## Context-Aware and Sequential Pattern Mining Based Recommendations for Research Papers: A Hybrid Approach

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### ABSTRACT

The availability of huge volumes of online research papers over the scholarly communities has been increasing rapidly with the evolution of the Internet. Meanwhile, several researchers confront troubles while retrieving suitable and relevant research papers according to their research necessities due to information overload. Besides, the research necessities vary from researcher to researcher according to their contextual state and the online behavior in sequential access. Conventional recommendation approaches for instance content-based filtering (CBF) and collaborative filtering (CF) utilize content features and rankings correspondingly, in order to produce recommendations for the researchers. In spite of this, it is inevitable to incorporate scholar's contextual information and sequential access behavior into recommendation procedure to generate accurate and personalized recommendations for research papers. Conventional recommender systems do not incorporate such information in the recommendation procedure to compute similarities of scholars and provide recommendations; thus, they are more liable to produce irrelevant list of recommendations in a scholarly environment. Moreover, conventional recommendation approaches generate inaccurate recommendations in presence of high level of sparsity in the rankings. In this article, we introduce a novel method for research paper recommendations that incorporates the benefits of collective filtering (CF), context-awareness, and sequential pattern mining (SPM) to propose research papers to scholars in a hybrid manner. Context-awareness in our methodology involves the scholar's contextual state, such as skill level and research goals; SPM is used to mine weblogs and reveal sequential access actions of scholars; and CF is used to measure predictions based on correlations between scholars and generate context-aware and sequential trend mining based recommendations for the targeted scholars. Experimental evaluations of our approach indicate the excellence of our approach over other baseline approaches in terms of precision, recall, F1, and mean absolute error (MAE).

Keywords: Research papers, Context-awareness, Recommendation approach, Hybrid recommendation, Collaborative filtering, Sequential pattern mining

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## NTRODUCTION

Digital libraries are striving to provide appropriate search results to Scholars, concerned with their interests. In this scenario, digital libraries are acquiring an abundance of academic resources, which is rising up consistently and may generate inappropriate recommendations going beyond the data limits [1]. Although, conventional recommender systems yield an enormous aggregate of appropriate and inappropriate

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results to regular keyword-based searches [2] concerning with the interests of Scholars. Apparently, traditional recommender systems are punier to recommend most suitable research resources to the scholars which may cause wackness emanating from irrelevant results due to the cold-start problem [3-5] and ranking sparsity problem [6,7]. To elucidate this issue, several recommendation methods [8,9,18-24,10-17] have recently appeared to provide Scholars with more appropriate and suitable results. These recommendation methods sort out results according to the interests of Scholars by filtering appropriate and inappropriate results. While, in the last decade, a slew of studies on Recommender Systems have been conducted in a number of domains, including e-commerce, e-health, information management, and elearning. [25].

The abundance and the consistent vehemence of volumes of information over the scholarly websites necessitated such approaches that yield convenience for the scholars to acquire the most relevant information and accelerate the resource filtration process [26]. Although there is a plethora of techniques the scholars exploit to access their personalized contents, for instance, they can access their personalized contents just by typing some specific keywords, while they prefer to acquire their personalized contents immediately and automatically without any hurdle. However, the traditional recommender systems occasionally misfit on their demand and scholars ruin a lot of their time just in searching for their relevant contents. Thus, the anticipation of appropriate results is a noteworthy component of a digital library in the ecosystem of research resources. Meanwhile, digital libraries are utilizing intelligently personalized recommender systems [27] to assist users by providing appropriate research resources according to their interests and partialities [28]. Recommender Systems can control the excess of information via filtration and customization of data to the users' necessities [29,30]. Thus recommender systems usually accumulate data about the activities of users on the website and create user models to filter out the partialities of users extracted either directly or indirectly [31].

Since the past few years, recommender systems are utilizing such an information that portrays the contextual state of the user with the intention of producing more appropriate and customized recommendations [32,33]. Such information comprises demographics (name, age, email, gender etc.), in addition to context and contextual informational material such as cognitive processes, topics, and research goals [34]. For further understanding, we can explore this through an example, the recommended research resources to a postgraduate master's student looking for "hybrid method" for his final thesis may differ from those resources that are recommended to a postgraduate doctoral student for his Ph.D. dissertation on the same subject. The logic behind it is that they are looking for different requirements according to their tasks, research goals, and their educational level.

The contextual information is deliberately considered the major source of exactitude among recommender systems [32,35]. Researchers are accentuating to utilize contextual methods for the recommendation of items to users in particular conditions [33,36]. Another approach to handle this issue and to provide appropriate recommendations to the users is web personalization [37]. In the web personalization, previously accessed behaviors of the users during web surfing are modeled then the obtained knowledge is utilized to predict the access behavior of a present user to assist personalization [38]. Several conventional approaches for recommendations, such as CF [39,40] and content-based CF [41,42] are introduced in the past two decades. Moreover, the weblog mining approaches are utilized in recommender systems such as Association Rule Mining (ARM) [43,44] and Clustering [45,46] that derive usage patterns from the weblogs or web servers matching with the interests of users. Although, Sequential Pattern Mining algorithms [47-49] are more suitable for the prediction of next pages on the web as compared to the clustering and ARM [38].

In this study, we presented a hybrid approach that combines both Sequential Pattern Mining and Contextaware recommendation algorithm to generate a new recommender system for research papers' recommendations. The implications of this study illustrate the hybridization of collaborative filtering with contextawareness to integrate contextual information of the scholar in the recommendation process, while SPM algorithm is mongrelized with collaborative filtering to mine weblogs and disclose the sequential access patterns of the scholar. The novelty of this study that discriminate it from past studies comprise:

To produce more tailored recommendations, we first introduce the scholar's context-awareness and sequence access trends into the recommendation process. Contextawareness is used to incorporate the scholar's contextual data, while sequential access patterns are used to filter the recommendations correctly.

