Model Driven Approach to Risk Aware Recommender System

Abstract—Traditional methods used for context aware recommender system are not efficient enough to accommodate the increase in the number of source of available information(sensors and usage data) or the time for re-calibrating and re-programing to accommodate a new data source. There are available resources for methods that generate good recommendations but lack the criteria to decide when to deliver those recommendations to the user. In many applications, such as recommending personalized content, it is also important to consider the risk of upsetting the user so as not to push recommendations in certain circumstances, for instance, during a professional meeting, early morning, late-night. Therefore, the performance of the recommender system depends in part on the degree to which it has incorporated the risk into the recommendation process. In this paper we discuss the model-driven approach to separates the analytics logic from the technical big data platform in order to allow Domain Experts to change platform components later, without rewriting the analytics code. This paper also discusses the dynamic risk sensitive recommendation system called DRARS (Dynamic Risk-Aware Recommender System), which models the context-aware recommendation as a bandit problem.

Index Terms—Software Engineering, Recommender System, Big Data.

1 INTRODUCTION

In recent times, Recommender systems can take advantage of semantic reasoning capabilities to overcome common limitations and improve the recommendations quality. These systems uses domain ontologies to enhance the personalization: on the one hand, users interests are modeled in a more effective and accurate way by applying a domain-based inference method; on the other hand, the matching algorithm used by our content-based filtering approach, which provides a measure of the affinity between an item and a user, is enhanced by applying a semantic similarity method. It has been shown that a bridge between the contents and connectivity within a website tremendously improves user experience. Current research in the are of recommender system has been focussed on the context aware recommender system. A context-independent representation may lose predictive power because potentially useful information from multiple contexts is aggregated. The ideal context-aware recommendation system would, therefore, be able reliably to label each user action with an appropriate context and effectively tailor the system output to the user in that given context. The majority of existing approaches to recommender systems focus on recommending the most relevant content to users using contextual information and do not take into account the risk of disturbing the user in specific situation. However, in many applications, such as recommending personalized content, it is also important to consider the risk of upsetting the user so as not to push recommendations in certain circumstances. Therefore, the performance of the recommender system depends in part on the degree to which it has incorporated the risk into the recommendation process. The risk in recommender systems is the possibility to disturb or to upset the user which leads to a bad answer of the user. A recommendation system which only utilizes the web usage logs and structural data of the website, is not sufficient to evolve with the same pace as that of the website which undergoes change of contents(addtion of new information and/or deletion of unimportant information). On the other hand, the content-based recommendation approach requires deep knowledge of the massive inventory of products offered on the website i.e. each item must be profiled based on its characteristics. For a very large inventory (the only type of inventory you need a recommender system for), this process must be automatic, which can prove difficult depending on the nature of the items. Apart from the above mentioned issues the resommender system should also account for the risk associated with the generation of recommendation results, which might have a potential to upset the user. Therefore there is a need to consider the risk factor into recommendation result generation. Although, many researchers have focussed their efforts in the direction of overcoming this problem, many domain experts still feel the procedure of setting up a recommendation system to be cumbersome and complex due to lack of domain models and standard implementations. There is also a lack of domain specific support such as domain specific language and models, to address this issue. In order to develop a model for the risk aware web recommender system we need to gather some parameters on which the output of the system depends. The selected parameters are web logs and user data, web page content, dwell time calculation, click through rate, search queries and web page content. After the determination of the parameters that affect the design of the system, we need to get the data from these parameters for establishing rules and relationships amongst various entities in the system. The information extracted from the system parameters will be utilized to develop the model of the system. We will carrying out the objective of building a meta-model out of each relationship that we establish from the data obtained from the parameters and then combine them to produce the overall design of the system. In order to test the validity of

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the system, we will discuss the model in terms of its scope of implementation in the field of risk based recommender for personalized healthcare and stock recommendation for the portfolio management. The intention behind using these two scenarios is to evaluate the risk for generating recommendation and evaluating the recommendentations generated by the model. A domain-specific language (DSL) is a computer language specialized to a particular application domain. This is in contrast to a general-purpose language (GPL), which is broadly applicable across domains, and lacks specialized features for a particular domain. We discuss high-level models using domain specific languages. Many interesting issues exist in the area of DSL design and development. In the design process, non-trivial choices are to be made, each of which can have an effect on the usability or even viability of a DSL. The purpose of the domain specific language for our system is to allow its users to implement a risk aware recommendation system with reduced complexity of achieving. Domain specific languages aim at raising the abstraction level, thereby lowering the complexity of achieving a specific task.

The paper is broadly divided into multiple sections. The first section deals with the introduction of the concepts that are important for understanding the system. The second section deals with the discussion of the related research for developing the model. The third section focuses on the design and verification of the system model. The paper then presents the conclusion and results.

