Toward a Knowledge-based Personalised Recommender System for Mobile App Development

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Abstract
Over the last few years, the arena of mobile application development has expanded considerably beyond the balance of the world's software markets. With the growing number of mobile software companies, and the mounting sophistication of smartphones’ technology, developers have been building several categories of applications on dissimilar platforms. However, developers confront several challenges through the implementation of mobile application projects. In particular, there is a lack of consolidated systems that are competent to provide developers with personalised services promptly and efficiently. Hence, it is essential to develop tailored systems which can recommend appropriate tools, IDEs, platforms, software components and other correlated artifacts to mobile application developers. This paper proposes a new recommender system framework comprising a fortified set of techniques that are designed to provide mobile app developers with a distinctive platform to browse and search for the personalised artifacts. The proposed system make use of ontology and semantic web technology as well as machine learning techniques. In particular, the new RS framework comprises the following components; (i) domain knowledge inference module: including various semantic web technologies and lightweight ontologies; (ii) profiling and preferencing: a new proposed time-aware multidimensional user modelling; (iii) query expansion: to improve and enhance the retrieved results by semantically augmenting users’ query; and (iv) recommendation and information filtration: to make use of the aforementioned components to provide personalised services to the designated users and to answer a user’s query with the minimum mismatches.

Keywords: Mobile Applications Development, Recommender Systems, Semantic Analytics, User Profiling, Machine Learning.

1. Introduction
Mobile apps have opened up vast prospects in communications and have established dissimilar dialogues, allowing people to communicate, companies to conduct business activities, governments to provide services to their affiliated citizens, educators to facilitate delivering learning materials, to many other domains and sectors. According to Gartner[1], by 2022 enterprises will carry out 70 percent of their software interactions through mobile devices. Therefore, mobile software companies are contending to provide new and distinctive services and tools that eventually lead to the emergence of mobile applications which combine the functions of a computer and a telephone, and provide advanced services at various levels. However, designing and implementing a smartphone app is not a trivial undertaking; the difficulty lays in the fact that Mobile Application Development (MAD) is a sophisticated task that comprises a series of challenges and decisions to be made through all development lifecycle long until deployment[2]. In fact, the existing development approaches to support front and back-end tools for MAD are inadequately aligned to support multi-experience requirements [3].

Some of the key challenges to MAD can be categories as follows: (1) Different mobile operating systems: the specifications’ heterogeneity of the current mobile operating systems (IOS, Android, Windows Mobile etc.) hardens the process of developing a consistent application observing the hardware and software requirements
of each mobile device with a different mobile operating system. (2) Different mobile development environments: The criteria to select the appropriate development environment for a certain mobile project domain are unclear and hard to quantify. For example, developers find choosing between the native development approach and cross-platform development approach is not an easy task despite some guidance and benchmarks provided to aid this process[4]. (3) Peak instability of cross-platform tools and approaches: the cross-platform development ecosystem has witnessed several changes and growth in term of the incorporated tools and technologies[5]. This constant proliferation of cross-platform frameworks mislays significant effort in selecting adequate tools which fit developers’ expertise and project’s specifications considering time and budget constraints. (4) Miscellaneous issues: The development of a smartphone application comprises other related issues such as; the elements of GUI design, application structure, IDE(s) selection, development cost, security and privacy, etc.

The aforementioned issues impede mobile app developers before and during the development process, especially when a critical technical glitch or bug occurs that requires a prompt response. Therefore, developers should be reinforced with an earnest mechanism to help them obtaining a pertinent knowledge to fulfil their need before and during conducting the development process. Developers, consequently commonly rely on online sources to address technical problems encountered through their MAD [6]. However, with the copious online platforms that provide forums for developers to obtain expertise, appropriate tools, IDEs, platforms, environment settings, and other artifacts, it takes a quite a long time for a developer to pursue knowledge that is related to his/her domain. Hence, it is essential to develop tailored frameworks/systems which can recommend appropriate tools, IDEs, platforms, environment settings, and other artifacts to mobile application developers. Also, these frameworks should provide the capacity to regularly collect, store and filter solutions, ideas and thoughts acquisitioned from ubiquitous knowledge bases and Q&A repositories.

