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Multi-agents and learning: Implications for Webusage mining

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ABSTRACT

Characterization of user activities is an important issue in the design and maintenance of websites. Server weblog files have abundant information about the user's current interests. This information can be mined and analyzed therefore the administrators may be able to guide the users in their browsing activity so they may obtain relevant information in a shorter span of time to obtain user satisfaction. Web-based technology facilitates the creation of personally meaningful and socially useful knowledge through supportive interactions, communication and collaboration among educators, learners and information. This paper suggests a new methodology based on learning techniques for a Web-based Multiagent-based application to discover the hidden patterns in the user's visited links. It presents a new approach that involves unsupervised, reinforcement learning, and cooperation between agents. It is utilized to discover patterns that represent the user's profiles in a sample website into specific categories of materials using significance percentages. These profiles are used to make recommendations of interesting links and categories to the user. The experimental results of the approach showed successful user pattern recognition, and cooperative learning among agents to obtain user profiles. It indicates that combining different learning algorithms is capable of improving user satisfaction indicated by the percentage of precision, recall, the progressive category weight and F_1-measure.

Introduction

Web user drowns to huge information and faces the problem of being overloaded with information due to the exponential growth for both the number of online available Web applications and the number of their users. This growth has generated huge quantities of data related to user interactions with the Websites, stored by the servers in log files. On the other hand, the degree of personalization that a Website is able to offer in presenting its services to users represents an important attribute contributing to the site's success. Hence, the need for a Website that understands the interests of its users is becoming a fundamental issue. If properly exploited, log files can reveal useful information about user preferences.

Reinforcement learning is the name of a set of algorithms for control systems that automatically improve their behaviors

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by trying to maximize the rewards received from an environment. Q-Learning is an example of reinforcement learning. Fuzzy C Means (FCM) is an unsupervised learning technique that became a good candidate method to handle ambiguity in the data, since it enables the creation of overlapping clusters and introduces a degree of item-membership in each cluster. A multi-agent system (MAS) is a system composed of multiple interacting intelligent agents within an environment. MASs can be used to solve problems that are difficult or impossible for an individual agent. There are few related studies regarding utilizing the combination of FCM and Q-learning for MAS in Webusage mining field. Kaya et al. [1] have introduced an approach based on utilizing the mining process for modular cooperative learning systems. It incorporates fuzziness and online analytical processing (OLAP) based mining to effectively process the information reported by agents. A fundamentally different approach have been proposed by Tesauro [2] introduced "Hyper-Q" Learning, in which values of mixed strategies rather than base actions are learned and in which other agents' strategies are estimated from observed actions via Bayesian inference. Tuyls et al. [3] discussed the use of traditional Reinforcement Learning (RL) algorithms in MAS and utilized in games using the replicator equations and dynamical equations. Matignon et al. [4] were interested in learning in MAS especially RL methods, where an agent learns by interacting with its environment, using a scalar reward signal as performance feedback. Li [5] has considered a channel selection scheme without negotiation for multi-user and multi-channel cognitive radio systems. To avoid collision incurred by non-coordination, each user secondary learns how to select channels according to its experience. Multi-agent RL is applied in the framework of Q-learning by considering the opponent secondary users as a part of the environment. Tan [6] has used reinforcement learning to study intelligent agents in which each agent can incrementally learn an efficient decision policy over a state space by trial and error. When the only input from the environment is a delayed scalar reward, the task of each agent is to maximize the long term discounted reward per action.

Web Usage Mining (WUM) can be broadly defined as preprocessing, pattern discovery then the analysis of useful information from the World Wide Web data based on the different emphasis and ways to obtain information. Lakheyan and Kaur [7] have presented a survey on WUM along with its functionalities and FCM algorithm for the retrieval of data from the search engine. Castellano et al. [8] have presented an approach for clustering Website users into different groups to generate common user profiles. These profiles are intended to be used to make recommendations by suggesting interesting links to the user via using FCM and directing users toward the items that best meet their needs and interests. Few works have been reported in Web-based MAS directed approaches integrating FCM and RL. For Example, Taghipour et al. [9] have proposed a novel machine learning perspective toward the problem, based on RL. It models the problem as Q-learning employing concepts and techniques commonly applied in the WUM. Web personalization technology enables the dynamic insertion, customization, or suggestion of content in any format that is relevant to the individual user. Birukov et al. [10] suggested that the Web developer needs to know what the user want and her/his interest to customize the web pages via learning her/his navigational pattern, based on the user's implicit behavior and preferences and explicitly given details. Various approaches have been defined to discover applicative techniques to get higher and corrective recommendations for user surfing. Reddy et al. [11] claimed that the Website structure and the users' profiles may constitute supplementary data for such a process while the Weblog files are the input data in a WUM process. The paper introduces a methodology for Learning in Web-Based Education System (LWBES) in two phases, the FCM to categorize user behavior into user interest category-list and the reinforcement learning to categorize user behavior into user interest link-list inside the category-list. The paper is organized into four sections. The second section introduces the description of the LWBES methodologies, the third section presents the experimental results, its evaluation, and discussion, and finally the conclusion and the future work.

LWBES methodology

A model of the website in which this methodology should be investigated on contains categories of downloadable materials. Each category is represented by collection of materials and each material is represented by a URL. The primary objective of LWBES can be stated as follows. Suppose a set $\mathrm{R} = \{\mathrm{R}_i | \ i$ is the number of the webpage R in a category$\}$ of URLs composing a Website and u is a user interactively navigating the Website. The problem is to obtain a personal-list (or recommendation-list) for u, $\mathrm{R}_\mathrm{u} \subseteq \mathrm{R}$, which is a set of URLs that are ranked based on u's interests. In general, to acquire a personal-list for a user, the process goes through four phases which are given in the following:

1. Webusage: Data about user perceptions such as navigation behaviors are collected.
2. Obtaining user insights: Usually this data require further processing for inferring information which is used in the later phases.
3. Ranking the items: The inferred user interests are utilized to provide the predicted user personal-list utilizing offline and online processes.
4. Adjusting user settings: LWBES obtains the resulted navigation behaviors from the user and employs it to refine the user settings based on the user perceptions.

LWBES consists of one interface with two kinds of users which are student and admin. The user logs into LWBES by providing user name and password. The user searches it by entering a keyword and the results of the search are ordered according to two main coordinates based on categories and links. The knowledge base of LWBES is based on a database model that appears as a star schema in which materials are in the center of the graph. The study is centered on the user and materials, therefore the duration in which the user stays in a material Webpage is an important consideration. As user server log file is tracked, the user satisfaction is needed to be captured as the user spends more time in a Webpage which affect the Webpage category weight. Therefore user "satisfaction" can be deduced from the user behavior while surfing. Sen and Weiss [12] presented a useful distinction between requirements for learning about passive components (such as databases), active components (such as agents), and learning about interactive components (such as organizational