1.1 Context Aware Recommender Systems (CARS)

When recommending a personalized content, it is not sufficient to consider only users profiles and documents. It is also important to recommend documents adequate to the users situation. Therefore, a good recommendation depends on how well the recommender system (RS) has incorporated the relevant contextual information into the recommendation process. Recently, some RS have taken the context into account, being called Context-Aware Recommendation System (CARS). However, for a long time many works deal with the context in other areas, like IR, mobile-learning and advertising since context become inescapable. The notion of context appeared in several disciplines, like computer science, linguistics, philosophy, psychology, etc., and every discipline gives its own definition, often different from the others, which is more specific than the generic definition i.e. conditions or circumstances that have an effect on something. Therefore, there are several definitions of context across varied disciplines. In context-aware computing, the authors in [26] have considered the context as a key component to increase human-machine interactions, and they have given the subsequent definition of context that is now ordinarily accepted: Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves. [37]. According to Grudin [39], the context acquisition is the process through which contextual information is captured. The context can be obtained by different methods, depending on the contextual information that the system needs. Context models

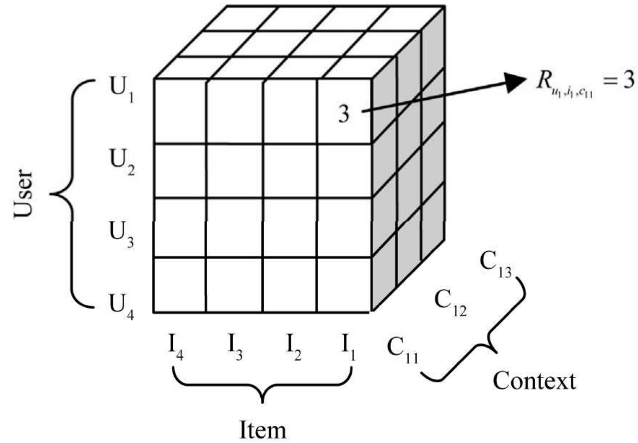

Fig. 1. Attribute-value model proposed by [67]

Phases	Tasks		Products		
Domain Analysis	Modeling of domain concepts		Concept Model	Domain Model	
Domain Analysis	Variability Modeling	Goal Modeling	Goal Model	Domain Model	
Domain Analysis	Variability Modeling	Role Modeling	Role Model	Domain Model	
Domain Analysis	Modeling of Role Interactions		Role Interaction Models	Domain Model	
Domain Design	Architectural Modeling	Agent Society Modeling	Multi-agent Society Model	Architectural Model	Model of the multi-agent framework
Domain Design	Architectural Modeling	Agent Interaction Modeling	Agent Interaction Model	Architectural Model	Model of the multi-agent framework
Domain Design	Architectural Modeling	Cooperation and Coordination Modeling	Coordination and Cooperation Model	Architectural Model	Model of the multi-agent framework
Domain Design	Modeling the Knowledge of the Multi-agent Society		Model of the Multi-agent Society Knowledge		Model of the multi-agent framework
Domain Design	Agent Modeling		Agent Knowledge and Activity Models	Agent Models	Model of the multi-agent framework
Domain Design	Agent Modeling		Agent State Models	Agent Models	Model of the multi-agent framework
Domain Implementation	Mapping from design to implementation agents and behaviors		Model of agents and behaviors		Implementation Model of the Multi-agent Society
Domain Implementation	Mapping from agent interactions to communication acts		Model of communication acts		Implementation Model of the Multi-agent Society
Pattern extraction and representation			Software Patterns and Pattern Systems		

Fig. 2. System Modelling Phases[32]

formalize the representation of the context as a structure (ontology, class of vectors of terms, set of concepts, etc.) or a set of specific and different information structures. We present now the most interesting models found in the literature. The most simple context models are based on attribute-value pairs to represent context, where attributes capture various characteristics of contextual elements. An attribute-value model is used in [34] for representing the context of each users item. First, they build a user profile. The basic data source of the technology is a user-items matrix, A(m, n). It stores the ratings which are given by m users for n items. m denotes the users information U(u1, u2, ..., um), and n denotes the items information I(i1, i2, ..., in). If a user u rates an item i, it generate a rating Ru, i, which is between 0 and 5. Where 5 is the best rating. So their context is modelled as follows: C = (C1,C2, ...,Cn) , where C presents one type of contexts, such as Time and i consists of many different variables. For example, in the type of Time, there are several values (such as morning, noon, afternoon, and evening). And a user may have different interest for the same item in different variables of one type of context. So they give the definition of Ci = (Ci1,Ci2, ...,Cik).To introduce context on their model they consider a User Item Context Rating model. There is Rus1,i1,C11 which means the user us1 gives a rating whose value is for the item i1 in the variable c11 of context C1. So there are many models which store the ratings given by all users for every item in each context variable. Attribute-value models are frequently used because they are particularly easy to manage. However, they lack of semantic, since no relation between attributes and/or values are given. The main benefits of object modelling come from being commonly understood by application developers to know the encapsulation between object and class. The context is described by a number of elements, which characterize the various aspects of the entitys situation. This entity can be a user, an object, a place, among others. The context is represented by the class Description of Context of the UML class diagram. This class represents the contextual factors which are subclasses of an abstract class called element of Context.

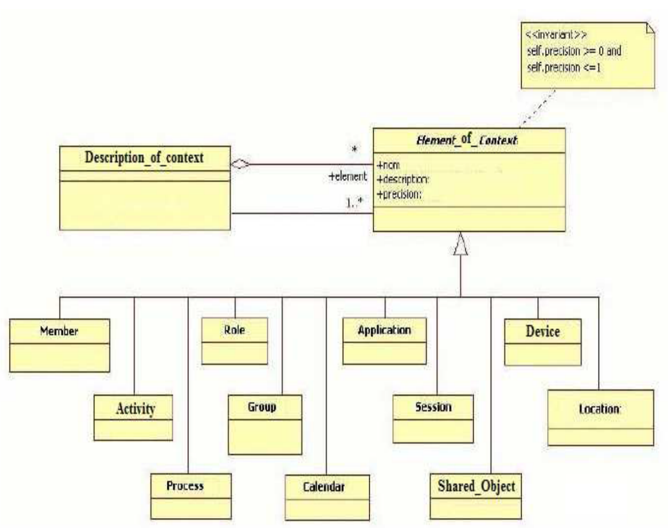

Fig. 3. Object-oriented model proposed by [34]