Recommender Systems (RSs) have been extensively used in various sectors, leveraging the advancements of embedded sophisticated algorithms and the profusion of supported knowledge bases. Hence, RSs have brought a plethora of benefits spanning from e-business[7], to health informatics[8], to social networks[9], to entertainment[10], to many other applications[11]. RSs in the context of software development provide proposed services to fulfill developers’ needs considering their skills and the project’s specifications. These services uphold developers with relevant and well correlated array of prescribed solutions to their technical questions, thus saving tremendous time and effort. However, there is a lack of RSs which target mobile app developers. In particular, MAD entails various differences in terms of development environment and software project requirements. For example, the mechanism followed to develop and deploy a native mobile app is different from a regular web app. The technicalities embedded into MAD domain requires also distinguished skills and necessitate special interface elements and development tools.

This study aims to provide developers with personalised services through a comprehensive and time-aware knowledge-based recommender system that will be designed to recommend and retrieve code snippets, Q&A threads, tutorials, libraries, and other external data sources and artifacts to assisting developers with their mobile app development. In particular, the new proposed RS framework comprises the following add-ons; (i) domain knowledge inference module: including various semantic web technologies and lightweight ontologies; (ii) profiling and preferencing: a new proposed time-aware multidimensional user modelling; (iii) query expansion: to improve and enhance the retrieved results by semantically augmenting users’ query; and (iv) recommendation and information filtration: to make use of the aforementioned components to provide personalised services to the designated users and to answer a user’s query with the minimum mismatches.

This paper is organised as follows: Section 2 presents the state-of-the-art review to the currently conducted efforts in the area of RS and its application on software development. Section 3 provides a detailed discussion on the proposed framework including all modules and techniques. Paper finishes with a conclusion summarises the main contributions of this paper and sheds the light on future research directions.
2. Related works

RSs have recently gained an extensive attention from the research community due to the abundant of information which hardens the process of linking users with looked-for artifacts in minimum efforts and time. In software engineering, building an operative RS is even more imperative as developers have to deal with information derived from vast and dissimilar data sources that are retrieved in different formats, such as code snippets, technical tutorials, API documentations, Q&A websites, etc.[12]. It is evident that developers confront several problems and obstacles before and during their software development projects lifecycle [2]. This section lays the technical background of this study by presenting state-of-the-art review of key techniques which are incorporated to design RSs for software development.

Authors of [13] presented MAPO system for processing source files and clustering the included API methods which are analysed to infer ranked list of API usage patterns by finding similarity with the developer context. Another attempt is MUSE [14] which recommend to the developer certain code exampled by examining source codes and cluster code snippets. Usage Pattern Miner (UP-Miner) [15] was designed to automatically mine usage patterns of API methods from various source codes. Experiments conducted using Microsoft codebase dataset to evaluate Up-Miner have proven its effectiveness and outweighed baseline approaches using certain metrics. Authors of [16] presented Multi-Level API Usage Patterns (MLUP) system as an approach for quarrying and inferring the co-usage relationships between various methods of the API of interest across interfering usage scenarios. They incorporate DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering technique to assemble API methods that are commonly used coherently in software development projects. RSs for software testing are also proposed; SoTesTeR [17] is a platform for recommending testing and quality assurance techniques using content-based approach. Authors of[18] introduced a prioritising mechanism for software testing using test cases clustering technique to minimise time and effort of conducting regression testing for software maintenance activities.

The use of crowdsourcing recommendation in software development has been extensively investigated since 2006[19-21]. Authors of [22] presents reinforcement learning into crowdsourcing recommendations to tackle the dilemma of cold start by incorporating "explore & exploit" strategy to improve the effectiveness of the recommender system. A multi-models technique for engineering recommender systems is proposed by [23] where authors present a standard software architecture for RSs particularly designed for critical contexts of software systems. Authors or [24] developed a RS utilizing dissimilar knowledge silos to suggest attack patterns based on the use case descriptions in order to alert developers and stakeholders with the possibilities that their software system can get compromised by mimicking the attacker’s attitude during the premature stages of software development process. Assisting game developers is also presented in [24] as a RS which incorporates AI to decrease work load, improve self-efficacy, and improve accuracy. Domain modelling as another important area of research, thus authors of [26] support these endeavours by designing a system for automated modelling recommendations. Linking developers with relevant tasks in open calls system has been also tackled in [27] where authors designed content-based recommendation methods to automatically tie tasks with developers.

