Computational intelligence-based personalization of interactive web systems

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Abstract:- The main Computational Intelligence (CI) models for personalization of interactive web systems are identified as Fuzzy Systems, Genetic Algorithms, Neural Networks, Artificial Immune Systems and Swarm Intelligence which includes Particle Swarm Optimization, Ant Colony Optimization, Bee Colony Optimization and Wasp Colony Optimization. These models are reviewed and compared regarding their inception, functions, performance and application to personalization of interactive web systems. A taxonomy for personalization of interactive web systems based on CI methods is proposed. It uses two approaches to personalize web-based systems as profile generation and profile exploitation. Based on this taxonomy a general procedure and recommendations for personalization of interactive web systems are suggested. Future directions for application of CI modelling for personalization are discussed.

Key-words: Personalization, computational intelligence, taxonomy, web systems, modelling.

1 Introduction

The Internet and the World Wide Web (WWW) were first introduced to the public in the early 1990s and it was estimated that the number of servers on the WWW doubled every fifty three days in that year [42], [43]. In 2005, a dramatic milestone in Internet history was passed as the one-billionth user went online. The second billion is expected to be added by 2015. The current growth rate from the years 2000 to 2009 is estimated at 380% [69] and it is estimated that Internet use will continue to grow by an unanticipated 18 percent per year [43]. As the WWW continues to grow at an accelerated rate, the size and complexity of many websites grow along with it. Millions of users who have made the Internet an integral part of their livelihood continually face great difficulty interacting with web interfaces. Users are bombarded with a world of information at each click. It is increasingly time consuming, confusing and frustrating for website visitors to find the information they are looking for. The Internet was initially controlled by the user but now the user can easily feel controlled by the Internet.

To regain user control a user-centered design approach [33] to website development is necessary. Web personalization is a major part of user-centered design which addresses key user issues. It can be defined as any set of actions that can tailor the Web experience to a particular user or a set of users [57]. Web personalization can be automatic or customized. Automatic personalization uses implicit data and requires little or no user intervention. In customized personalization users explicitly state their preferences. Research has been done on the benefits of automatic over customized personalization, or some combination of these two extremes [32], [68].

Personalization techniques, whether automatic or customized, seek to better learn about users so that accurate user models can be created that will satisfy user preferences presently and at future visits. Web Usage Mining (WUM) or data mining techniques involves implicit methods for user modeling. As a user interacts with the web system his activities are tracked such as navigation, duration on pages and menu and content selections are just a few. All this raw web usage data is saved on web server logs and contains hidden information about user habits and preferences as well as unnecessary data. Analysis of user data discovers individual web usage patterns which is instrumental in user modeling for personalization of the interactive web interface.

Processing web usage data to create accurate user models is crucial for effective personalization. A more accurate user model reflects better knowledge about the user's preferences. Information filtering, information extraction and information retrieval are three techniques which can be used to derive useful information from web usage data. These approaches have been widely used but effective personalization includes intelligence rather than simple content recommendations.

Collaborative filtering involves making personalized recommendations to a user based on preferences of other users with a history of similar website use. DynamicProfiler [70] is a content-based collaborative filtering technique which generates dynamic user profiles for personalization. This approach on its own however has scalability problems and relies on subjective user preferences that change over time.

Common problems in gathering, processing and analyzing web usage data using these standard techniques are scalability, processing time and accuracy of learning techniques. Ideally a perfect learning technique will be able to 'think' like the user by learning present user behavior and dynamically adjusting to changing user patterns. To come as close to this ideal as possible techniques which artificially mimic the intelligence of users are applied. It is increasingly becoming evident that intelligent approaches, typically using computational intelligence techniques, are satisfying the shortcomings of traditional approaches and achieving user satisfaction [53], [57].

In the following the eight main Computational Intelligence (CI) techniques are reviewed with emphasis on their application to personalization of interactive web systems. A taxonomy for personalization of interactive web systems is proposed. The CI methods are then analyzed and based on the taxonomy recommendations for personalization of web interactive systems are developed.

