Learning and Knowledge Management Toolbox for Cognitive Radio Network Applications

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Learning mechanisms are essential for the attainment of experience and knowledge in cognitive radio (CR) systems, exposed to high dynamics with often unpredictable states. Such learning mechanisms can be associated with user and device profiles, context and decisions. This paper provides a synopsis of basic learning functionalities and relevant requirements for the collection and processing of information that can lead to exploitable knowledge. The paper also provides an overview of potential implementation approaches for these functionalities that exploit diverse machine learning techniques.

Introduction

Learning mechanisms are essential for the attainment of experience and knowledge in a Cognitive Radio (CR) system [1]. Such mechanisms can be associated with user and device profiles, context and decisions. The learning of profile information focuses on the dynamic inference and estimation of current and future user preferences. The acquisition and learning of context information encompasses mechanisms for the system to perceive its current status and conditions in its present environment, as well as estimating (and forecasting) the capabilities of available network configurations. Finally, learning related to decisions addresses the building of knowledge with respect to the efficiency of solutions that can be applied to specific situations encountered. Based on knowledge obtained through the exploitation of such learning mechanisms, decision-making mechanisms can become faster, since the CR system can learn and immediately apply solutions that have been identified as being efficient in the past. Moreover, knowledge obtained through learning mechanisms may be shared among nodes of a system. Thus, more reliable and more optimal decisions can be made by exploiting knowledge obtained through learning mechanisms.

In this context, this paper presents various basic learning functionalities and relevant requirements for the identification, collection and processing of information that can lead to exploitable knowledge. The paper also provides an overview of potential implementation approaches for these functionalities that exploit diverse machine learning techniques.

Scenarios

This section introduces a set of indicative scenarios focusing on information acquisition and processing, learning and knowledge management. The target of these scenarios is to provide an overview of CR applications where learning and knowledge management play an important role. In this respect, the particular scenarios have been selected as they include different facets of information acquisition, processing and exploitation in the scope of advanced coexistence technologies for radio optimization in licensed and unlicensed spectrum.

Knowledge based management of reconfigurable B3G infrastructures

This scenario focuses on the operation of a Cognitive Network Management System (CNMS), which constantly monitors the network context and is able to detect that a problematic situation (e.g. severe Quality of Service (QoS) degradation) has occurred in a network area (Figure 1).

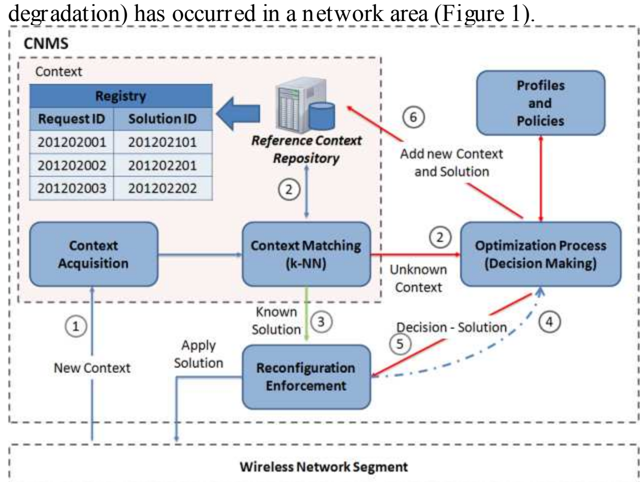

Figure 1: Knowledge based management of reconfigurable B3G infrastructures [2]

The CNMS is able to handle such problematic situations by making the appropriate decisions for the reconfiguration of the managed infrastructure. Moreover, the CNMS stores information on encountered contextual situations including the solution that was applied for handling them in a Reference Context Repository. This allows considering past network interactions so as to allow faster and more efficient handling of problems. The on time reaction of the CNMS guarantees the smooth network operation and the provision of services and applications at the desired quality levels.

Self-optimization of cognitive user devices

This scenario considers the behaviour of user devices that can comprise various awareness functionalities so as to decide in an autonomous manner on the actions they have to take in order to ensure that all of their running services are constantly obtained at the best possible QoS level. The need for action comes from the volatile context of the network environment. There can be several operators in the area, offering the same services but with different quality and reliability. The user device, based on the knowledge and experience developed over time, when faced with similar contextual situations, can autonomously make appropriate reconfiguration decisions and continue to operate efficiently despite the changing network conditions. A high-level view of the process of self-optimisation of cognitive devices is provided in Figure 2.