Another thread of efforts has been undertaken to suggest software-based components to the developers[28, 29]. Authors of [30] created a RS with the use of machine learning algorithms to predict and recommend to developers the best cross-device component-based interfaces. Further, evaluation and selection of the software components were addressed through a methodology proposed by Jandav et al [31] using hybrid knowledge based system technique to evaluate and recommend software packages for decision makers. An approach for providing recommendations on developing a RS is proposed by[29] where authors built a system called “RecoLibry-core” aimed to collect components from third-party systems to assist in developing recommender systems. Commercial Off-The-Shelf (COTS) components are also significant artifacts which provide developers with high level objects to satisfy their needs[32]. Authors of [33] presented an knowledge-based personalised recommender system to infer and retrieve COTS components based on domain and linguistic ontologies. Their approach, however neglected several semantic-based repositories when they built the component-based and user-based profiles. Amongst the conducted exertions in constructing knowledge-based recommender systems,
CROSSMINER initiative [34] established a large-scale project where authors automatically collect resources and components from various open source repositories and delivering them to the developers in terms of recommendations using built knowledge-based RS. The outcomes of this initiative are depicted in [12, 35, 36].

The aforementioned techniques, however, are mainly relying on clustering approaches which commonly neglect the semantics of artifacts. Also the developer’s preferencing and profiling dimension of these approaches is inadequate and inferior and is neglected in the embodied techniques. Also, the proposed RSs do not exclusively target mobile app developer. To the best of our knowledge, this is the first attempt to tackle this issue by presenting a knowledge-based time-aware personalised recommender system for mobile app development. Next section will present the proposed system and its embedded components.

![Figure 1: Overarching System Architecture](image)

### 3. Proposed System Architecture

Figure 1 illustrates the overall architecture of the proposed system. As depicted in the diagram, the framework comprises five main stages as follows:

#### 3.1 Acquisition and pre-processing

At this stage, heterogeneous types of data are generated from different online repositories including tutorials, API Documentations, Q&A repositories, to name a few. Those knowledge bases that provide APIs to access and retrieve their online content will be incorporated in this study. Besides, data acquisition will also include accessing and collecting social data pertaining to users of the system. Several APIs will be utilized to extract batches of social data in a timely fashion.

Various pre-processing techniques are carried out after data acquisition phase. Those processes include data cleansing and restructuring. Data cleansing process scrutinises datasets to detect and cure, for instance, corrupted, incorrect, redundant, and irrelevant data. Data restructuring insures data consistency. In particular, datasets are commonly retrieved in dissimilar data formats (JSON, XML, CSV, etc.). This heterogeneity of data types require initiating a data structuring process to integrate datasets obtained from different data islands into a single solo of coherent and integrated dataset. This will facilitate managing and analysing this structured dataset in the next stages of data analytics.

#### 3.2 Domain Knowledge Inference

This is the “semantic kitchen” where mobile development domain ontology will be constructed to provide formal representation of the designated knowledge through identifying all the related concepts within the domain and the relationships between them. This domain ontology will provide a common shared vocabulary to be used for modelling the domain with all embodied properties and relationships.
Moreover, ontologies and various semantic web technologies and repositories are used to infer implicit knowledge from textual content as well as to model and represent the knowledge. In particular, this module will embody the ontology and semantic data interlinking techniques which facilitates the interoperability of information. The interlinking and enrichment process incorporates dissimilar vocabularies and Linked Open Data repositories such as Friend-of-a-Friend (FOAF) [37], Dublin Core (DC) [38], Simple Knowledge Organization System (SKOS) [39], Semantically-Interlinked Online Communities (SIOC) [40] to be used to enrich the semantic description of resources obtained from the crawled datasets using an annotation component. In addition to ontology and vocabulary reuse, interlinking includes the semantic relationship between similar entities stored in other datasets.

The main objective of this module is twofold: to build the domain ontology for mobile app development, and to use the incorporated lightweight ontologies to enrich this domain ontology with specific semantic conceptual representation of entities obtained from the collected datasets. The second objective is to assist in the process of users’ profiling and preferencing by means of detecting their domains of knowledge and interest obtained from examining and semantically enriching their social data content.

### 3.3 Profiling and Preferencing

This stage aims to build a profile for each developer based on her interests and domain(s) of knowledge observed for a long time. The profiling and prefencing process will be designed to implicitly and explicitly detecting developers’ interests through their information seeking and behaviour. To achieve this objective, users/developers will provide their user_ids of the OSNs platform and/or filling up a form that will be used to frame users’ interests and requirements. In particular, the explicit profiling will be attained by soliciting the user to fill up a designated online form to obtain the factual and available information about their domain preferences and projects they’re currently working on. However, people is commonly trying to avoid this approach as they are not willing to disclose their personal information or because they find it tedious. Therefore, this paper aims to overcome this issue by providing a hybrid approach to attain the user profiling [41]. Hence, users’ interests and preferences will be inferred by analysing their content onto OSNs, thereby constructing an overarching approach toward better user profiling which will help the recommender system to obtain tailored and personalised results for each user.