Further, to compute the similarity of research resources, we seize the contextual information of the scholar into account to boost up the prediction accuracy.

Finally, we explain the excellence of our recommendation approach joining CF, CA, and SPM via practical implications that our approach outperforms other related approaches in terms of accurate recommendations.

Though, the rest of this study is ordered as follows. Section 2 of this study discloses background information of recommendation techniques, subsequently the section 3 portrays related work to our study, while section 4 demonstrates recommendation paradigm and the hybrid approach, though, in section 5 we provide the practical implications of our approach, and finally, in section 6 we extract conclusion and the future work of our study.

## BACKGROUND

Recommender systems have substantial rank as a solution in Research Papers' recommendations to overcome information-excess trouble. All they are categorized according to those practices that are used in the field of recommendation. Burke [50] and Jannach et [51] discriminated recommendation al. several approaches including collaborative filtering, hybrid recommendation approach, and recommendation approaches based on demographics, knowledge, the contents, and utilities. Furthermore, some contemporary recommendation practices include Fuzzy-Based recommendation approach, Ontology-based [52], Context-aware based [53,54], Trust-awareness based [55], and Social Network-based [56] recommender methods. In this segment, we impart a succinct overview of those recommendation methods that concern to our study.

## COLLABORATIVE FILTERING

Goldberg et al. [57] initiated the term "Collaborative Filtering" in 1992 and stated that "information filtering can be more effective when humans are involved in the filtering process". In simpler words, an approach through which we recommend academic contents to the current scholar on behalf of the past experience of other scholars having the same interest is called collaborative filtering. Compared to the content-based filtering approach, collaborative filtering provides three benefits: 1) content independent [58], [59], [60], 2) quality assessment [61], and 3) serendipitous recommendations [60]. The likeliness of two distinct users is estimated on the foundation of likeliness corresponding to the past-ranking experience of the users [59,62]. A rank determines the interest-level of the scholar for some specific contents. The principle behind CF is the calculation of likeliness between two distinct items or searchers. In this setting, the K-Nearest Neighbor (KNN) is broadly exercised algorithm for CF [3,63]. Fig. 1 demonstrates the recommendation procedure in CF. Collaborative Filtering associates with searchers and entities. We can express a Rank function in a conventional Collaborative Filtering RS as follows:

#### R: Scholar \* Content $\rightarrow$ Rank



Figure 1. Process CF Recommender.

Table 1: Rank matrix for CF				
	Entity 1	Entity 2	Entity 3	
1 <sup>st</sup> scholar	4	5	?	
2 <sup>nd</sup> scholar	1	3	5	
3 <sup>rd</sup> scholar	5	5	3	
4 <sup>th</sup> scholar	3	4	5	
5 <sup>th</sup> scholar	4	5	4	

Since they deliberate only the Scholar and Content aspects in their recommendation practice, thus this ranking function is two-dimensional (2D). The conventional recommendation dilemma entails the approximation of ranking of entities that the client has not checked yet [54]. Table 1 demonstrates the illustration of a 2D ranking matrix. 1st scholar's rank of entity 3 can be forecasted/predicted on the basis of 1st scholar's likeliness to other scholars in the respect of their rank of entity 1 and entity 2.

However, CF is the most trendy Recommendation technique [64], its major problem is, it results in a drawback when new clients and new entities are added [5,65]. This new client and new entity drawback trouble are usually stated as cold-start recommendation problem [5], [4] that happens in those cases where it's impossible to provide consistent recommendations because of the deficiency of preliminary ranking for latest entities and clients [3], [59]. Further weaknesses accompanying to CF comprise sparsity and scalability problems. Data sparsity is associated with the absence of overlapping in ranking partialities due to the ranking of some clients on the similar entity.

### 2.2 Hybrid Recommendation Approach

The hybrid filtering approach for recommendations mongrelizes the attributes of dual or multiple recommendation approaches, for instance, CF and CB recommendation approaches to acquire assistance from the strengths of both practices and get better performance [66], [67]. Hybrid Recommendation Approach is very worthwhile since it is capable to overthrow most of the constraints experienced by distinctive recommendation techniques. Past researches on recommendation systems have exposed the significance of Hybrid Recommender System and stated that joining diverse recommendation approaches provides enhancement, improvement, perfection, and expansion in performance [67–69].

Table 2: Rank	Matrix in C	ontext-Aware Recon	nmendation
Approach			
Scholars	Object	Expertise Level	Ranking
1 <sup>st</sup> scholar	$J_1$	Beginner	5
2 <sup>nd</sup> scholar	$J_1$	Superior	3
3 <sup>rd</sup> scholar	$J_1$	Beginner	5
4 <sup>th</sup> scholar	$J_1$	Intermediary	?
5 <sup>th</sup> scholar	$J_1$	Intermediary	4

#### 2.3 Context-Aware Approach for Recommendations

Dey et al. [70] stated that 'context' signifies some information used up in the classification of the state of an object. An object might be a place or any other entity that is deliberated to be significant to the collaboration between end-users and applications, also it comprises both the end-users and applications. The scholar's qualitative knowledge in this section of the study contains his or her level of competence and goals. As the apprentice receives more knowledge, these qualitative properties change according to the circumstances. On the basis of the context used in that particular area, the context-aware recommendation approach delivers suitable, relevant, and correct recommendations to a specific searcher. [71]. In the setting of context-aware, the ranking is demonstrated as a function of searchers, entities, and context; thus, the rank function preserves to be expressed in three dimensions (3D) as follows:

## R: Scholar \* Content \* Context $\rightarrow$ Rank

In the above 3D representation, Scholar and Content relate to the domain of Searchers and Entities, while rank relates to the field of rankings, and Context is the circumstantial knowledge linked with the application [54]. The ranking dimension of Scholar was lengthened with the intention of combining context dimension which might be helpful in the personalization of suggestions/recommendations corresponding to the context of the user. Table 2 portrays the example of a rank-matrix in the consequences of the Context-Aware recommendation approach along with expertise level as context.