2 Computational intelligence models for personalization of interactive web systems

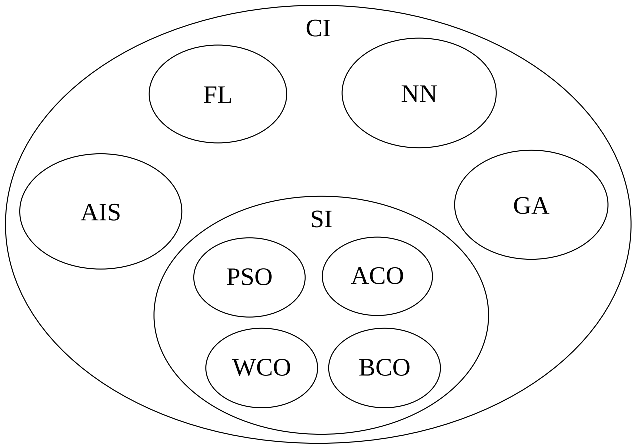

Fig. 1: CI techniques

Computational Intelligence (CI) has been defined as "the study of adaptive mechanisms to enable or facilitate intelligent behavior in complex and changing environments" [19]. CI is a major subcategory of artificial intelligence and has been an ongoing and evolving area of research since its term was coined by John McCarthy in 1956. Different CI methods currently exist and the ones considered in this paper are illustrated in Fig. 1.

A timeline indicating the major milestones in the development of these eight CI techniques is given in Fig. 2. They will now be explained in order of their appearance in the timeline given. Each model will be explained in terms of its inception by notable researchers, functioning, and applications with special mention in the area of web based personalization and its flaws as found in literature.

1956	1920s	1943	1962	1965	1974	1989	1992	1995	Mid 1990s	2005
John McCarthy coined the term 'AI'	Lukasiewicz three-valued logic, beginnings of FL	Warren McCulloch and Walter Pitts credited with work done on the modern era of NN	John Holland laid foundation for modern GA	Lotfi Zadeh introduced FS	Lotfi Zadeh introduced the term 'FL'	Gerardo Beni and Jing Wang first introduced the term 'SI'	Marco Dorigo introduced 'ACO'	James Kennedy and Russell E. Eberhart founded PSO	Interest in AIS arose	Bees Algorithm introduced

Fig. 2: CI timeline

Fuzzy Systems (FS) is maybe the oldest CI technique as it has foundation in mathematical concepts dating as far back as the 1920s. It was Lotfi Zadeh however who first introduced it in his 1965 paper [73]. Zadeh proposed that there exist not just two truth values but rather multi-valued logic. In 1974 the term Fuzzy Logic (FL) was also introduced by Zadeh [72]. This concept mimics the way people think, that is, with reasoning rather than precise. The mathematical application of this concept makes it possible for truth values to not just be one or zero but have intermediate values as well. Since its inception, FL has been applied to areas such as control systems, gear transmission, braking systems in vehicles, controlling lifts, home appliances, controlling traffic signals and information retrieval systems.

Fuzzy methods were also found to be instrumental in web-based personalization when used with web usage mining data. User profiles have been prediscovered from each user's saved history of website use and then intelligently processed using fuzzy approximate reasoning to recommend personalized URLs [22]. Processing of user profiles with fuzzy concepts has also been used by information retrieval systems to provide users with personalized search engine results [35]. Based on users web usage history data, fuzzy methods have been used to categorize or cluster web objects for web personalization [6]. Fuzzy logic has also seen success when collective or collaborative data mining techniques were combined and used to improve the quality of intelligent agents in the Internet context to provide more personalized service to users [53]. Fig. 3 illustrates these applications of FL to personalization of interactive web systems.

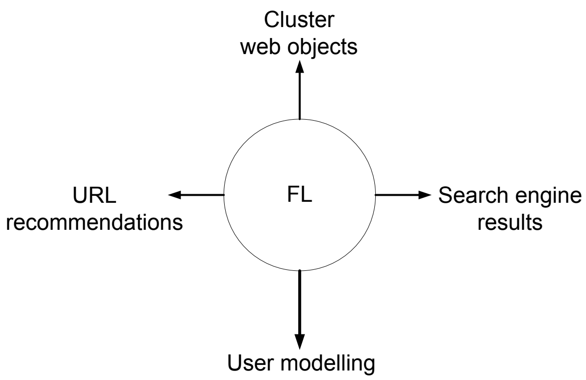

Fig. 3: Applications of FL to personalization of interactive web systems

FL is not without its flaws. There exist many ways of interpreting fuzzy rules, combining the outputs of several fuzzy rules and defuzzifying the output, it is occasionally hard to follow, does not always give definitive answers and harder to program for the fuzzy part.