1.2 Multi-Armed-Bandit Problem

The Multi-Armed Bandit (MAB) or k-armed bandit problem is a sequential decision making process studied in the fields of statistics, machine learning, among others. The problem is originally described by as a process, where the system must select one of several arms or resources. For each selected arm, a reward is received. The objective is to find a selection strategy that maximises the cumulative reward. In the scope of RS, an arm is a resource or a document from the collection and a reward corresponds to the satisfaction of the users interest w. r. t. the document. This satisfaction can be explicitly expressed or implicitly inferred (e.g., from the number of clicks on the document). The objective of the recommendation is to maximise the cumulative satisfaction of the user by recommending him interesting documents. RS based on MAB problem commonly assumes to have no prior knowledge about the reward of each document and thus should explore rewards from different documents in an effective strategy. The best strategies are those that incorporate the need to balance exploration (pulling different documents to identify the best one) and exploitation (pulling the expected best document to maximise the reward). MAB problems have also applications in areas as diverse as clinical drug trials, web advertising and many other decision-making problems. In the MAB problem, the system pulls resource i at time t and receives a reward ri(t) from that resource. The objective is to find a strategy that maximizes the sum of the received rewards after time T. This problem has been studied both in finite time T and also for infinite time T. Furthermore, many different problems have been derived from the classical MAB problem, as, for example, the following ones. The stochastic multi-armed bandit problem considers that each resource i has reward ri(t) at time t generated from a probability distribution Ri. The system does not have prior knowledge of these distributions and the distributions are fixed over time. In the adversarial multi-armed bandit problem the rewards of each resource have been set a priori by an adversary. The rewards generated by the adversary are bounded in [0, 1]. The objective of the adversarial framework is to identify the best resource to repeatedly play for all iterations, rather than finding the best resource for each individual iteration. This is a restrictive assumption in realistic scenarios in which the optimal resource to select can change between iterations. The one-armed bandit problem is a special case of the MAB problem. The system must choose between a resource with unknown expected reward and a resource with known expected reward. The problem, in this form, has been first studied for sequential clinical trials, where a treatment has to be chosen between a drug with known probability of success and a new drug with unknown probability of success. The MAB problem with covariates first introduced that considers the scenario where the system observes context information (like number of click, time spent)prior to each resource. In this problem, the expected reward of each resource is a function of this context information represented in the form of a covariance. It has been argued in that such context information exists in many applications and incorporating this into bandit problems is a more realistic representation of real-world problems. For example, covariate information such as age, sex and weight could influence the probability of success of a food recommendation. All of these variants to the MAB problem need to be solved by trying to make the best strategy in exploration-exploitation. In what follows we describe these strategies (Bandit algorithms) and we try to find out the most interesting algorithm adapted to our needs.

2 Related Work

There have been a lot of implementations of web recommendation systems and these implementations have under-