Amongst several attempts to build user profiling and preferencing, this study has adopted and improved the multi-dimensional semantic technique presented by [42] to model users profiles. This model is an extension of the multi-dimensional user profiling model depicted in [43]. As illustrated in Figure 2, the model is composed of a set of dimensions that are used to frame the user’s profile. Those dimensions are briefed as follows:

1) **Personal Data Dimension**: This refers to the set of user’s attributes which border the user identity. This dimension can be detailed to examine various personal and demographic data, yet in our context, we are more interested in few attributes that would help to build the model. In particular, we primarily focus on information such as, developer’s age, location, job title, years of experience, social media user_ids, etc.

2) **Domain of Interest Dimension**: This dimension aims to provide specific insights into users’ domains of interest. Those attributes will be concluded using an explicit approach (i.e. online filling-up forms) and/or an implicit approach (social networks content). Items of this dimension include information about the development domain that the developer is specialised in (health, business, education, misc., etc.). Also data pertaining to the developer’s preferred app development methods is also captured (Native, Hybrid and Cross Mobile App). This dimension also includes software development methodologies (Waterfall, SCRUM, Spiral, Extreme, etc.) and software repository hosting services which are those online facilities that provide file archiving services to the affiliated members where developers can store and manage their source codes online (GitHub, Buddy, AzureDevOps, etc.). The developer’s domain of interest comprises also other items such as preferred programming language(s), preferred IDEs, etc.
3) **Software Project Dimension**: This dimension aims to gather the available information about the software project which is being developed by the users. This entails a set of all procedures describing the software project which include: functional and non-functional requirements, IDEs, Modelling types (domain, design, etc.), programming paradigm (Object-oriented, reactive programing, component-based software engineering, etc.), front-end and back-end development tools (UI design tools, SDKs, cross-platform support, etc.), etc.

4) **Development Environment Dimension**: This dimension addresses various aspects of the environment and facility provided to develop a mobile software application in general (computer-assisted software environment). These contain aspects such as infrastructure, back-end servers (data services, authentication-authorization, Integration, APIs, etc.), testing tools, debugging and troubleshooting tools, for developing, testing and debugging an application or program, etc. This dimension differs from Software Project dimension in that development environment dimension provides a generic description for the working environment and facilities available and do not designate any specific mobile software project.

5) **Security and Privacy Dimension**: This is mainly to insure personal privacy and security by indicating all security rules and privacy policies that are set to attain this objective. This is crucial particularly as current business firms are pushing toward BYOD (Bring Your Own Device), where employees can conduct business activities using their own smartphone devices. Therefore, developers should insure to attain the security and privacy dimension through app security wrapping and encryption techniques. Also, the intended approach will insure to keep the identity of the developers undisclosed, this also applies to details of the undergoing software development project and other confidential aspects.

6) **Temporal Dimension**: It is evident that the aforementioned dimensions changes contextually and temporally. For instance, users’ interest(s) may change, and their knowledge commonly evolves over time [44-50]. Hence, Profiling and Preferencing module will insure to update user’s dimensions in
regular bases. This will be attained by regularly collecting and analysing developers’ social data content, also by the explicit feedback and updates obtained from the developer, thereby providing up-to-date awareness of user’s behaviour onto those platforms and reflect that on the recommender system as well. This tactic helps providing more efficient recommendation results and preserves the correctness of temporally updated information.

7) **Delivery Dimension**: This is dimension aims to provide the mechanism on how and what information will be delivered to the users which will be essentially the browsing and search results of the information filtration and recommender system and how these results will be displayed to the user. In other words, delivery dimension will embody the following aspects; information filtration, recommendations, information presentation (visualisation), etc.

8) **Quality Dimension**: This dimension addresses and measures the quality of the user profiling and preferencing approach and how well the model satisfies the user’s requirements. This dimension will be framed by several evaluation metrics which are formulated to measure the effectiveness, functionality and reliability of the proposed profiling technique.