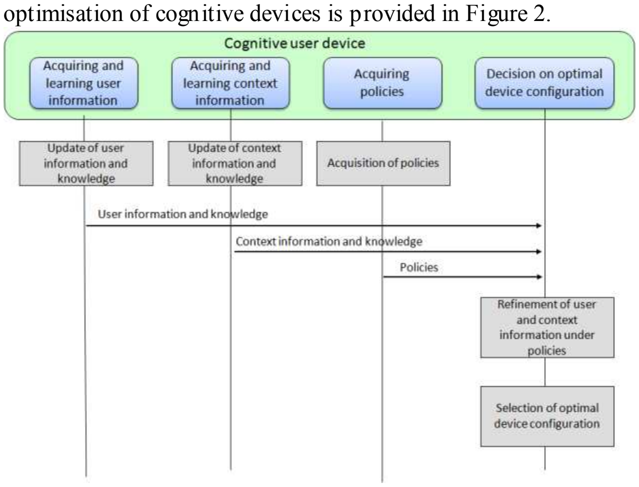

Figure 2: Self-optimization of cognitive user devices

Cognitive systems and opportunistic networks

This scenario addresses the use of Opportunistic Networks (ONs) for enabling devices to communicate over infrastructure networks even if there is no direct connection to an infrastructure network [3] (Figure 3).

ONs are operator governed (through the provision of resources and policies) and can be coordinated extensions of the infrastructure for a particular time interval. In the scope of this scenario various learning and knowledge mechanisms can be useful. These include mechanisms for the identification and learning of context information, such as identification of spectrum opportunities [4] for the set up of ONs, of candidate ON nodes such as devices in the vicinity, identification and learning of user preferences.

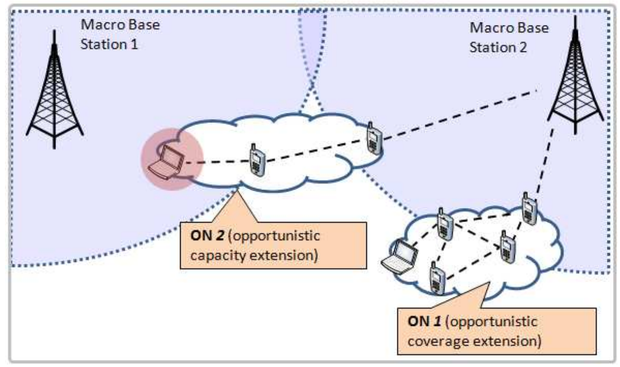

Figure 3: Coverage and capacity extension with ONs

Learning and Knowledge Management mechanisms

This section provides an overview of learning mechanisms (Figure 4) which can be derived from the analysis of the scenarios outlined in the previous section.

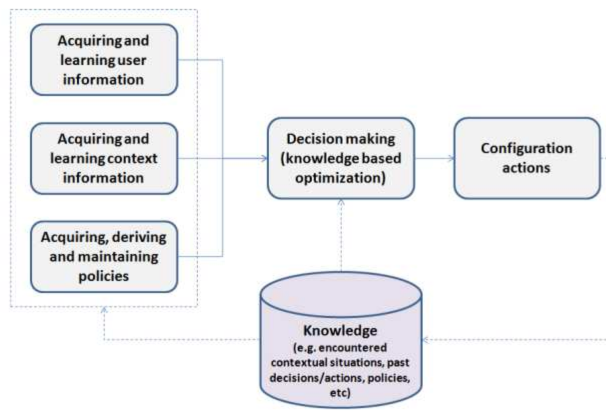

Figure 4: High-level view of learning functionalities in the scope of self-management in CR systems

Acquiring and learning user information

The goal of this mechanism is to acquire, maintain and process information on user preferences and behaviour, as well as the capabilities of the user device. Indicative information includes (i) the set of potential configurations e.g. (the Radio Access Technologies (RATs) that the mobile device is capable of operating with, the associated spectrum and transmission power levels), (ii) the set of services that can be used and the sets of QoS levels associated with the use of a service, (iii) the utility volume associated with the use of a service at a particular quality level (Quality of Experience (QoE)), and (iv) the maximum price that the user is willing to pay in order to use certain services at specific QoS levels, i.e. for a certain QoE. Furthermore, this functionality deals with learning elements of the user behaviour. The term "utility" here is "borrowed" from economics, where utility is used to express the satisfaction obtained from the consumption of goods or services. In this scope, the utility volume provides a ranking (by order of preference) of service and QoS combinations, similar to the Mean Opinion Score. User preferences may vary depending on the contextual situation and may change over time. Therefore, the utility volume depends on a range of context-related, observable parameters. More specifically, the utility volume, apart from the service and QoS level, may be related to the location of the user, the time zone, the user role and the feedback obtained from the user.