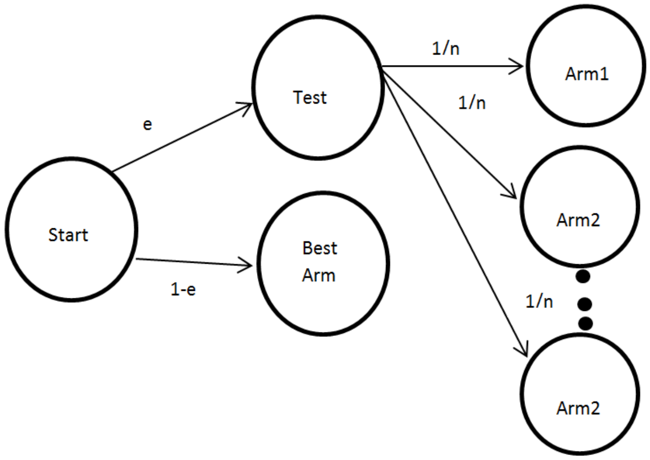

Fig. 4. Multi-armed bandit Approach

gone a lot of improvements over the time but very few of these implementations addresses the problem of generating recommendation for dynamic content websites. K Suneetha and Usha Rani[56] have presented a web page recommendation algorithm using weighted sequential patterns and markov model. S. Abrishami, M. Naghibzadeh and M. Jalali[47] utilizes semantic web usage mining and collaborative filtering for improving web recommendation systems. Li and Zaiane[29] propose an approach for building Web recommender systems where three information channels are exploited: web access logs, the structure of a visited web site, and the content of visited web pages. The terms within visited web pages are used to partition visit sessions into overlapping sub-sessions, called missions. Their preliminary experiments show improvements on the quality of recommendations by considering content and connectivity of Web pages in addition to usage history. Girardi and Marinho [3] have compiled a domain model by combining web usage mining techniques with Semantic Web technologies to acquire implicitly user feedback by further integrating the currently used content-based information filtering approach with collaborative filtering techniques, improving the quality of the recommendations with a hybrid approach. Bouneffouf [*] have introduced R-UCB algorithm for risk-aware recommender system that considers the risk level of the users situation. Xing Yi[5] demonstrated how dwell time is computed from a large scale web log and how it can be incorporated into a personalized recommendation system. Many applications of usage mining on the development of Web personalization systems have been published. Some of them are following briefly described. WebPersonalizer [40] is a research prototype that uses clustering techniques for the automatic discovery of aggregated user profiles. The system generates recommendations based on the proximity between the current user profile and the previously discovered profiles. In [43], an approach for Web personalization based on a dynamic clustering technique is also proposed. WUM [50] is a system that offers multi-user customization functionality by modifying the hyperlinks of a particular Web page to include links to pages that have been visited by customers and not by non-customers. The modified Web pages are presented once in a session, to non-customers, with the ultimate goal of turning them into customers. ROSA (remote open site agents) [34] is a multi-agent architecture that facilitates integration of different mining methods and permits the discovered knowledge to be verified and updated automatically. Besides usage data, other complementary sources or channels can be exploited to improve the quality of the patterns discovered by Web usage mining, such as Web content, Web structure, and even special domain ontologies [38]. Mobasher et al. [40] introduces a general framework for the automatic personalization based on Web usage and content mining. In this work, the user preferences are automatically learned from Web usage data and integrated with domain knowledge and the site content. This has the potential of eliminating subjectivity from profile data as well as keeping it up-to-date. Furthermore, it was experimentally showed that the integration of usage and content mining increases the usefulness and accuracy of the resulting recommendations. Li and Zaiane [38] propose an approach for building Web recommender systems where three information channels are exploited: web access logs, the structure of a visited web site, and the content of visited web pages. The terms within visited web pages are used to partition visit sessions into overlapping sub-sessions, called missions. Their preliminary experiments show improvements on the quality of recommendations by considering content and connectivity of Web pages in addition to usage history. Usage patterns discovered through Web usage mining are effective in capturing item-to-item and user-to-user relationships and similarities at the level of user sessions. Without the benefit of deeper domain knowledge, such patterns provide little insight into the underlying reasons for which such items or users are grouped together. In Dai et al. [16] a general framework for using domain ontologies to automatically characterize user profiles containing a set of structured Web objects is introduced. In this work, a Web site is considered as a collection of objects belonging to certain classes. Given a collection of similar user sessions, obtained, for instance, through clustering, each containing a set of objects, it has been shown how to create an aggregate representation of the whole collection based on the attributes of each object as defined in the domain ontology. This aggregate representation is a set of pseudo objects characterizing objects of different types commonly occurring across the user sessions. A new class of Web usage mining methods and techniques has appeared in the context of the semantic Web, an approach for enriching the Web with machine-processable information with meaning organized on different abstraction levels [37]. This new area of research is being named Semantic Web Mining [6, 52]. The idea of Semantic Web Mining is to improve the results of web mining by exploiting the semantic structures of the Web, as well as to use web mining to help building the semantic Web.

3 System Parameters

In order to develop a model for the risk aware web recommender system we need to gather some parameters on which the output of the system depends. The selected parameters are web logs and user data, web page content,

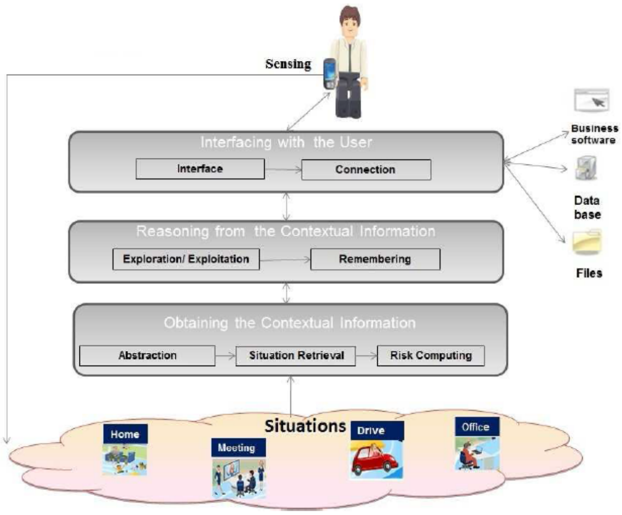

Fig. 5. System Design for existing Risk Aware System [120]

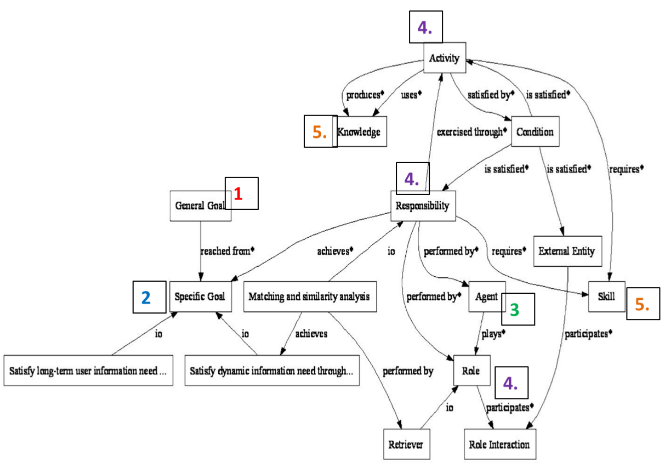

Fig. 6. Role Modelling for recommender system [32]

dwell time calculation, click through rate, search queries and web page content. After the determination of the parameters that affect the design of the system, we need to get the data from these parameters for establishing rules and relationships amongst various entities in the system.