Several aspects of searching in CA recommendation approach can influence the partialities of a scholar, the ranking marked by the scholar, likeliness, and expectation/prediction for the targeted scholar. Such as, the Expertise-level context of a 1st scholar in Table 2, changes from Beginner to Intermediary that can impact the rank of research properties. Using contextual likeliness of other scholars, we can predict the rank of a 1st scholar for item J1 whilst changing the context of expertise-level from Beginner to Intermediary. Enclosing the context of the scholar into the practice of recommendation would help to enrich the personalization of recommendations to the targeted scholar.

We can acquire the contextual information directly, indirectly or across deducing the context [54]. The direct approach includes manual or physical input from the searchers, on the other hand, an indirect approach for contextual/circumstantial information is captured spontaneously from the surroundings. We can also deduce contextual information by the means of data mining or some other statistical approaches [54], [72].

There are three models to incorporate contextual information into a recommender system, these are a namely contextual model, pre-filter contextual model and post-filter contextual model [54].

In a pre-filter model of the context, we can pick out and assemble the appropriate set of data, entries or rankings using the current contextual information denoted as c [54]. Afterward, the rank can be anticipated by the means of any conventional two-dimensional (2D) recommendation approaches on a particular set of data [72].

## 2.4 Research Paper Recommendations based on the Context-Awareness

Context-Aware recommendation approach in Research Studies recommends academic resources to the scholars on behalf of the existing context of the scholar. Accumulation of contextual information of the scholar into the recommendation procedure assists more precise, appropriate, and suitable recommendation of the digital library's resources to the scholars with parallel rankings according to the context of the scholar. The aptitude to integrate further contextual information into recommendation procedure constructs hybridized contextaware recommender models those are more specific to the partialities of the scholar.

#### 2.5 Sequential Pattern Mining

In 1995, Agrawal and Srikant [73] introduced some set of rules of exploring all subsequences that seem frequently in the sequence database we provided with, called Sequential Pattern Mining (SPM) [74,75]. A sequence is well organized set of items. Basically, SPM algorithm mines the databank containing sequences seeking iterative patterns (common sequences) that are useable for concluding the bond amongst all the subordinates in data for appropriate recommendations. Generalized Sequential Pattern (GSP), Free Span, SPADE and Prefix Span are the most commonly used algorithms to deploy SPM [75]. In GSP, mining is originated on Apriori's principle where child subsequence generation and test techniques are employed to extract the progressive pattern [73][76]. According to Apriori's principle, "All nonempty subsets of a frequent item-set must also be frequent" [75]. Eventually, GSP minimizes the inquiry zone by trimming it that is valuable to some

extent because GSP also loses its efficiency upon big data (a vast database). Spade is another procedure that performs mining operations by expanding the subsequences of a specific entity at once by Apriori candidate generation principal [77]. It decomposes the search zone into sub-lattices that can be managed autonomously in RAM. It's a better technique for sure but is fruitless for mining ongoing sequential configurations. Conversely, one more prediction based quarrying algorithm is available called PrefixSpan.

Firstly, it examines the entire database (forecasted) to find repeated sequences and count them. After it, PrefixSpan scans merely the prefix subsequences along with their corresponding postfix subsequences [78]. It just counts the occurrence of an item or items by using "divide and conquer" strategy without generating any candidate. Its only drawback is the formation of a proposed database [76]. FreeSpan classifies the database and subdatabases based on an anticipated set of items and then mines [78]. At the start, it generates f-list (frequency item list) from listed iterative sequences in the database and then models a trilateral matrix of concerned sequences that is valid for small projections. However FreeSpan may create various deep projections and if the estimated database contains high occurrence, it can't be shrinkable [75].

By reviewing all these systems, it is clear that GSP is more reliable and efficient than Spade and FreeSpan in the performance race. Even though PrefixSpan has better execution time and memory usage than GSP but the blend of Apriori towards GSP makes it matchless [74,75]. We implemented GSP in our area due to its small execution time (negligible) for moderate-sized sequence databases. Furthermore, as stated by [79,80] the GSP algorithm is capable to capture all possible subsequences even omitted a single one. Hence, it is appropriate for practice in Research atmosphere due to its great precision.

#### **RELATED WORK**

Kiyoko Uchiyama et al. [81] presented a first Japanese research paper recommender system that recommends international research articles just by typing Japanese keywords into a search engine. They utilized two approaches in their system: 1) Keyword-based and 2) Author-based approaches to select a seed paper. Their hybrid approach mongrelizes CF as the author-based and Content-based approach as a keyword-based approach. They ensured the effective and the efficient retrieval of the required research papers by the user who expects to get the appropriate results. Although they could not maintain the cold-start problem properly in their study, so they considered expanding their study in future to handle cold-start problem entirely. Qi He et al. [82] designed a new non-parametric probabilistic paradigm to measure context-based consequences concerning with the context of citation and document. They developed a contextaware recommender prototype for CiteSeerX digital library. They approved the efficiency and the scalability of their paradigm by massive assessment in CiteSeerX digital library. Basu et al. [83] presented a recommender system that extracts the profile of the reviewer from the web and recommends conference paper submissions to him on the base of abstracts of the papers and the profiles of the reviewers. This is an essential step towards a most generic issue identified as Reviewer Assignment Problem (RAP) by the Wang et al. [84].

Shaparenko and Joachims [85] intended а recommendation approach using convex optimization and language modeling for the recommendation of research documents. In the case of the large corpus, their system retrieves k-most related research documents on the base of cosine similarity index. Although, in the large digital libraries, the relativity measurement on the behalf of the full text is a time-consuming task. Chandrasekaran et al. [86] portrayed an approach for the recommendations of the technical papers which utilizes the publication record of the user and generates a model of his profile. All this profile information is stored in CiteSeerX library and the system recommends technical papers to users according to their profile information. The profiles of users and documents appear in a classified concept tree with already explained notions from the Computing Classification System of the ACM. Their approach calculates the similarity between the profile and the document via weighed tree edit distance. In our study, the contextual information can also be realized as profile information of the user. Although, our system utilizes more appropriate and stronger information as compared to predefined notions in the previous study. Strohman et al. [87] composed a citation recommender system for academic research studies. They combined text attributes and citation graph attributes linearly in their recommender system to determine the relevance between two documents. Their conclusion illustrates that likeliness between citations and Katz distance [88] is the most significant attribute.