Acquiring and learning context information

On the network side this mechanism enables collection of the status of network elements (Base Stations), the status of their environment as well as that of user devices [5]. Essentially, each element may use monitoring and discovery procedures [6], which can be sensing based [7], and/or pilot channel based [8]. Monitoring procedures provide, for each network element of the segment and for a specific time period, the traffic requirements, the mobility conditions, the current configuration in terms of operating parameters (e.g., spectrum assignment, power level, etc.) and the QoS levels offered. Furthermore, it includes procedures for capturing the channel state information which is reflected by the estimation of the mean signal-to-noise ratio (SNR) value for each sub-carrier. Context information is used by the system for the assessment of Key Performance Indicators, utilised for addressing potential problems and triggering appropriate optimization procedures whenever necessary. Diverse types of context information storage may be applied depending on the aforementioned types of information. The notion of Reference Context Repository, briefly outlined in the previous, enables the storage of formerly encountered contextual situations in addition to the corresponding solution that was selected by an optimisation process for addressing these situations. The concept of Radio Environment Maps (REMs) enables storage of context and policy information [9].

On user devices this mechanism enables devices to obtain information about the network context in a radio environment with various coexisting technologies. Such network context information should include data about available access technologies in a given area and their corresponding status (e.g. used frequencies, available resources, coverage, etc.), information about the device status (e.g. coverage at the current location, power available, technology capabilities, etc.), information about the status of other devices in the area (e.g. activity, ability to cooperate, etc.). It should be noted that such information can be directly obtained at the mobile device (e.g. received power level) as well as at other nodes (e.g. load level in a given access point). Therefore, appropriate mechanisms are required which enable the exchange of context information/knowledge between nodes in a cognitive network. Learning context information on devices aims to estimate the most likely capabilities (in terms of QoS parameters, such as bit-rate), that can be achieved by a given configuration, in a given location, time zone, etc. Such estimations can be exploited in order to increase reliability of decisions. Functionality for learning context information also enables estimation of situations that are likely to be encountered in future time points, given a certain situation in the current time zone, thus enabling proactive handling of certain circumstances.

Acquiring, deriving and maintaining policy information

This mechanism is responsible for the acquisition, derivation and management of information related to policies. Policies specify rules or constraints that should be taken into account for the selection of the optimal configuration of a service area, network element or user device. In this sense, policies refine the set of data comprised in context information.

Policies are usually stored in a database. A policy database may be used as a central storage point of the policies and policy users in the network. Such a database enables keeping track of active users and active policies in the network as well as user–policies associations. Policy information should form a set of database tables such that fast and efficient usage of the stored information is enabled when required.

A key feature related to policies in a CR system is the derivation of spectrum sharing policies on the spectrum vacancies (currently not utilized by Primary Users) for the Secondary Users (SUs). The policy derivation requirements can be divided based on the:

- Input parameters (Sensing based and Non-sensing based);
- Type of derivation (Reactive, History/Predictive derivation)*;*
- Type of policies (Based on the location, Based on the functionalities, *Connectivity* based, *Spectrum* based).

The derivation of spectrum policies may be realised in a static or dynamic manner. The static approach relies on long term environment measurements, allows learning of certain repetitive behaviours in the network and leads to derivation of static spectrum sharing policies. The dynamic approach relies on shorter real-time measurements which enable policy derivation coping with the dynamism of the wireless environment on a shorter time scale.

Learning related to the efficiency of decisions

The goal of this mechanism is to build knowledge related to decisions regarding the system configuration and to exploit this knowledge in order to decrease the time required to reach a decision. More specifically, this functionality comprises mechanisms that allow storing information about problems that occur (e.g. QoS degradation) as well as their solutions. Furthermore, this functionality comprises mechanisms to identify whether a problem currently addressed is similar to an older one for which a solution is already available. This allows for the overall decision making process to speed-up since it becomes less complex due to the limited number of choices that should be checked. Thus required system adaptations can be performed faster.

This mechanism should enable recording and storing of information on situations encountered, actions that were taken in reaction to these situations and potentially, information on the effectiveness/efficiency of decisions taken. A simple way of implementing this is with the use of an appropriate registry table. Implicitly some of the requirements for this functionality are related to requirements for context acquisition.

A key requirement for this functionality is related to the ability of the system to identify similar contextual situations, so that it can be derived whether a previously selected and enforced action should be applied directly without the need of executing anew the decision making process. The direct application of known (good) solutions facilitates the reduction of the time required to handle contextual situations.