Artificial Neural Networks (ANN) or simply Neural Networks (NN) is another CI method. DARPA Neural Network study states that "…a neural network is a system composed of many simple processing elements operating in parallel whose function is determined by network structure, connection strengths, and the processing performed at computing elements or nodes" [17]. Like the previous methods NN also mimics a biological process, the human brain. A NN is made up of layers, neurons, weights and biases at each layer and various training and learning functions. NN are trained using test data to process given inputs and determine the fitness to given outputs. The modern era of NN is credited to work done by Warren McCulloch and Walter Pitts [67] in 1943 and has since been applied to areas such as character recognition, image compression, classification, data processing and robotics.

A NN can be trained to group users into different categories or clusters. This is useful in personalization as each user group may possess similar preferences and hence the content of a web interface can be adapted to each group [12] [66]. NNs can also be trained to learn the behavior of website users. Inputs for this learning can be derived from web usage mining data [13] and collaborative filtering techniques. The learning ability of neural networks can also be used for real time adaptive interaction instead of only common content and static based personalization [40]. A NN was used to construct user profiles [5]and to categorize e-mail folders [28]. Fig. 4 illustrates these applications of NN to personalization of interactive web systems.

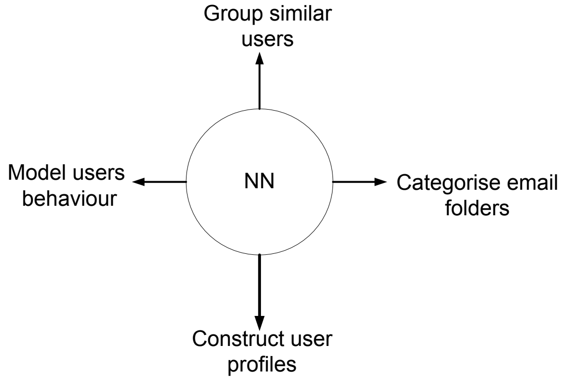

Fig. 4: Applications of NN to personalization of interactive web systems

Overfitting is known to be a main disadvantage of NNs. This occurs when there are too many parameters to be satisfied and as a result it is very difficult, if not impossible, to derive a solution which fits all parameters. Another problem is the black box effect as its parameters are not easy to select and understand. Problems also arise with the processing time of NN as they first need to be trained with a large sample size before the actual data can be trained. Larger NN may also require longer processing time. Interpreting a learned neural network can be a difficult problem. Combining NN with other CI methods however has been more practically useful and some of these hybrids will be discussed later in this paper.

CI also covers the realm of Evolutionary Algorithms (EA) which uses some mechanisms inspired by biological evolution such as reproduction, mutation, recombination and selection. The most popular EA are Genetic Algorithms (GA). As its name imply, GA mimic the gene structure in humans based on evolutionary theory. The concept of genetically inspired algorithms date back to as early as the late 1950s but it was John Holland in 1962 who is notably known to have laid the foundation for later development of GA as we know it today [23], [25]. GAs have been applied to areas such as aerospace engineering, microchip design, biochemistry, molecular biology, code-breaking and distributed computer network topologies just to name a few. So widespread is its use that GA is described as "solving problems of everyday interest" [52].

Data mining provides a wealth of valuable user knowledge used for website personalization however, it is not without its flaws. GA have been used to address some of these flaws and tackle different problems in web mining including search and retrieval, query optimization and reformation, and document representation and personalization [56]. GA has also been applied with user log mining techniques to get a better understanding of user preferences and discover associations between different URL addresses [47]. By GA was included randomness in content filtering rather than strict adherence to predefined user profiles. This is known as the element of serendipity in information retrieval. This modified GA was introduced for optimal design of a website based on a multiple optimization criteria taking download time, visualization and product association level into consideration [7]. The use of GA for dynamic optimization and evolution of web pages is work yet to be explored. Fig. 5 summarizes these applications of GA to personalization of web systems.

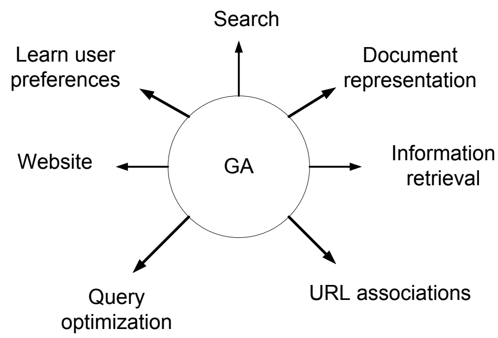

Fig. 5: Applications of GA to personalization of interactive web systems

Some concerns with GA do exist however. The main issues are the time and computational power needed to run a GA may be taxing, one exact solution is not guaranteed [20], [24] and when a solution is achieved it may be sub-optimal [38].