Nallapati et al. [89] presented a recommender paradigm known as Pairwise-Link-LDA that demonstrates the appearance or disappearance of the relevance between each couple of documents. Thus, their approach is not scalable for outsized digital libraries. They also presented a simpler recommendation paradigm alike to the paradigm of Erosheva et al. [90], and Cohn and Hofmann [91]. Joeran Beel et al. [92] surveyed a literature on research paper recommender systems. In their study, they reviewed 62 recommendation techniques and concluded that 55% techniques utilized content-based filtering for the recommendations of research papers. They stated that the only eleven techniques focused on collaborative filtering and all of them couldn't utilize explicit rankings effectively. Yang et al. invented such a system for the recommendations of research papers, although their searchers were "too lazy to provide ratings"[93]. Beel et al. [92] portrayed that the mainstream (71%) of all techniques were weighed via offline assessments that are not a good approach according to some studies [19]. The closing remarks, they surveyed the different recommendation classes comprising recommendations, stereotyping, co-occurrence collaborative filtering, graph-based recommendations, global relevance, content-based filtering, and the hybrid recommendation techniques.

Zohreh Dehghani et al. [94] systematically reviewed recommender systems on the base of scholar contextawareness. They discussed two main categorized techniques for recommendations, classical and contextual techniques and the results of their study portray, contextual information utilized in digital libraries is basically classified into three groups, comprising the user, the document, and ecological contextual information. Franke, Geyer-Schulz, and Neumann [95] surveyed recommendation services for digital libraries in 2008. They cataloged a small number of recommender systems exploited in digital libraries, while they observed that a few

recommender systems such as CiteSeer and Amazon didn't have excellent digital libraries; thus, they were omitted. Furthermore, IEEE Xplore and ACM have not presented their recommendation methods utilized in their Recommender systems, thus, their study is limited to address them. Their survey portrays, scientific recommender systems absolutely have substantial advantages for researchers as well as for students, although they are not valid in digital libraries due to the current social trend towards recommender systems. Sean M. McNee et al. [96] mainly focused on four recommendation algorithms to deal with the domain of research at libraries and to avoid pitfalls: 1) Naïve Bayesian Classifier, 2) User-Based Collaborative Filtering, 3) Probabilistic Latent Semantic Indexing (PLSI) as collaborative algorithms and 4) Textual TF/IDF-based approach. Pitfalls are the traps where recommender systems get stuck and don't provide appropriate recommendation results. They surveyed humanrecommender interaction to evaluate the satisfaction level of humans towards recommender systems and performed the user study in depth to comprehend the differences among recommender algorithms. Over 130 users participated in their online survey of research study recommendations from the ACM DL. Their study results suggested that a suitable algorithm must be selected for a specific domain and information seeking of the user.

Roberto Torres et al. [58] used a hybrid method combining collaborative filtering and context-based algorithms to develop a recommender system for research papers. They experimented with their algorithm via both online and offline resources, on the dataset of 102,000 research studies obtained from the repository of research papers from the computer science section of the CiteSeer digital library as an offline resource and 110 American and Brazilian users of the web interface of their recommender system as an online resource. They concluded that the hybrid approach performs better than an individual algorithm. Bahram Amini et al. [1] intended to propose a framework to incorporate the background information of the scholar and investigated the significance and the usability of the background information in a digital library. They used the terminology 'frequencies' as an ontological paradigm for the background information of the scholar and to enrich the

notions in the notion hierarchy, they utilized ODP and WordNet. Their hierarchical paradigm of background information provides the comfort to calculate notion similarities along with the updation of ontology. They experimented with the small number of scholars via CiteSeerX and portrayed good enough improvements in the term of precision utilizing background information of the scholar. Dean et al. [97] presented a study that illustrates NCore an open source software platform, shows and examines its design, instruments, and packages. The architecture of NCore is used to create flexible and cooperative digital libraries.

Zohreh Dehghami et al. [98] investigated contextual information having an influence on the procedure of making the decision and the selection in the RSs of Digital Libraries. They followed up a grounded theory to carry out semi-structured interviews, while the scientific research ground (SRG) framework is the core idea of their study. The SRG framework locates users in an assortment of circumstances during the interaction with information systems. As their study deals with circumstantial information in an academic context and scholarly contextual information can't be simplified to RSs in other fields such as e-commerce. Marko A. Rodriguez et al. [99] presented KReef RS that is context-sensitive in terms to sustain the academic communication process. KReef upholds a resource-rich and graph-based model to academia, including articles, conferences, people, funding opportunities, journals, calls, organizations, etc., and the variety of their associations with one another. Wan-Shiou Yang and Yi-Rong Lin [100] combined common-citation analysis, information repossession, and co-author affiliation evaluation methods with a CiteRank algorithm to find out appropriate and prime articles. Overall, they designed nine methods to propose task-focused article RS and collected usage logs from the author's experimental server and downloaded articles (2000 to 2006) from CiteSeerX to test these nine variants of their proposed approach. In their study, their intended Content-Citation methodology overtook the Relevant-citation count, Relevant-CiteRank, and Relevant-only methods. As they accumulated articles from 2000 to 2006, the aging effects might be observed with time.