### 3.4 Query Expansion (QE)

QE aims to improve and enhance the information retrieval systems by conducting a process of augmenting user’s query with more terms, thereby obtaining better retrieval results. This process is commonly attained automatically or interactively (semi-automatically). In Automatic Query Expansion (AQE) approach, the developed system is responsible to select and augment query with new terms, which differs from the interactive QE approach in which the latter infers potential terms and leaves the task of query augmentation to the user [51]. In terms of semantic-based approaches, semantic QE can be classified into two main categories; linguistic-based, ontology-based and hybrid approaches [52]. Linguistic-based QE approaches refer to those techniques that generate senses of terms from thesauruses and linguistic repositories. Ontology-based approaches derive the new extended terms by the means of semantically mapping knowledge represented in term of classes (concepts) properties and relationships as depicted in domain ontologies. Hybrid QE exertions attempt to benefit from the two aforementioned venues to provide a consolidated list of new terms to enhance a user’s query.

This study will follow the AQE mechanism where user’s query will be augmented automatically with the help of a hybrid semantic-based QE approach. Therefore, Ontologies will used to capture domain knowledge inferred from the query and to enrich the semantics of its textual content, by providing explicit conceptual representation of entities identified in the query. Further, we will make use of WordNet¹, which is a lexical vocabulary constructed mainly to establish relations between terms through Synsets. Synsets (or synonymies) are the set of interconnected words, terms or phrases which refer to the same semantic meaning, such as the words “programming, programing, computer programming, computer programing” are all point to the same semantic concept, “programing”.

In this study, a user’s query will initially be pre-processed, stemmed and tokenised. Then the list of extracted keywords will be semantically mapped with the corresponding entities and concepts captured in the incorporated ontology. The interlinking with other related entities embodied in other repositories datasets supports interoperability, thereby extending the query terms with more convergent terms to improve the retrieval output.

### 3.5 Recommendation and Information Filtration

Information filtration refers to the process of sieving out and delivering the right personalised information to the user. This is in fact the most imperative task of any typical IR system. However, this is not a conventional task; particularly with the increasing proliferation of big data which hardens the exertions of collecting, processing, analysing and filtering information. Therefore, IR systems should be designed to provide

¹ [https://wordnet.princeton.edu/](https://wordnet.princeton.edu/)
personalised services to the designated users, and also able to effectively answering user’s query with the minimum mismatches.

This study aims to design a consolidated system that offers the developers the capacity to browse and navigate through an enriched and customised catalogue of technical specifications, latest industry updates, coding snippets, tutorials, Q&A, and a plethora of other personalised and tailored artifacts to the affiliated users. Furthermore, the intended approach will allow developers to search the knowledge bases and retrieve hoped-for results that match with their preferences, profile criteria, working environment and software projects specifications. This section will shed the light on two crucial tasks of the anticipated system.

Task 1. Personalised IR Filtration: One of the main objectives of this research is to build a system which allows a developer/user to search through a comprehensive list of artifacts, and retrieving a list of those with the high relevancy and minimum mismatches in a ranked order style. To obtain this objective a developer need to submit his/her query to the system comprising a set of keywords. Then, a semantic based query expansion technique is applied to these keywords incorporating user’s profile and his/her preferences, thereby a consolidated set of new keywords are added to the query providing an expanded one. The expanded query will pass through the filtration module which is responsible to examine and retrieve a potential list of highly relevant artifacts. This curated list of artifacts will be raked through the similarity ranking module. Similarity ranking will be attained through incorporating Vector Space Model (VSM) [53]. VSM is a term weighting scheme used in IR where the retrieved documents are sorted according to their relevancy degree. In VSM, a document is commonly represented by a vector of index terms exported from the document’s textual content. Those index terms are associated with their computed weights representing the significance of the index terms in the document itself and within the entire corpus. Likewise, a query is modelled to a list of index terms and weights that represent the importance of each index term in the query. Cosine similarity is one of the core techniques of VSM that is used to compute the similarity between two vectors (a document and a query). This is through calculating the cosine value of the angle between vectors, thus finding those documents with high relevancy to the query where the smallest the angle, the greater the similarity between the document and the query. Cosine similarity relies on the theoretical notion of Term Frequency-Inverse Document Frequency (TF-IDF). TF-IDF measures the importance or significance of a term to a certain document exists in a corpus of documents. It comprises standard notions which formulate its structure; Term Frequency (TF): is used to compute the number of times a term appears in a document. TF expresses the importance of the term in the document. Document Frequency (DF): is a statistical measure to evaluate the importance of a term to a document in a corpus of texts [54]. Inverse Document Frequency (IDF) is a discriminating measure for a term in the text collection. It was proposed as a cornerstone of term weighting, and a core component of TF_IDF[55]. It is used as a discriminating measure to infer the term’s importance in a certain document(s) [56]. TF_IDF combines the definitions of TF (the importance of each index term in the document) and IDF (the importance of the index term in the text collection), to produce a composite weight for each term in each document. It assigns to a word t a weight in document d that is: (i) highest when t occurs many times within a few number of documents; (ii) lower when the term t occurs fewer times in a document d, or occurs in many documents; and (ii) lowest when the term t exists all documents.