Swarm Intelligence (SI) is a CI technique based on the collective behavior of animals in nature such as birds, fishes, bees, ants and wasps. SI has been implemented since the first living organisms on the planet, but the term was first introduced by Gerardo Beni and Jing Wang in 1989 [21]. SI itself has been divided into different sub-techniques based on the animal behavior in nature being modeled computationally.

Particle Swarm Optimization (PSO) was founded in 1995 by James Kennedy and Russell Eberhart to model the convergence behavior of a flock of birds [27]. There have been many variations over the years but there are some basic characteristics of the PSO model. Every version uses a population of particles which are randomly initialized in the search space. The topology describes the connections between the particles and well known topologies include the global best and local best topologies [55]. Typically each particle in PSO also possesses a velocity which helps determine its movement in the search space. Inertia weights were introduced to PSO to control explosion of the algorithm [71]. Parameters have been added or modified in the PSO algorithm over time in efforts to enhance its speed, accuracy and optimization abilities. PSO works by randomly initializing particles in a search space then allowing each particle to adjust its position based mainly on topology, velocity, inertia weights and other constants or parameters defined. This interaction continues until a stopping condition is met or convergence to a minimal or maximal point is achieved. Some applications of PSO include function approximation, clustering, optimization of mechanical structures and solving systems of equations.

Like the previous techniques, PSO can be used for analyzing unique behavior of web user for processing of web access log data and user profile data [3]. Personalized recommendations based on individual user preferences or collaborative filtering data has also been explored using PSO. This was done by building up profiles of users and then using an algorithm to find profiles similar to the current user by supervised learning [8]. Personalized and automatic content sequencing of learning objects has been implemented using PSO [37]. Research has also been done using PSO as a clustering technique but no use of this approach to clustering [41], [63] was found in relation to website personalization.

Another SI technique is Ant Colony Optimization (ACO) which was introduced by Marco Dorigo in 1992 [1], [18]. This technique models the behavior of ants that leave the nest to wander randomly in search of food and when it is found they leave a trail of pheromone when returning to the colony. ACO resulted in the development of the shortest path optimization algorithms and has applications in routing optimization in telecommunications networks, graph coloring, scheduling and solving the quadratic assignment problem.

ACO has been used to classify web users in web usage mining (cAnt-web usage mining algorithm) allowing personalization of the web system to each user class [4]. This algorithm however has low performance scalability and high computational complexity.

Bees Colony Optimization (BCO) is one of the more recent and lesser known of SI techniques. The basic principles of collective bee intelligence were introduced in 2001 [48]. The Bees Algorithm for combinatorial and functional optimization was introduced in 2005 and mimics the food foraging behavior of swarms of honey bees [51]. Applications in this field include training neural networks for pattern recognition [15], data clustering [16], tuning a fuzzy logic controller for a robot gymnast [14] and information retrieval [34]. BCO has been applied to interactive web systems to improve the information retrieval systems of search engines [49] incorporating web usage mining data [65], However the issue of personalization has not yet known to be directly addressed.

Wasp Colony Optimization (WCO) or Wasp Swarm Optimization has not yet been exploited in comparison to the other SI methods. It models the behavior of insect wasps in nature [54], [58]. Applications include clustering, optimization of logistic processes in supply chains [50] and factory operations [64]. WCO has also been applied to the NP-hard optimization problem known as the Multiple Recommendations Problem. This problem occurs when several personalized recommendations are running simultaneously and results in churning where a user is presented with uninteresting recommendations [58]. Further research has to be done however, using WCO on real, scalable and dynamic data sets. Fig. 6 illustrates these applications of SI to personalization of web systems.

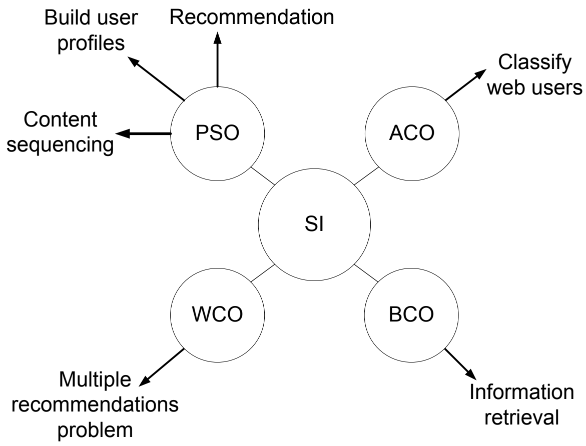

Fig. 6: Applications of SI to personalization of interactive web systems

“Artificial Immune Systems (AIS) are adaptive systems, inspired by theoretical immunology and observed immune functions, principles and models, which are applied to problem solving" [36]. The foundations of this CI technique began as early as 1986 [26], however it was not until the mid 1990’s that interest in the subject arose [29], [31], [61]. Applications of AIS have been solving pattern recognition problems, classification tasks, cluster data and anomaly detection.