A study [26] addressed a novel fuzzy linguistic Recommendation System that assists in gaining the

performance of the searcher to describe his profile. They permitted users to impart their partialities via imperfect fuzzy linguistic partial relationship. They encompassed tools to supervise inadequate information during the provision of the user's preferences, and, in that's way, they improved the acquisition of the user profiles. Some measurement techniques have been utilized by the recommender systems for research papers [101-103] such as index h [104], bibliographic coupling [105], and co-citation [106] approaches. Other related studies on this field comprise recommender system for educational digital library [107], academic notifying services [108], automatic accumulation of academic studies [109–111], expert research [112], research discoveries via recommender systems [113,114], academic events recommender system [115], venue recommendations for research papers [116], patent citation recommendations [117], and recommendations for research datasets [118].

The hybrid recommender paradigm shown in figure 2 demonstrates an architectural view of functionalities of our hybrid recommender approach. As shown in Figure 2, the main working areas of recommendation paradigm are scholar profile, a research object model, contextualized data arrangement, CF research recommender engine, the SPM algorithm, and contextualized recommendation modules. In this sub-segment, we illustrate the functionalities of these major working areas of the paradigm.

The scholar profile module accumulates and saves informational material and partialities about the scholar. Informational material stored in scholar profile is fetched by the means of both direct and indirect approaches. The data of scholar such as individual demographics (name, age, email, gender etc.) in addition to context and contextual informational material such as cognitive processes (conceptual, factual, procedural, and meta-





## 4 Recommendation Paradigm and our Hybrid Algorithm

We present a hybrid recommender approach in our study that unites CA, CF and SPM algorithms for the recommendation of research papers. This segment of study portrays the recommender paradigm (Figure 2) and likewise illuminates how this hybrid recommender approach actually works in this scenario.

4.1 The recommender paradigm for the recommendation of research resources

cognitive), topics, and research goals (understand, remember, apply, analyze, evaluate and create) [34] among others are accumulated in scholar profile. Our proposed hybrid recommendation system operates the contextual data to personalize the scholar's profile and preferences. In the same way, the research object model comprises informational material about research sources. This module keeps data about research resources that contain the format of research resources which is usually text and image. Research resources would be suggested to the targeted scholar on the basis of a scholar's rating on research resources and relative information.

In the contextualized data arrangement module, weblogs are being clean-up, the data of the scholar's contextual and contextual information and research resources are prepared into an appropriate format for further assessment using the recommendation system. Afterward, the research recommendation engine module investigates the contextualized data resulting from the collection of the scholar's partialities, the information of context, and the ranks. Using contextualized data, the CF Research Recommender Engine calculates the likelihood and predicts rankings for the targeted scholar captivating the importance of the scholar's context. Thenceforth, the CF research recommender engine composes top Z recommendations of research resources on behalf of contextualized scholar's partialities.

In the next module, the SPM algorithm stands for Sequential Pattern Mining algorithm. The SPM algorithm used in our recommendation paradigm is responsible for weblogs mining to determine the scholar's sequence access patterns for the targeted scholar. Afterward, these patterns are applied to the top Z recommendations outcomes, to sort out recommendations consistent with the scholar's sequence access patterns. At the end of the day, the targeted scholar obtains pure contextualized recommendations based on the context, contextual knowledge, and sequence access patterns of the scholar.

#### 4.2 Hybrid Approach Taking into Practice

The hybrid recommendation method presented in this paper outlines three main phases of the recommendation: 1) the incorporation of context c into the recommendation procedure using a pre-filtering contextual method, 2) the estimation of the likelihood of the scholar and the prediction of the ranking of study tools on the basis of contextualized results, and 3) the output of the top Z contextual recommendations for the targeted scholar and the use of the SPM algorithm for the findings to figure out the final recommendation. Each of these three steps are graphically visualized in the recommendation model seen in Figure 2 and listed in detail in this section.

## 4.2.1 Integrating contextual information into the recommendation system

In order to incorporate contextual knowledge (Figure 2) into the recommendation framework, we have followed a contextual pre-filtering approach[54]. Using background

pre-filtering, we can quickly integrate with any traditional recommendation method. In this sense, one element of the gualitative knowledge of the scholar is the extent of competence. The level of expertise is used as the background factor in the hybrid methodology of this analysis and varies over time and situations as the level of expertise of the scholar increases. For example, a scholar with a little bit of specific experience in a specific subject area might have an early level of expertise as a context. However, if a scholar gains more experience over time, the expert-level background of the scholar may shift to the intermediary. Main contextual details on the degree of competence shall be collected during the registration of a new scholar. At the time of enrolment in the recommended system, a new scholar is tested with certain online appraisal questions to decide the level of competence of the scholar on behalf of the obtained test score. The technique for collecting the data concerned with a scholar's level of knowledge has also been used [119]. Subsequently, the suggested framework updates the scholar's profile, and then periodically, by performing the online information level examination, maintains a database of the scholar's qualitative level of expertise.

Contextual data are utilized to compute scholars' similarities and to predict rank of research resources by the targeted scholar. For further understanding, just consider Table 2 (which is previously discussed in section 2) as an example, to recommend the research resources to a targeted scholar whose *expertise level* = {intermediary}, for the calculation of rank likeliness and predictions the system will consider the contextual information of only those scholars whose expertise level is similar to the targeted scholar as *expertise level* = {intermediary}.

For the sake of calculation of contextual data and to utilize them by our recommender system, we classify the context of *expertise level* with three distinct values as follows:

# Expertise level = {beginner, intermediary, superior} = {0, 1, 2}

According to this classification, these assigned values {0, 1, 2} to the elements of *expertise level* are utilized to determine contextual rankings.

