant of contextual modelling approaches. The resulting comparison reveals that contextual post-filtering yield the best-of-breed contextual method when realised in the best way but may provide the worst result if utilised poorly.

An empirical comparison of movie recommendation domain has been presented in [46]. The comparisons across the three contextualization paradigms reveal that none of the techniques was superior to others in all situations. However, random forest-based contextual approach and item splitting of pre-filtering tend to provide excellent performance.

While [34, 37, 39-46] performed the comparisons based on accuracy alone, [47] put into consideration also the diversity of recommendation to compare the several pre-filtering, post-filtering, and contextual modelling approaches to determine which method is superior to others and under which situation.

The limitations of [34, 37, 39-46] were that; first, their comparisons solely consider predictive accuracy that within the literature proven to be not sufficient for a utile and satisfactory recommendations [48]. Secondly, the comparisons were strictly marginal and failed to determine the region where one approach outperforms the others and under what situations. Also, the comparisons mainly consider a domain of application such as e-commerce in the case of [34, 37, 39-45], and movie domain in the case of [46]. Such findings cannot be generalised across other domains of applications because factors that are significant in one domain may be entirely irrelevant in another and different dataset may contain different contextual information.

A more detailed and comprehensive analysis of pre-filtering, post-filtering, and contextual modelling methods were carried out in [23]. In addition to considering the predictive accuracy, the authors also take into account the diversity of recommendations. Furthermore, in addition to the marginal comparison, they also rigorously present the regional analyses. We summarised these comparisons in Table 2.

Table 2. Comparisons of the Recent Researches Across the Three Contextual Paradigms

S/N	Research Reference	Comparison	Type Of Comparison	Factors Considered	Evaluation Measures	Dataset
1	[34]	Contextual and un-contextual	Marginal	1) data sets 2) The degree of contextual information 3) The granularity of customer segments 4) Types of predictive models 5) Types of dependent variables used 6) Types of performance measures.	Accuracy and area under the ROC curve (AUC)	E-commerce
2	[35]	Un-contextual, Pre-filtering and post-filtering	Marginal	1) Type of data (Contextual and non-contextual)	Accuracy	E-commerce
3	[29]	Pre-filtering and post-filtering	Marginal	1) Type of data	Accuracy	E-commerce
4	[36]	Un-contextual and Pre-filtering contextual	Marginal	1) Type of data	Accuracy	E-commerce
5	[37]	Un-contextual, Pre-filtering and post-filtering	Marginal	(1) Recommendation tasks (2) The number of overall recommendable items (3) The performance metrics (4) The number of items in the recommendations list (5) The granularity of the context	Accuracy	E-commerce
6	[40]	Un-contextual, pre-filtering, post-filtering and contextual modelling	Marginal	(1) Type of data (2) Context granularity (3) Different level of item aggregation (4) Different neighbourhood sizes (5) Seven recommendation engines (6) Several performance measures	Accuracy	E-commerce
7	[42]	Pre-filtering, post-filtering and contextual modelling	Marginal and Regional	(1) Type of the recommendation task (2) Context granularity (3) Type of recommendation data.	Accuracy and Diversity	E-commerce
8	[32]	Un-contextual, pre-filtering, post-filtering and contextual modelling	Marginal	(1) recommendation strategies (2) Type of data set	Accuracy	E-commerce
9	[39]	Un-contextual, Pre-filtering,	Marginal	(1) Types of data sets (2) The granularity of contextual knowledge	Accuracy	E-commerce

Table 2. Comparisons of the Recent Researches Across the Three Contextual Paradigms

S/N	Research Reference	Comparison	Type Of Comparison	Factors Considered	Evaluation Measures	Dataset
		post-filtering and contextual		(3) Dependent variables (4) Types of predictive models (5) Performance measures (6) Clustering algorithms		
10	[41]	Pre-filtering, post-filtering and contextual modelling	Marginal	Type of data	Accuracy	Movie
11	[38]	Contextual and un-contextual	Marginal	(1) Market granularity (2) Dependent variable (3) Context granularity	accuracy and the misclassification costs	E-commerce
12	[18]	Pre-filtering, post-filtering and contextual modelling	Marginal and Regional	(1) Type of the recommendation task (2) Context granularity (3) Type of recommendation data.	Accuracy and diversity	E-commerce

5. Challenges and Future Recommendations

Researchers are now developing an interest in the area of the recommender system, especially with the emergence of context-aware recommender systems in the early 2000s. The approaches used in generating context-aware recommendations are classified into pre-filtering, post-filtering and contextual modelling approach as depicted in Figure 1. (See section 1). Considering contexts in the recommendation process proved to enhance the general performance of recommender systems in various application domains. However, the improvement largely depends on the several factors considered in the recommendation process. Therefore, companies need to identify the essential factors that will maximise their profit before adopting a method.

As can easily be seen from Table 2, previous analysis between pre-filtering, post-filtering, and contextual modelling approach mainly evaluate the recommendation algorithms based on the performance accuracy alone. To enhance users' satisfaction and utility of recommendation, the comparisons across these three paradigms need to consider other evaluation measures such as serendipity, novelty, and diversity. From the literature, each recommendation strategy results in different recommendation outcomes. Therefore, companies would like specific recommendations methods for various business application settings betting on factors concerning their business applications. Thus, there is a necessity for in-depth comparisons to spot the particular factors that affect recommendation algorithms and also the contextualization approaches. Moreover, the existing analyses are limited to e-commerce domain. The comparisons need to cover other vital domains identified from the literature (see [49]).

We hope that the current RS researchers will aim at performing series of comparisons between the different variant of each of the pre-filtering, post-filtering and contextual modelling approaches across different domains of applications and different experimental settings and conditions. It will also be imperative for this researchers to propose some hybrid metrics to induce a stronger balance between different evaluations measures.

6. Conclusion

In this paper, we provided a complete survey of the state-of-the-art comparisons between pre-filtering, post-filtering, and contextual modelling approaches. We presented and described the various novel approaches of each of the three contextualization paradigms. We then pointed out significant challenges that require being addressed by the existing RS researchers.

This paper is meant to assist researchers and practitioners in comparing the three contextualization paradigms to select the best alternative according to their strategies. We hope that this paper will trigger the current RS researchers in moving towards performing series of analysis between pre-filtering, post-filtering, and contextual modelling approaches by considering several factors and different scenarios to ascertain a deeper understanding of their tradeoffs.

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