Already AIS has been applied to personalization of interactive web systems. The human body was represented by a website, incoming web requests were antigens and learning was paralleled to the learning of the immune systems to produce the right antibodies to combat each antigen. By this analogy an AIS based on web usage mining was used as a learning system for a website [46]. Fig. 7 illustrates this application of AIS to personalization of interactive web systems.

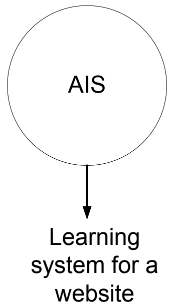

Fig. 7: Applications of AIS to personalization of interactive web systems

AIS are thought to be advantageous in its ease of adaptation to the changing and dynamic web environment however this method faces some challenges. AIS is slowly drifting away from its immunological roots due to naive approaches, other biological systems work together with the immune system but AIS isolates the natural immune system and recent theories in the natural immune system is not incorporated in AIS and so limits its success [59].

These eight CI techniques were initially developed independently of each other. It is common practice however to combine CI techniques to create a hybrid. Hybrids seek to overcome the weakness of one technique with the strength of another. Several hybrids have also been applied to personalization of web systems.

The topology and parameters of NN were used to obtain the structure and parameters of fuzzy rules. The learning ability of NN was then applied to this set of rules forming a hybrid neuro-fuzzy strategy for web personalization [10].

The ability of evolutionary techniques such as GA, to extract implicit information from user logs was combined with fuzzy techniques to include vagueness in decision making [62]. This FL-GA hybrid allowed more accurate and flexible modeling of user preferences.

User data obtained from web usage data was stored in a database and was the input for a NN. The weights and fitness functions derived from NN training was optimized using GA to derive classification rules to govern GA-NN-based personalized decision making in eBusiness [2].

A fuzzy-PSO approach was introduced to personalize content based image retrieval. User logs were analyzed and used as the PSO input. Fuzzy principles were applied to the PSO velocity, position and weight parameters [11]. Fig. 8 illustrates these applications of hybrid CI techniques to personalization of web systems.

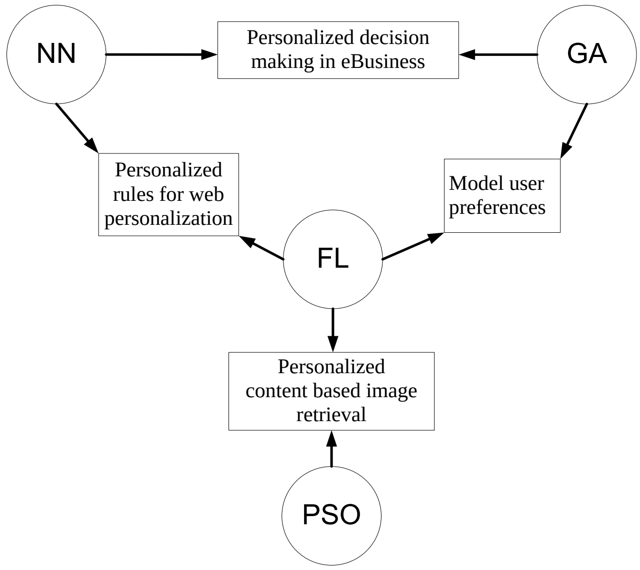

Fig. 8: Some hybrid CI techniques for personalization of interactive web systems

3 Personalization of interactive web systems using CI models

Previous work has been done on ways to classify personalization. Motivations for personalization were classed as either work related or socially related [9] and applied to mobile phones and eCommerce web pages. In another approach, intelligent personalized agents on the Internet were deeply analyzed. From this analysis three broad categories were determined: Profile generation and maintenance, Profile exploitation and other issues. Ten common features were further identified under these three categories [39]. Personalization of interactive multimedia content was classified under the categories of content and presentation management, user interaction and group personalization [44]. Fig. 9 illustrates these three approaches to classifying personalization.