Docitive Networks

Despite cognition and learning having received a considerable interest, the process of knowledge transfer, i.e. teaching, over the wireless medium has received fairly little attention to date. To this aim, in [10] a new and largely unexploited paradigm referred to as docitive radios has been introduced. The term docitive comes from "docere" ="to teach" in Latin, which relates to radios (or general networking entities) which transfer their prior knowledge to other radios. These radios are not only supposed to teach end-results (e.g. in form of "I sense the spectrum to be occupied"), but rather elements of the methods of getting there. It capitalizes on the advantages but, most importantly, mitigates major parts of the above-mentioned drawbacks of purely cognitive radios.

As illustrated in Figure 5, the canonical cognitive cycle is advantageously extended by “docition”. It is realized by means of an entity which facilitates knowledge dissemination and propagation with the non-trivial aim to facilitate learning. With this valuable knowledge at hand, a newcomer CR is able to reduce the exploration phase and increase its performance. In [11], docition is applied in the context of femtocell networks. Said femtocells use Q-learning, an algorithm coming from reinforcement learning, in order to allocate the optimal power and frequency to transmit. In this context, the most “expert” femtocells share their Q-tables with the newcomer femtocells that join the network. Within this extended cognitive cycle, newcomer femtocells capitalize on docition to use the knowledge of “expert” radios and avoid learning from scratch. The benefits of docition are gauged against regular cognitive radio networks, showing better speed of convergence and higher accuracy.

Docition is inspired by the so-far-successful problem based learning (PBL) concept used at schools. In PBL, teachers are encouraged to be coaches and not information providers with the aim to have pupils work as a team using critical thinking to synthesize and apply knowledge, apprehend through dialogue, questioning, reciprocal teaching, and mentoring. Translated back to the wireless setting, this implies a distributed approach where nodes share potentially differing amounts of intelligence acquired on the run. This, in turn, is expected to sharpen and speed up the exploration process. Any achieved gains, however, need to be gauged against the overhead incurred due to the exchange of docitive information.

The potential impact of docitive networks into next generation high capacity wireless networks is ensured by means of latest European Telecommunications Standards Institute Broadband Radio Access Networks (ETSI BRAN) standardisation activities [12].

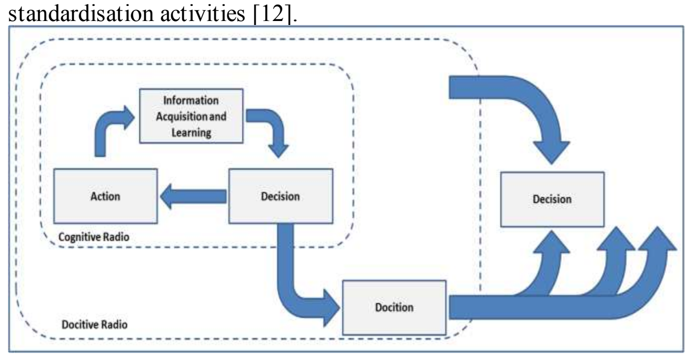

Figure 5: Canonical cycle and its extension through docition

An overview of potential implementation approaches

Learning and knowledge management mechanisms for Cognitive Radio Applications may be implemented by exploiting a variety of machine learning and pattern recognition approaches, including Bayesian Networks, Neural Networks, Fuzzy Cognitive Maps [13], etc. This section provides an overview of potential (indicative) approaches for the implementation of learning and knowledge management for Cognitive Radio Applications, focusing on a sub-set of machine learning techniques.

Learning user preferences with the use of Bayesian statistics

This sub-section presents an approach for dynamically learning user preferences regarding the perceived QoS level per service/application [14], with the use of Bayesian statistics concepts. The aim is to estimate the probability of the level of user satisfaction for a specific service and perceived QoS level, given a certain location and time zone.

The user profile can be modeled as a collection of parameters that can be classified in two main groups: observable and output parameters. Observable parameters include the currently running services/applications, corresponding QoS levels and associated QoS parameters, location, time zone and provided user feedback. User feedback is obtained in the following manner. The user initiates a specific service. At the initial stages it is considered that the user is indifferent between service provision choices. Every time the user obtains a service, a rating facility, embedded in the learning mechanism, allows the user to rate how much he/she liked the particular service provision. Different rating options are provided, enabling also non-technology expert users to provide the system with feedback on their preferences. Users are also given the choice to decline providing a rating. The value of output parameters is dynamically updated over time based on the value of observable parameters. The focus here is on one output parameter, namely the utility volume. The utility volume provides a ranking, by order of preference, of service and QoS combinations. User preferences may vary depending on the contextual situation and may change over time. Conditional probabilities for the utility volume are calculated. These yield the most likely user preferences per QoS level, which in turn can be used as input in a decision making mechanism for deciding, for instance, on the most appropriate configuration of a user's device.