4.2.2 Determining similarities of research and

#### calculating predictions of research resources

At the first level, contextual information is acquired by the recommendation system. Afterward, using *research recommender engine* component (see fig. 2) further computation is performed on contextual information i.e. similarities of scholars and predictions of rankings of research resources. Though, for the calculation of similarities of rankings, the system accumulates contextual information into account scholar's account. In this study, we exercised the *Pearson correlation coefficient* to calculate similarities between two those different scholars [51] who have the same *expertise level*. Contextual similarities Sim ( $C_s$ ,  $C_u$ ) between the targeted scholar s and scholar *u* is computed as follows (Eq. 1):

$$Sim(C_{s}, C_{u}) = \frac{\sum_{a=1}^{n} (R_{s,a} - \overline{R_{s}}) (R_{u,a} - \overline{R_{u}})}{\sqrt{\sum_{a=1}^{n} (R_{s,a} - \overline{R_{s}})^{2}} \sqrt{\sum_{a=1}^{n} (R_{u,a} - \overline{R_{u}})^{2}}} \dots (1)$$

Where  $R_{s,x}$  is the ranking provided to the research resource x by the targeted scholar s and Rs is the mean rank of all the rankings delivered by the targeted scholar s on the basis of contextual information of scholar.  $R_{u,x}$  is the ranking provided by the scholar u to the research resource x and Ru is the mean rank of all rankings delivered by the scholar u on the basis of contextual information of the scholar, while n is the sum of the numbers of the research resources. Disparate of CF, contextual knowledge is used to calculate the rank and the mean rank.

To calculate the expectations of contextual rankings of research resource y for the targeted scholar, the KNN (k nearest neighbors) method is used for those scholars who are acquired in Eq. 1 with the highest similarity index and ranked the research resource y [51]. The goal of this study is to calculate a prediction of the rank  $R_{s,y}$  by the targeted scholar s for a new research resource y utilizing the ranks provided by other similar scholars (nearest neighbors) to y. To calculate the predicted rank  $P_{s,y}$  of research resource y by the targeted scholar s, we exploit formula in Eq.2 for the predictions [51]:

$$\mathsf{P}_{\mathsf{s},\mathsf{y}} = \overline{R_s} + \frac{\sum_{u=1}^n (R_{u,y} - \overline{R_u}) \times Sim(C_s, C_u)}{\sum_{u=1}^n Sim(C_s, C_u)} \dots (2)$$

Where Ps,y portrays the predictions for the targeted

scholar s for the research resource y, Rs has been discussed in Eq. 1, n symbolizes the overall quantity of scholars in the region, Ru,y is the rank rated by the scholar u to the research resource y, and Sim(Cs, Cu) indicates the contextualized similarity between targeted scholar s and scholar u.

## 4.2.3 Making contextualized recommendation results and the SPM algorithm application

According to the scholar's sequential access patterns, GSP/SPM algorithm is used for the production of the contextual recommendations to the top Z to filter out top Z research recommendation outcomes. In this study, to make suitable and efficient recommendations for research resources we preferred the GSP algorithm. The top Z research recommendations of research resources for the targeted scholar s are produced on the basis of contextualized resemblances or similarities of scholars predicted rankings. All the procedure of and recommendations is demonstrated in algorithm 1 where N is a set of research resources  $\{x, y\}$  and research resource x has been ranked by the targeted scholar and the research resource y denotes unranked research resources by the targeted scholar whose predictions of ranks are being pursued. C denotes context which is named as expertise level in this study. The expertise level has three elements which are {beginner, intermediary, superior} and symbolized by three distinct digits {0, 1, 2}. Rs,x represents the rank of research resource x by the targeted scholar s, while Ps,y denotes predicted rank for the unranked research resource y by the targeted scholar s. Other scholars which are symbolized by the character u have ranked research resource y. When the top Z recommendations have been acquired, we apply the GSP algorithm on the output of the recommendations to filter out top Z research recommendations based on the scholar's sequential access patterns. Algorithm 1 portrays the complete process of producing the final output utilizing the GSP algorithm.



Rankings

R c {1, 2, 3, 4, 5}

Output

Prediction of Ranks, Finalized results of hybrid approach, top Z Approach

1: Starting:

2: s є S, u є S, x є N, y є N

3:  $u = u_1, u_2, u_3, \ldots, u_n$ 

4: **for** (j = 1; j <= n; j++) **do** 

5: calculate targeted scholar's contextual similarity Sim ( $C_s$ ,  $C_u$ ) using Eq. 1

#### 6: end for

7: Predict rankings  $P_{s,y}$  for the targeted scholar *s* for unranked item *y* using Eq. 2

8: produce *top Z* contextual recommendations

9: Employ GSP algorithm on *top Z* 

10: The ultimate recommendation output for the targeted scholar *s* 

Determining all sequence access patterns using the GSP algorithm includes three major levels:

- 1. Discovering the support of each research resource (level one)
- 2. Producing all possible frequent sequences (contender sequence production)
- 3. Deleting all those sequences that have a lowest support count level than the minimum (pruning level)

In research resource recommendations, the sequence access patterns of the scholar are significant and should be deliberated in the process of recommendations. Thus, the GSP utilized primary top Z recommendations to filter out recommended outcomes in accordance with the sequential research patterns of the scholar. The ultimate contextualized recommended outcomes to the targeted scholar are dependent on both the contextual state and the sequence access patterns of the scholar.

## EXPERIMENTS AND EVALUATIONS

### 5.1 The Experiment process and Dataset

A chain of tests has been performed to test the efficiency of our hybridised recommendation methodology (GSP-CA-CF). For experimental purposes, a real-world dataset was obtained from a public university research library. For the span of 4 months from October 2020 to January 2021, the overall number of scholars who used

the digital library for their scholarly purposes during the experiment was 250. The digital library helps academics to list study services on a scale of 1–5 (1–most unrelated, 2-fairly unrelated, 3-unrelated, 4-related, 5-most related). Our recommendation methodology is capable of proposing research resources to academics by relating their bias and historical background. Primary qualitative knowledge (level of expertise) has been collected by a scholar's registration process in the digital library and is also revised on an intermittent basis when a scholar uses the digital library to retrieve online research materials. The primary background of the scholar's history, level of expertise, changes regularly and situationally as the scholar's profile progresses towards improvement. A scholar's level of expertise may shift to a novice, an intermediate or a superior, depending on the situation. When gathering datasets, the ranks of scholars and the past history of scholars have been derived from the recommendation framework database, and sequence access patterns have been achieved through mining weblogs through the application of the GSP algorithm. In addition, for experimental calculation purposes, the dataset was broken down into an traning subset (80 per cent) and an test subset (20 per cent) as defined in Table 3. In order to validate the efficacy of our hybrid recommendation method, three additional algorithms (GSP, CF, and CF-CA) were evaluated using the same data set as seen in Table 3 and their results were compared.