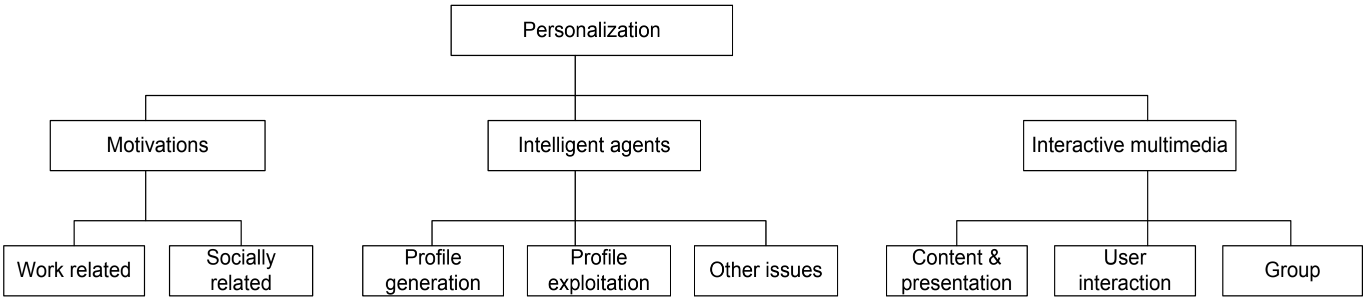

Fig. 9 Personalization taxonomies

On analysis of these three existing taxonomies, it was found that the taxonomies of motivations and interactive multimedia viewed personalization from a different perspective than is intended in this paper. The taxonomy of intelligent agents was however found to be very closely related and comparable to CI methods. In his 2002 paper however, Montaner [39] described personalization from an application point of view. He analyzed various personalized systems and focused on personalized recommendation services offered by these systems. This paper is written from an implementation view point and seeks to classify personalization and to provide recommendations for model selection.

Montaner identified steps in the personalization process under three groupings. Two of these groupings were found to relate to CI as well and are profile generation and profile exploitation. Building on Montaner's taxonomy, Profile exploitation is further subdivided into personalized content and personalized navigation. CI methods are also classified using this proposed taxonomy and according to their implementations on interactive web systems found in literature. Fig. 10 illustrates the main steps in the personalization process, outlining the flow of information and distinguishing between profile generation processes and profile exploitation processes. In Fig. 11 is given the classifications of CI models implemented in profile generation and profile exploitation processes.

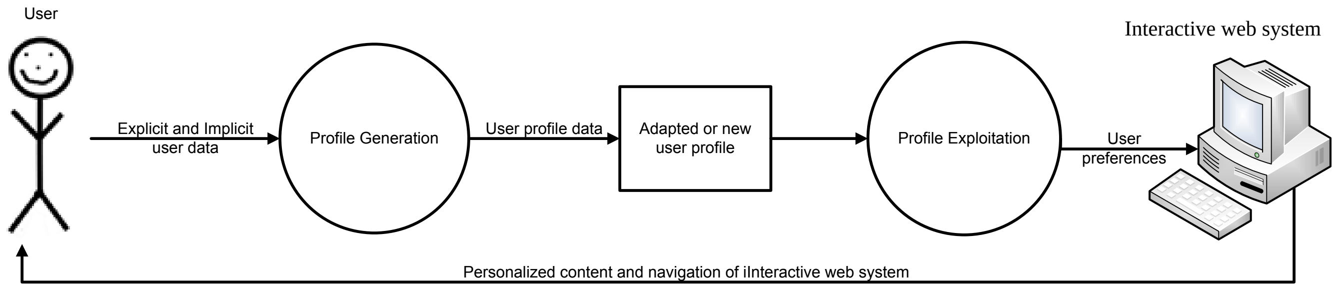

Fig. 10: Procedure for personalization of interactive web systems based on taxonomy