3.1 Web logs and Usage mining

The aim of Web usage mining has been to support the human decision making process. Thus, the outcome of the process is typically a set of data models that reveal implicit knowledge about usage patterns of users. These models are evaluated and exploited by human experts, such as a market analyst who seeks business intelligence, or a site administrator who wants to optimize the structure of a site and enhance the browsing experience of visitors [47]. Although most of the work in Web usage mining is not concerned with personalization, its relationship to personalization issues has brought promising results. Web personalization is a sub-area of adaptive hypermedia that aims at providing actions that tailors the Web experience to a particular user, or a set of users [9]. This process is composed of two

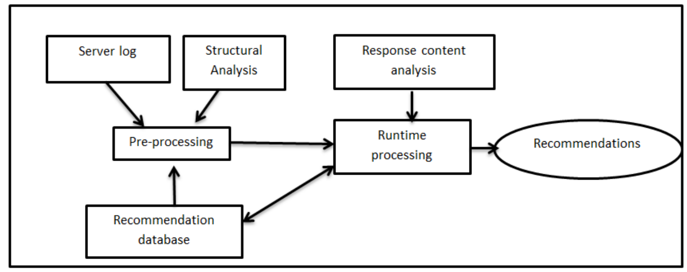

Fig. 7. Diagram of a Web usage based Recommender system

components [40]: an off-line component, responsible for the data preparation and specific usage mining tasks and an online component, responsible for the user data collection and the generation of personalized services to users, based both on the discovered patterns and their current browsing activities. The knowledge discovered through the usage mining process serves as operational knowledge to personalization systems. A Web personalization system can offer a great diversity of functions, ranging from simple salutation to more complex ones such as the adaptation of user interfaces [9]. Pierrakos et al. [47] propose a generic classification scheme for Web personalization functions. The proposed scheme takes into account what is currently offered by commercial systems and research prototypes. Four basic classes of personalization functions were identified in this scheme: memorization, guidance, customization and task performance support. These classes are briefly described below. A detailed description of this topic is provided in [20, 40].

3.2 Dwell time and Click Through Rate(CTR)

Traditionally, simplistic user feedback signals, such as click through rate (CTR) on items or user-item ratings, have been used to quantify users interest and satisfaction. Based on these readily available signals, most content recommendation systems essentially optimize for CTR or attempt to fill in a sparse user-item rating matrix with missing ratings. Specifically for the latter case, with the success of the Netflix Prize competition, matrix-completion based methods have dominated the field of recommender systems. However, in many content recommendation tasks users rarely provide explicit ratings or direct feedback (such as like or dislike) when consuming frequently updated online content. Thus, explicit user ratings are too sparse to be usable as input for matrix factorization approaches. On the other hand, item CTR as implicit user interest signal does not capture any post-click user engagement. For example, users may have clicked on an item by mistake or because of link bait, but are truly not engaged with the content being presented. Thus, it is arguable that leveraging the noisy click-based user engagement signal for recommendation can achieve the best long term user experience. In fact, a recommender system needs to have different strategies to optimize short term metrics like CTR and long term metrics like how many visits a user would pay in several months. Thus, it becomes critical to identify signals and metrics that truly capture user satisfaction and optimize these accordingly. However, utilizing dwell time in a personalized recommender system intro-

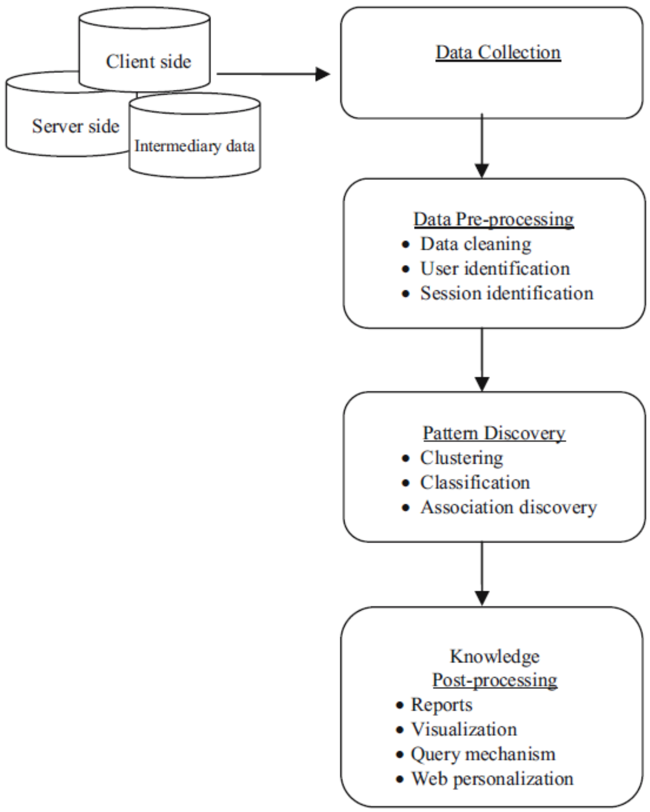

Fig. 8. Web Usage mining Process.

duces a number of new research and engineering challenges. For instance, a fundamental question would be how to measure dwell time effectively. Furthermore, different users exhibit different content consumption behaviours even for the same piece of content on the same device. In addition, for the same user, depending on the nature of the content item and the context, the users content consumption behaviour can be significantly different. Therefore, it would be beneficial to normalize dwell time across different devices and contexts. Also, recommender systems usually employ machine learning-to-rank (MLR) techniques and collaborative filtering (CF) models, with a wide range of features, to obtain state-of-the-art performance. Using dwell time in these frameworks is not straight-forward. Accurately computing item-level dwell time from web-scale user browsing activity data is a challenging problem. As an exam- ple, most modern browsers have a multi-tabbed interface in which users can open multiple stories simultaneously and switch between them. In the multi-tabbed setting, figuring out the tab that captured the users attention is non-trivial. In this paper we describe two complementary methods to derive dwell time, one via client-side logging and the other via server-side logging. We have also con- ducted a simple study comparing these two approaches. Although client-side logging can capture fine-grained user behavior and has the potential of being highly useful, there is a lot of dependency on browser implementation and potential for large amounts of data loss. Therefore, when the client-side data is not available, we resort to reasonable approximation methods through server-side logging. Thus, we can reliably compute dwell time in a real world setting.