Table 3: The description of the dataset.				
No. of	No. of	No. of	Context-	Rank-
Scholars	RR	Ranks	Scale	Scale
250	467	20153	1 – 3	1 – 5

### 5.2 Outcomes

The leading motive of our study was to invent a hybrid recommender approach on the base of CF, CA, and SPM algorithms for the recommendations of research resources in the ecosystem of digital libraries. In this subsection, we intend to impart experimental analysis consequences and the assessment measures to evaluate the performance and efficiency of our invented hybrid recommendation technique (GSP–CA–CF).



Figure 3. The accuracy of neighborhood size



Figure 4. Prediction quality against sparsity.

#### 5.2.1 Experiment on Accuracy

A set of experimental activities were carried out while fluctuating the neighborhood sizes to bring about an optimal size of the neighborhood for appropriate outcomes to be utilized in consequent experiments. size Meanwhile. the of nearest neighbor in recommendation approach significantly influences both prediction accuracy and eminence of recommendations [120]. Likewise, a chain of experiments was conducted to evaluate the prediction accuracy for the all 4 methods with various sizes of neighbors and the prediction accuracy was evaluated by the means of MAE (Eq. 3) which implied the higher prediction accuracy when it has the lower value.

MAE = 
$$\frac{1}{n} \sum_{i=1}^{n} |p_i - r_i|$$
 .... (3)

In the given equation, n symbolizes the total of cases in the chain of the experiment, pi indicates predicted rank of an item while ri represents the actual rank [121]. Figure 3 expresses the sensitivity of neighborhood in terms of size and the prediction accuracy against the size of near most neighbor for all 4 methods evaluated using MAE (fig 3).

Figure 3. illustrates that by the time as we intensify the neighborhood numbers from 5 - 20 the prediction accuracy of our hybrid technique (GSP - CA - CF), in addition with other approaches (CF-CA, GSP, and CF), increases and acquired the optimal accuracy of prediction at the number of 20. Subsequently, the representative curve of all four algorithms (GSP- CA-CF, CF-CA, GSP, and CF) sets up to mount at minor intervals; henceforth, the tendency of the accuracy of recommendation techniques descends since the quantity of neighbors exceeds the value of 20. Thus, we nominated 20 as the optimum size of the neighborhood for the remaining tests. Moreover, it can also be perceived from fig 3 that our hybrid approach delivers better accuracy as compared to the other three algorithms at the point of any near most neighbor.

#### 5.2.2 Experiments of various sparsity levels

An experiment was carried out to test the effect on the precision of our hybrid recommender method of the different sections of sparsity. The experiment was done using the size 20 of the neighbourhood and was the optimal value for the neighbours. The initial sparsity of our data is 82.74% and Figure 4 indicates the results on the statistical performance of sparsity.

Results from Figure 4 reveal that in contrast to three other recommendations, the hybridised recommendation method (GSP-CA-CF) has the lowest level of MAE at all levels (CF-CA, GSP, and CF). The MAE of GSP–CA–CF and CF-CA and CF algorithms are also growing as the degree of sparsity grows. In comparison, during the steady improvement in sparsity, there was a small variation in MAE in the GSP algorithm. Therefore, Figure 4 shows that our hybrid recommendation method defeats

three other prediction algorithms at all points of sparsity.

#### 5.2.3 Performance measurement

The aim of our hybrid approach to digital libraries is to educate scholars on valuable, supportive, advantageous and useful research resources. We have been using the F1 estimation accuracy and recall measurements to test the recommendation efficiency of our hybrid solution (GSP-CA–CF).

Three other recommendation approaches, Cf-CA, CF and GSP, were tested by us by F1 precision and recall and compared our hybridized recommendation methodology (GSP-CA–CF) with three other recommendation techniques. Precision and recall were easily processed using the confusion matrix in Table 4.

Table 4. Confusion matrix			
	Recommended	Not Recommended	
Retrieved	True Positive (tp)	False Negative (fn)	
Not Retrieved	False Positive (fp)	True Negative (tn)	

While processing with precision and recall measures, research resources were ranked in accordance with the scale of 1-5, further, research resources ranked 1-3 were deliberated "irrelevant" while the research resources ranked 4-5 were marked as "relevant". Precision is the quotient of recommended research resources to the sum of selected research resources [64,122].

$$Precision = \frac{Recommended \, Research \, resources}{total \, research \, resources} = \frac{tp}{tp+fp}...(4)$$

In the other hand, recall is the quotient of research services adequately recommended for the most important research resources [64,122].

$$\operatorname{Recall} = \frac{\operatorname{Properly} recommended research resources}{\operatorname{Most} related research resources} = \frac{\operatorname{tp}}{\operatorname{tp} + fn} \dots (5)$$

Table 5 illustrates the performance measure of our presented hybrid recommender technique (GSP–CA–CF) with the comparison of other approaches, respectively GSP, CF, and CF-CA, regarding the precision and recall for several figures of recommendations.

From table 5, it is obvious that our hybrid recommender technique (GSP–CA–CF) beats all three other techniques in the context of precision and recall measures together at any point of recommendation. The values of precision and recall, correspondingly, of our hybrid recommender approach, are given bolded in the last two columns. It is also noticeable that the increased number of recommendations decreases the values of precision for all the evaluated algorithms in Table 5.

F1 measurement matrix unites precision and recall together into a unit of value for the comfort of assessment, in addition, to acquire a stable vision of performance [120]. The F1 measure equalizes both precision and recall.