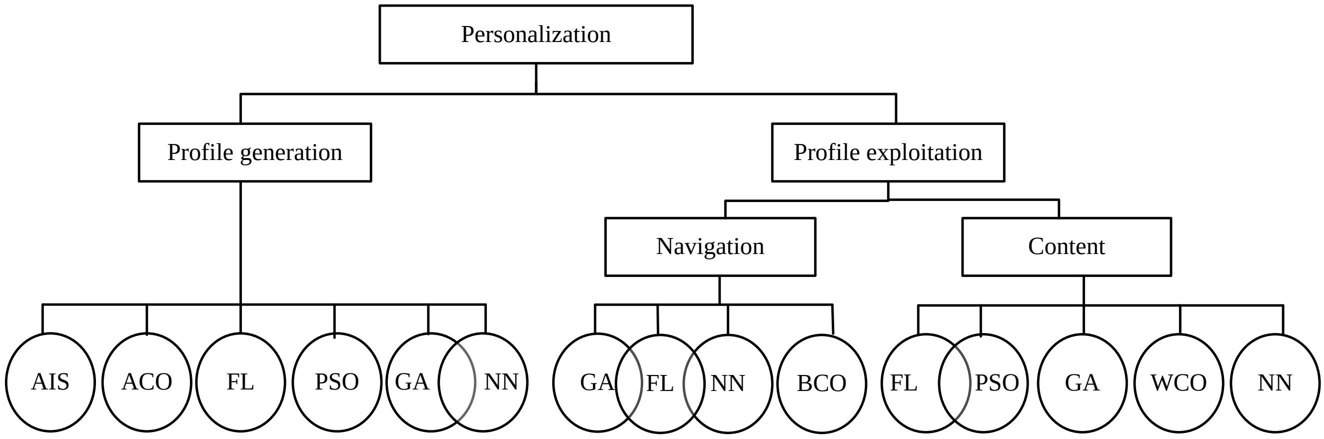

Fig. 11: Taxonomy for personalization of interactive web systems using CI

3.1 Profile generation

Profile generation here involves all the steps from user interaction with the web based interface to creation of the actual user profile or model. The steps in profile generation are usually done in offline mode. In Fig. 13 the user initiates and continues the cyclic adaptation of the interface. The user first provides implicit and explicit information to the system and feedback should also be encouraged. All this raw user data is collected but is not very useful in this state. Preprocessing involves interpreting raw user data and selecting which data to use so that is makes better sense for the rest of the system. Filtered user data from this process is then the input for initial pattern discovery for new users. If the user is not new this filtered data can be combined with existing user data for discovery of new user patterns. Throughout this profile generation process the learning and modeling capabilities of CI techniques can be applied.

Six CI methods found in previous work which were applied to user profile generation of interactive web systems are FL, NN, GA, PSO, ACO and AIS. This is illustrated in Fig. 11.

FL models are constructed to identify ambiguity in user preferences [6] however there are many ways of interpreting fuzzy rules and translating human knowledge into formal controls can be challenging.

NN can be trained to identify similarities in user behavior [12]. For proper training the sample size must be large and the NN can be complex due to overfitting.

Both PSO and GA can be used to link users' behavior by profile-matching [8]. PSO was found to outperform GA in terms of speed, execution and accuracy.

Most PSO algorithms are not robust in their parameterization.

ACO was used to model users with relative accuracy and simplicity [4]. Its computational complexity causes long computing time. PSO approach was found to be faster when compared to ACO [30].

AIS was used to dynamically adapt profiles to changing and new behaviors [73]. The theoretical concept of AIS is not fully sound however [74], since in reality other human systems support the functioning of the immune system and these are not modeled. The artificial cells in AIS do not work autonomously therefore the success or fail of one part of the system may determine the performance of the following step.

A hybrid method uses GA to optimize the input values of a NN, to maximize the output [74]. In this way the slow learning process of NN is helped with the optimization ability of GA.

3.2 Profile exploitation

Profile generation here includes all the steps from the already generated user profile to deployment of what has been learnt about the user to provide a personalized interactive web-based interface. Different sources of user data can contribute to the pool of knowledge about the user. One such user data source is collaborative filtering where the profile of the user in focus is matched with profiles of other users of the web based system for similarities. In this way it can be assumed that the preferences of other similar users may appeal to the user in focus. The initial user profile may consist primarily of user data independent of social influences. It is also possible to perform the collaborative filtering process with profile generation. In such a case the user profile will reflect not just preferences of the user but also preferences of others. Another source of data for user adaptation and learning is from stereotyped data. This was defined by Montaner [39] as “using descriptions of the people to learn a relationship between a single item and the type of people that like that object". Profile exploitation then involves selecting what data will be further used for decision making to provide a personalized system. Next this intelligently combined and filtered user data is evaluated on its accuracy for providing user satisfaction. Satisfaction can be measured in the ability of the model to predict user interests yet including elements of diversity and serendipity. Till now all the processes have been done in offline mode. The final process which is also part of profile exploitation is deployment of what is learnt about the user. This can be done in real time and involves visible improvements in the interface of the web based system, working within the options available to the user. The user then interacts with this personalized web-based system and the cycle begins again.

In Fig. 11 it is illustrated that two main approaches to personalize interactive web systems have been identified as personalization of navigation and personalization of content.