4 Measuring and Formalizing MAB for Risk Aware web Recommender System

Some existing works take into account the risk in different application areas, like reinforcement learning and robotics. In these works the risk is measured with two types of uncertainty: parametric and inherent. Some works also use an hybrid of both types. The variance of the cost approach is related to the imperfect knowledge of the problem parameters. For instance, in the context of Markovien Decision Process (MDPs) and addressing inherent uncertainty, Howard and Matheson [80] have proposed to use an exponential utility function, where the parameter of the exponent controls the risk sensitivity. Another approach considers the percentile performance criterion, in which the average environments reward and its variance lead to decide the best action to select objects. The risk aversion factor is used which indicates excessive deviation from the expected values. The main advantage of variance of cost approach is the ability for computing the risk without the need of an expert, however this leads to a cold start at the beginning of the process. The expected environment cost approach is related to the stochastic nature of the system.

We describe the algorithms that consider the exploration-exploitation trade-off in RS. Compared to the standard MAB problem with a fixed set of possible actions, in RS, the old documents may expire and new documents may frequently emerge. In this setting, the algorithm needs to explore continuously new documents which may not be desirable to perform the exploration all at once at the beginning, as the beginning strategy, or to decrease monotonically the effort on exploration, as the decreasing strategy. Few research works are dedicated to study the MAB in RS, where they consider the users behaviour as the context of the bandit problem. In some places, we extend the e-greedy strategy by updating the exploration value dynamically. In each iteration, we run a sampling procedure to select a new e from a finite set of candidates. Probabilities associated to the candidates are uniformly initialized and updated with the Exponentiated Gradient (EG) . This updating rule increases the probability of a candidate If it leads to a users click. Compared to both e-beginning and e-decreasing strategy, this technique improves the results.

5 Domain Specif Language for Risk Aware web Recommender System

Most of the work in recommender systems focuses on a two-dimensional paradigm of recommending items to users or users to items (e.g., books to customers or customers for books). Although there are different types of approaches to deriving recommendations, including the ranking and marketbasket- analysis-based [114], the majority of the academic work in recommender systems and implementations of commercial systems, including Amazon and Netflix, focuses on the rating-based approach, where recommendations use explicit or implicit ratings provided by the end-users. Although the traditional two-dimensional user/item

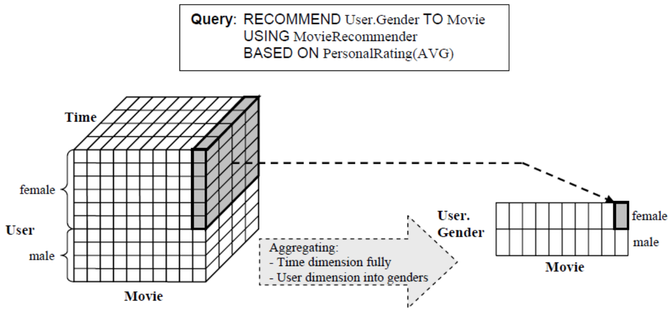

Fig. 9. An example of DSL for Recommender Systems [122]

paradigm described above is suitable for some applications, such as recommending books and music CDs, it is significantly less suitable for the context-rich applications, such as traveling or shopping applications. For example, when recommending vacations to travelers, one would likely recommend a different vacation to a customer in the winter than in the summer, i.e., the time-of-travel context is clearly important when making recommendations. Similarly, when recommending groceries, a smart shopping cart needs to take into account not only information about products and customers, but also such information as shopping date/time, store, who accompanies the primary shopper, products already placed into the shopping cart, and its location in the store. Clearly, the two-dimensional paradigm of classical recommender systems is less suitable for these applications. However, the multidimensional approach described and the classical two-dimensional recommendation methods have one significant limitation in common. These methods are hard-wired by the developers into the recommender systems, are inflexible and limited in their expressiveness, and, therefore, neglect some possible needs of the users. For example, a typical recommender system would recommend the top k items to a user, or the best k users for a product. This situation is quite limited, especially in multidimensional settings, where the number of possible recommendations increases significantly with the number of dimensions. Therefore, there is a need to empower end-users and other stakeholders by providing them with the tools for expressing recommendations that are of interest to them. For example, Jane Doe may need a recommendation for the best two dates to go on vacation to Jamaica with her boyfriend. Also, Netflix or an on-demand movie service, such as provided by the Time Warner Cable, can envision a web-based interface to a multidimensional cube of ratings that lets the users express the recommendations that are of interest to them or automatically tailors recommendations based on a given context, such as the time of day or the day of week. For example, a certain user (e.g., Tom) may seek recommendations for him of top 3 movies and the best times to see them over the weekend, and he enters this request into the recommender system via the web-based interface. Such query-based recommendation applications are not limited to on-demand movies but are relevant to a broad range of recommendation applications, including retailing, financial, travel and other applications. Furthermore, we believe that flexible recommendation capabilities would be appealing to a variety of different users, and not just to the end-users who are direct recipients of recommendations. For example, such functionality would be useful to the analysts of a company providing recommendation services, who may want to take advantage of all the knowledge that their recommender system holds and analyze it from a variety of different perspectives (show me the top 2 movie genres for each user age bracket, etc.).