In the context of this research, this heuristic aspect will be incorporated into this model where the collected artifacts will be transformed to vectors embodying index terms mainly extracted from the textual content of these artifacts. Also the expanded user query will be also represented as a vector of index terms. Weights will be calculated for each term using TF-IDF technique and cosine similarity will be computed using the following formula:

\[
\text{similarity}(A,B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}
\]
Where $A$ and $B$ are vectors representing the term frequency vectors of an artefact and the query. The resultant similarity value should range between -1 indicating no similarity, to 1 denoting that components of both the artefact and the query are identical, while intermediate values show certain levels of similarity or dissimilarity. The retrieved artefacts from the cosine similarity technique will also be automatically scrutinised to exclude those which are not related to the user’s domains of interest, thus another filtration is conducted to find matches with the user’s interests obtained from the explicit or implicit approaches as depicted in the previous subsection. Consequently, those artefacts which cross with the recent identified user’s domains of interest will be assigned higher weights than those of less correlation.

**Task 2. Recommender System:** The intended RS will be also able to provide domain based recommendations to users using domain ontology and knowledge bases as an alternative to the conventional collaborative filtering and content-based RSs. Ontology-based RS is selected because knowledge-based recommender systems in general have proven aptitude to address both cold-start and rating scarcity dilemmas, therefore capable to hybridise with other recommendation methods [57]. Further, domain based knowledge bases frame the recommendations to augment the user-resource matching, thereby providing consolidated personalised recommendations [58]. Therefore, another tool will be designed to provide the user a facility, not only to search for artefacts, but also to browse them. Domain-based semantic similarity will be applied to show the most relevant artefacts to the user taking into consideration both user’s profile and software project specifications. To attain this task, various machine learning techniques will be incorporated to classify and predict the most relative artefacts for the user. Examples of these algorithms include; k-nearest neighbours classifier, tree-based classifiers, multi-class logistic regression, SVM classifier, to name a few.

The aforementioned tasks will be attained by insuring that user profiling and preferencing is updated in regular bases. The temporal dimension is decisive when designing and implementing a RS which is commonly neglected. The developer’s domain(s) of interest and expertise evolve over time. Moreover, the domain of artefacts they are seeking changes based on the project’s specifications, thus it deems necessary to tackle this fluctuation by asserting to keep the user profile tuned.

4. **Conclusion and Future Research**

This paper proposes a new tailored framework that is designed to support mobile app developers in their apps development process. This is through a consolidated and overarching system which is able to provide personalised services and can recommend appropriate tools, IDEs, platforms, environment settings, and other artefacts from dissimilar online resources. The proposed system is designed to regularly collect, store and filter solutions, ideas and thoughts acquisitioned from ubiquitous knowledge bases and Q&A repositories. In particular, the new proposed recommender system encompasses the following magnitudes: (i) domain knowledge inference module: including ontologies and various semantic web technologies and repositories; (ii) profiling and preferencing: a new proposed time-aware multidimensional user modelling; (iii) query expansion: to improve and enhance the retrieved results by semantically augmenting users’ query; and (iv) recommendation and information filtration: provide personalised services to the designated users and to answer a user’s query with the minimum mismatches.

Our future research aims to develop and extend the proposed system with all embedded modules. For instance, the domain knowledge inference module will be developed and various related ontologies and linked open data repositories will be selected and incorporated. Further, the user’s profiling and preferencing model will be extended and transformed to a domain ontology to factually and explicitly depicting concepts and relationships representing the mobile app developers’ profiles and their domain preferences. Query expansion is an important module which will be further scrutinised to insure applying, enhancing and combining state-of-the-art statistical-based techniques (such as word embedding) with semantic-based technologies. Finally, the intended recommender system and information filtration module will be designed and implemented to interlink the aforementioned components and also by utilizing state-of-the-art machine learning techniques.
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