Learning context information with the use of Bayesian Networks

In this case Bayesian statistics are used to estimate the future behaviour of candidate networks, in terms of QoS capabilities based on collected measurements.

The set of candidate networks is determined by the context of operation, the device profile and the policies of the Network Operator (NO). Initially, the context in which the user and device are found, and the capabilities of the device, provide the networks that are available in the area. The set of candidate networks is a subset of the available networks, as it comprises only those available networks that are compliant with the policies of the network operator. Compliance with the policies means that the NO allows the selection of the networks for the particular user and device.

Input, i.e. measurements from candidate networks, may be collected for offline or online analysis. In the current approach online analysis is applied. In online analysis the objective is to estimate the future state using the observations up to the current time. This estimation is modelled as a probability density function. The strong point of this approach is that no past observations need to be explicitly stored.

QoS levels for networks are considered as a combination of QoS parameters. Each parameter can refer to a specific aspect, e.g. bit rate, delay, etc. The QoS capabilities of the candidate networks are determined by the context of operation (e.g., interference conditions) and by the policies of the operator.

In summary, the overall learning process evolves as follows. Measurements are collected from the candidate networks, which are in line with operator policies. Based on these measurements, the conditional probabilities are updated, which provide an estimation of how probable it is that a specific QoS parameter will reach a certain value, given a certain network. The next step is the update of the probability density function values. The probability density function offers a more aggregate estimation regarding the probability to achieve a certain combination of QoS parameters, which corresponds to a QoS level, given a certain network. These probabilities can be exploited by knowledge-based network selection schemes [15].

Learning context information with the use of Self-Organizing Maps

This sub-section focuses on an implementation approach for learning context information with the use of Self-Organizing Maps (SOMs). The elements that serve as inputs for discovering the network capacity are parameters that are obtained given a configuration, e.g. Received Signal Strength Identifier, number of input bytes etc. The variable that expresses the network capacity is the bit rate.

According to this approach, SOM is used for mapping multidimensional data in a 2D-map. To do so, SOM requires a training process where the data are converted in data samples and, finally, in vectors which are mapped with respect to their resemblance. Thus, the created map depicts the clustering of data based on the resemblance of the corresponding vectors.

At this point, it is essential to clarify that the term "data sample" differs from the term "data" as follows. A data sample consists of more than one data. In fact, each data sample is a combination of values, each of which refers to a different observed parameter.

When applying the SOM approach, as soon as a pattern has been identified, a new data sample can be mapped on it using the same process. The identification of patterns in data is based on the Euclidean distance (selected due to its straightforward applicability) between vectors of data samples. Data samples that are similar to each other will be grouped into the same cluster. This means that the bit rate observed at the same time with the variables that formulate one data sample of the cluster is expected to be the same with the respective bit rate of the other data samples of the cluster. Thus, for inferring the network capacity the cluster in which a newly obtained entry belongs is identified. Further information about the SOM technique and its application to learning context information can be found in [16].

Enabling learning related to the efficiency of decisions with the use of k-Nearest Neighbour(s) (k-NN)

Learning related to the efficiency of decisions, requires the identification of the similarity of contextual situations so as to enable appropriate updating of information. For the identification of the similarity of contextual situations an approach based on the k-Nearest Neighbour(s) (k-NN) algorithm ([17]) can be applied. Elements of the current context information are compared with past network conditions (reference contexts) based on several threshold comparisons regarding the total number of users, the Euclidean and profile distance among users (the Euclidean distance is a typical metric used in k-NN algorithms) . More specifically, given the current context and the set of the reference contexts, the algorithm checks each reference context in order to find the closest one to the current context according to an overall distance. The overall distance is based on : (i) the total number of sessions distance;(ii) the total number of sessions per service distance; and (iii) the sessions distribution distance. Taking into account these sub-distances, the overall distance for each reference context from the current context is calculated as the sum of the distances calculated in each phase. The outcome is the reference context with the minimum overall distance from the current context, if such exists in the reference context repository. If no such context exists, then a new record is created in the repository for the current context. If it exists then the decision that was recorded for this solution is derived. In case it is rated as a "good decision" it can be applied without the need of running an optimisation process. In case the decision applied in the past has a bad rating the optimisation process can be triggered and the previously recorded decision can be replaced in the repository. In all cases, after the implementation of the decision, the rate on the efficiency of the decision corresponding to the identified context is updated accordingly.

Conclusions

The paper presented various basic learning functionalities for the identification and processing of information that can lead to exploitable knowledge in CR networks. The paper also provided an overview of potential implementation approaches for these functionalities that exploit diverse machine learning techniques.

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