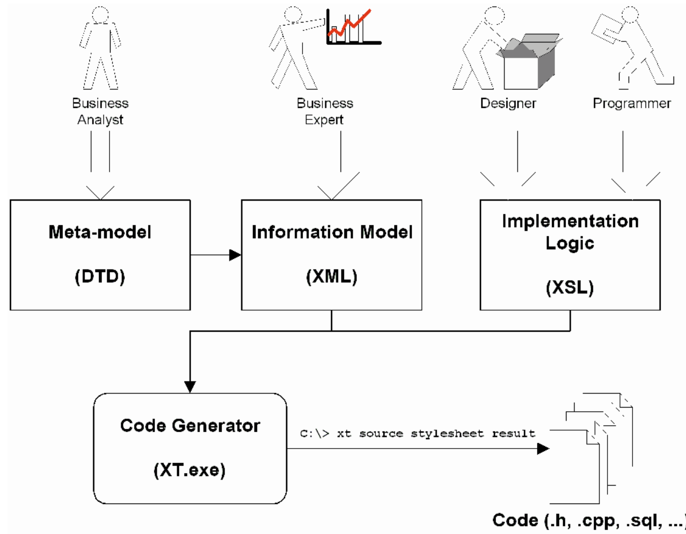

Fig. 10. Web Usage mining Process.

5.1 Code Generation from DSL

Domain-specific modeling tools and languages allow meticulous design analysis and automatic code generation, improving system quality. In contrast to standardized modeling languages like UML, domain-specific languages (DSLs) allow engineers to focus on the design decisions relevant to the domain and use the most suitable concepts and abstractions. Todays model-driven engineering (MDE) platforms, such as the Generic Modeling Environment (GME) and the Eclipse Graphical Modeling Framework (GMF), ease the creation of custom model editors for DSLs. Software engineers only need to define a metamodel a formal specification of a DSL and these platforms automatically synthesize a model editor that uses the DSLs symbols and enforces its syntax. Nevertheless, industry adoption of domain-specific modeling technologies has been more limited than that of standardized modeling solutions, particularly UML. One key reason for this disparity is that DSL analysis and code generation tools (often referred to as model interpreters) must be constructed manually. Meanwhile, UML-based analysis and code generation tools are available off-the-shelf. While domain-specific tools can perform more targeted analysis and more complete code generation, the difficulty of tool creation and maintenance reduces the appeal of domain-specific modeling, particularly for small- and medium-scale software systems.

6 Case Study: Stock Portfolio Recommendation

Generally a recommendation system suggests personalized choices from a large set of possible options with the objective

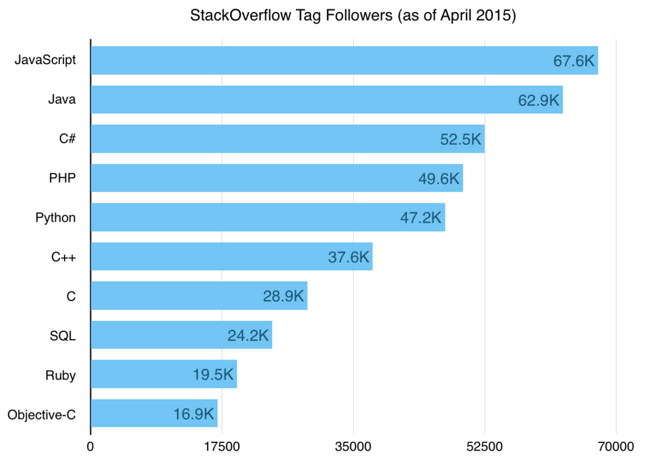

Fig. 11. Widely used programing Languages on StackOverflow based on tags.

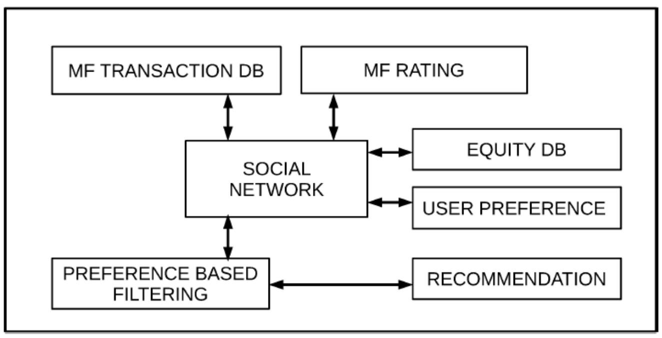

Fig. 12. Stock Portfolio Recommendation [93]

of reducing complexity decision making. The last decade has witnessed the emergence of lots of e-commerce portals offering such services to their users. Generally a recommendation system works on information filtering technique and provides information which is of the interest of the concerned user. Typically, a recommendation engine, which employs a set of algorithms, compares the users profile to some reference characteristics collected from the information item (the content-based approach) or the users social environment (the collaborative filtering approach), and seeks to predict the most suitable item for a particular user. The methodology proposed for stock portfolio recommendation system in this work aims at enhancing the profitability opportunity associated with stock portfolio recommendation by anchoring on the trustworthiness of mutual fund portfolio network. We could gain insight into the social investment relationships exist among stocks, which are otherwise hidden. By identifying the position of individual stocks we could determine the centrality associated with stocks in the entire portfolio network. Finally, a recommendation of a stock is offered matching the investor preference in creating a portfolio to the most relevant stock in the network. This kind of trust based social network recommendation system could be beneficial to both novice investors and first-time investors equally. The user is provided with a portfolio of relevant stocks in sync with their matched priorities. The