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \qquad \dots (6)$$

Figure 5 portrays the performance of our hybrid technique (GSP–CA–CF) compared with other recommendation approaches, respectively GSP, CF, and CF-CA, in the context of F1 measure. Figure 5 of this study implies an effective performance of our hybridized recommender approach (GSP–CA–CF) as compared to three other recommendation techniques regarding of F1 measure (Figure 5) for the complete figure of recommendations.

No. of	GSP		CF Simple		CF-CA		CF-CA-GSP	
rec.	precision	recall	precision	recall	precision	recall	precision	recall
4	0.01	0.40	0.01	1.00	0.01	1.00	0.01	1.00
8	0.01	0.40	0.02	1.00	0.02	1.00	0.03	1.00
12	0.02	0.36	0.03	0.92	0.03	0.89	0.04	0.92
16	0.02	0.37	0.04	0.92	0.04	0.92	0.05	0.94
20	0.03	0.37	0.05	0.93	0.05	0.93	0.07	0.95
24	0.04	0.38	0.06	0.94	0.06	0.94	0.08	0.96
28	0.04	0.38	0.07	0.95	0.07	0.95	0.09	0.96
32	0.05	0.38	0.08	0.92	0.08	0.96	0.10	0.97
36	0.05	0.39	0.08	0.89	0.09	0.96	0.12	0.98
40	0.06	0.39	0.09	0.87	0.10	0.97	0.13	0.99



Figure. 5 F1 metric of our hybridized technique compared with other techniques

## 5.2.4 Scholar Satisfaction with the recommender system

Finally, the satisfaction of scholars with our hybrid recommender system, against the recommendations provided by the system, was evaluated. To perform this evaluation, we administered a close-ended questionnaire to 900 scholars which strived to disclose whether the scholars were satisfied with the recommendation results or not. Erdt et al. [123] acknowledged "user satisfaction" as one of the most significant assessment measures for a recommender system. Figure 6 portrays the satisfaction level of scholars against the recommended outcomes of our hybrid recommender approach which revealed that mainstream of scholars (92%) was satisfied, while only a few (8%) scholars were not satisfied with the results.



Figure 6 Scholar satisfaction with recommended results of our hybrid approach

### DICUSSION

With the intention to measure the efficiency of our hybrid recommender approach (GSP-CA-CF), the same set of experiments were also performed for three other recommender techniques, the GSP, CF, and CF-CA algorithms correspondingly, on the same dataset. It was evident from the outcomes of experiments of our hybridized recommender technique (GSP-CA-CF) that our approach beats other three approaches in every aspect. For example, our hybrid approach (GSP-CA-CF) produces most accurate recommendations and predictions as compared to any other algorithm among the GSP, CF-CA, and CF algorithms. At the size of 20 of the neighborhood, the optimal accuracy of predictions was acquired. Our hybridized recommender approach (GSP-CA-CF) beats other recommendation approaches in the context of precision, recall, and F1 measures. Furthermore, our hybrid recommender approach delivered accuracy of predictions than any other better recommender approach at all levels of sparsity. Though, the MAE of CF, CF-CA, and GSP-CA-CF increased with the incremental change at all levels of sparsity, while the MAE of the GSP algorithm showed a very minor change as the sparsity level increased. It can be credited to the utilization of scholar's sequence access patterns instead of ranks to generate predictions of research resources. The results show that the combination of CA, CF, and SPM enhanced the quality and the performance of recommendations. Moreover, it was evident from the survey questionnaire that the mainstream of scholars was satisfied with the recommended results by our hybrid recommender system. The hybrid approach presented in this study is exercised to generate predictions and to provide recommendations for online research resources in the ecosystem of digital libraries. These recommendable research resources comprise articles, books, magazines, novels, lecture notes, etc. Even in the case of multi-interest scholar choosing various irrelevant subjects such as bio or statistics, our hybrid recommendation approach will predict research resources properly by the means of SPM algorithm for weblog mining to discover scholar's historic sequence access patterns that are beneficial to generate appropriate predictions. The presented hybrid approach (GSP-CA-CF) is flexible, adaptable, and with minor changes, it can also be reusable in other domains such as video recommendation and medical prescription recommendations.

## 5.4 Future trends for CA recommender systems in research papers

A simulative future trend in the research of contextaware recommendation approaches in the field of digital libraries is the encouraged research attention towards the application of context-awareness in digital libraries' recommender systems. There is a great transparency in the trend of hybridization of novel recommendation approaches like context-awareness with the conventional recommendation approaches in addition with the integration of other advanced technologies such as machine learning and data mining techniques into recommendation procedure. Recommenders methods like the digital library CA-based recommendation algorithm integrate background history into the recommendation process, such as knowledge levels and research goals, to produce, customized, personalized, and signified recommendations to meet recommendations that meet the desired results of scholars in the digital library ecosystem. Hybridization of recommendation methods is able to increase the quality of the recommended findings for the digital library recommendation framework.

### CONCLUSION

In this study, we presented a context-aware (CA) and sequential pattern mining (SPM) based hybrid approach for the recommendation of research papers to the scholars in a scholarly environment. For weblog mining, our approach employ GSP algorithm to discover sequential access patterns of the scholars; CA is utilized to integrate contextual state of the scholar like expertise level; and CF is employed to generate recommendations using the contextually arranged data. Furthermore, GSP employed to the catalogue of contextual is recommendations in accordance with the sequence access patterns of the scholar and produce final set of recommendations for the scholar. The combination of these approaches leads the personalization of the recommendations in accordance with the contextual state and sequential access behavior of the scholar. Experimental evaluations cover up that our proposed hybrid approach delivers better performance and qualitative recommendations. Furthermore, our approach can assist to alleviate data sparsity issue by utilizing information about contextual state and sequential access

behavior to generate predictions in case the overlapping rankings of the scholars are absent.

In our future research, we intend to use modern tools of artificial intelligence and data mining to hybridize emerging classification approaches with a view to the improvement and optimization of recommendations.

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