3.2.1 Personalized navigation

Personalized navigation includes WUM for personalized information retrieval, such as search engine results, and URL recommendations. FL, BCO, NN and GA were three main CI methods found for navigation personalization (cf. Fig. 11).

FL was used for offline processing to recommend URLs to users [45]. It is relatively fast, deal with natural overlap in user interests and is suitable for real time recommendations. Various FL testing however showed slightly lower precision and more difficult programming for the fuzzy part.

GA was applied for search and retrieval [56] but is it known to be more general and abstract than other optimization methods and does not always provide the optimal solution.

BCO was used for information retrieval [49] but it is not a widely covered area of research and currently there is a better theoretical than experimental understanding. ACO is similar to BCO and has seen more successful applications.

A hybrid between GA and FL was applied to this area. Fuzzy set techniques were used for better document modeling and genetic algorithms for query optimization to give personalized search engine results [62]. A neuro-fuzzy method combined the learning ability of NN with the representation of vagueness in fuzzy systems to overcome the NN black-box behavior and present more meaningful results than FL alone [59].

3.2.2 Personalized content

Personalized content refers to WUM for personalized web objects on each web page and sequence of content. FL, NN, GA, PSO and WCO were the main CI techniques found with applications in this area (cf. Fig. 11).

FL was used for a web search algorithm and to automate recommendations to eCommerce customers [71]. It was found to be flexible and able to support eCommerce application.

NN was used to group users into clusters for content recommendations [12] however overfitting problem still exists today

GA was applied to devise the best arrangement of web objects [7]. It was found to be scalable, however it is suggest to be used in collaboration with other data mining tools.

PSO was used to sequence learning objects [37] and was chosen because of relative small number of parameters compared with other techniques such as GA. PSO parameter selection is also a well researched area [60]. Using a modified PSO for data clustering was found to give accurate results [63].

WCO was applied on the churning problem of uninteresting content recommendations to users [58]. This is mostly a theoretical concept, not well tested on real data and other biological inspired algorithms have found more success such as ACO.
Fuzzy-PSO was created to help improve the effectiveness of standard PSO particle movement in a content-based system [11].

4 Conclusions

Eight main computational intelligence techniques were identified and critically reviewed regarding their application to personalization of web-based systems. A taxonomy with two main personalization categories as profile generation and profile exploitation was proposed. For profile generation FL, NN, PSO, GA, ACO and AIS were found to be the main CI techniques used and also a hybrid between GA and NN. Research studies show that PSO outperforms GA [8] and ACO [30]. PSO has relatively few parameters as compared to NN and has a more sound theoretical foundation than AIS.

PSO is also relatively easier to program and easier to interpret than FL. Of the five methods presented above for profile generation using WUM data, PSO seems to be the more tested, useful and well rounded method.

For profile exploitation CI applications were found using FL, GA and BCO for navigation and FL, GA, WCO, NN and PSO for content personalization. Hybrid methods were also identified for each. Similarly as with profile generation, all the CI algorithms applied to profile exploitation thus far possess inherent strengths and weaknesses. Introduction of new CI techniques for personalization should address the weakness of the previous methods, but should also be validated with a sound theoretical background and testing. PSO seems to achieve this compromise. The functioning of PSO has been given superior results to other CI techniques and it is also widely tested unlike more recent techniques.

In Fig. 12 are summarized the results of the review of the eight CI techniques regarding their application to personalization of web-based systems. Comparison was made based on five criteria which are simplicity of the method, speed of convergence, how sound or wholesome is its theoretical background, the model's ability to learn and adapt to given input and how much research has been done on testing the model. Here ☺ indicates that the model was found to perform well in comparison to the other models and ☹ indicates that model did not perform well in comparison to the others.

The hybrid techniques showed how the strength of one method complemented the weakness of another. PSO was credited with good performance as compared to the other methods however it is not without its flaws. Further work in this area may find useful combining PSO with other CI techniques to help with its inefficiencies. The more recent CI techniques methods also have a lot of room for exploration.

	CI Models								Hybrids			
	FL	GA	NN	PSO	ACO	BCO	WCO	AIS	FL-PSO	FL-NN	FL-GA	GA-NN
Simplicity	☹		☹	☺								
Speed	☺	☹	☹	☺	☹				☺			☺
Sound theory	☺			☺	☺	☹	☹	☹				
Learning ability				☺					☺	☺	☺	☺
Well tested	☺	☺		☺		☹	☹	☹		☹		☹

Fig. 12: Comparisons of CI models for personalization

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