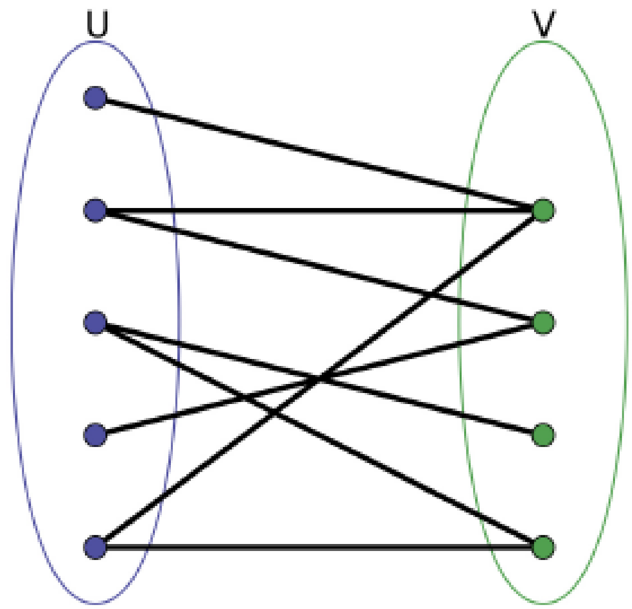

Fig. 13. Graph Representing Mutual Fund portfolio network [94]

mutual fund portfolio network is represented by means of a bipartite graph, where set of nodes U represents the mutual funds and set of nodes V represents stock invested by the mutual funds. An investment by a mutual fund in a particular stock is represented by an edge. The edge between mutual fund and equity will provide insight about the total number of shares and the invested value which will in turn assist in understanding the average investment bracket. From the this two mode network(bipartite graph) we can derive the 1-mode network, with stocks as nodes, using folding methods which operate directly on the matrix corresponding to the bipartite graph. Two stocks, in the 1-mode network of stocks, are connected if a mutual fund has invested in both the stocks.

7 Case Study: Risk Based Recommender for Personalized Healthcare

User specific risk based recommender systems that relate generally to dispensation of healthcare and specifically to the management of an individual users health risks are not readily found in the literature. Also missing from the literature are reports of user defined methods of combining technology with traditional clinical approaches for primary and secondary chronic disease prevention. Risk based personalized healthcare and associated health management relies on an efficient method of integrating user specific personal risk analysis as well as the resources utilized by the health care industry, including insurers, medical services providers and manufacturers, care givers and other participants in the users health care decision making. Efficiency has become increasingly imperative in the delivery of health care. This necessity has engendered a strong interest in consumer driven health plans, in which the premiums, contributory payment and other costs may be based on an array of factors, including the individual consumers status of health and assumption and assessment of health risks. Accordingly, it is ever more important to understand and quantify differences in health status when analyzing the cost efficiency of different health plans for the purpose of establishing employee contribution requirements. In such user-centric schemes, it is important for the users to have control of their health care decisions based on informative health guidelines. The general-purpose guidelines, when available, are not always interpreted by the users correctly. There is, therefore, a critical national need for reliable, personalized health guidelines incorporating users health risks and other relevant information for the user to make informed decisions at the risk stage of chronic disease. Providers of capitated health plans, on the other hand, can use such a system to contain costs through the use of timely interventions, especially in the case of chronic disease; their key requirement is a reliable means to identify and categorize user needs based on their individual health risks. There are many users with an interest in such a personalized health management system, including individual consumers, payors, health professionals and manufacturers, suppliers and providers and third party administrators of health products and services. Since it is possible to make personalized health information available to the diverse types of user groups with the help of the new media, therefore the providers of information dissemination networks and media may also be thought of as a user group whose needs intersect those of other groups of users of the system. Computer networks, including the Internet, make the information interactively available, including not only the health guidelines based on personal risk factors and health care management parameters but also peripheral information, such as, the products and services that can assist the user in following the guidelines. A method and system for personalized healthcare using reliable user defined criteria in a branded healthcare application that links general health guidelines with specific recommendations that are tied to healthcare guidelines would be useful as it would provide a means for a cost efficient outcome including the packaging for distribution across industries of personalized healthcare credits linked to general guidelines such as lose weight and exercise for use in early intervention of chronic disease. Outcomes can be measured by the same method and system.

8 Conclusion & Future Work

The proposed system may provide more relevant information to users in risky and dynamic environments. We have explored various requirements for an accurate risk aware web recommender system, considering the dynamicity of the content and the situation risk level. The model of a recommender system which is discussed in this paper aims at proposing more relevant information to the user with the help of user specific data such as web logs, user data, dwell time, search requests and click through rate (CTR). By establishing the relationship between the user specific data and the content of the website, this system evaluates the risk associated with the recommendation results. It may be further established in the future that tuning the recommendation results with the corresponding risk factor enhances the user experience. We have observed that the most appropriate representations of the users profile and context are respectively the multidimensional representation and the ontology representation. We also observe that the risk is never considered in existing recommendation system. This paper proposed a model for RAWRS, for Risk Aware Web-based Recommender System and approach its implementation with the validation of the model using real-world examples and discussing its implementation using the domain models and the domain specific language.

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