Machine Learning Assisted Cognitive Radio

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***Abstract*—$\mathcal{N}$ This survey paper characterizes the architecture and learning problems in cognitive radio (CR) as well as the significance of implementing artificial intelligence (AI) to solve such problems. Three main categories of machine learning (ML) technique and there working scenario have been discussed, and several implementations of ML to CR systems have also been introduced with their relative merits. In the conclusion, some considerations about future work are summarized.**

***Index Terms*—Artificial intelligence (AI), cognitive Radio (CR), machine learning, artificial neural network (ANN), support vector machine (SVM), reinforcement learning.**

I. INTRODUCTION AND MOTIVATION

THE term cognitive radio (CR) is initially been introduced in [1], which refers to radio devices that are capable of sensing and adapting to their environment. Despite various detailed definitions have been proposed, a CR is a software defined radio (SDR) which can automatically adjust its parameters (i.e. modulation, carrier frequency) to adapt to the environment by measuring and decision-making process. Haykin [2] envisioned a CR to be '*an intelligent wireless communication system that is aware of its environment and uses the methodology of understanding-by-building to learn from the environment and adapt to statistical variations in the input stimuli*'. CR aims to achieve two objectives: 1) permanent reliable communications in any RF band, at any location [3]; 2) efficient utilization of frequency spectrum resources.

As the dramatic popularity of wireless applications, RF spectrum is getting crowded. However, there are papers pointed out the low-efficiency usage of authorized radio spectrum: in the range from 30 MHz to 3.95 GHz, the average radio spectrum usage in New York City and Chicago are 13.1% and 17.4% respectively [4]. This average usage becomes 4.54% in Singapore where some frequency bands are heavily used whereas almost silence for the others [5].

II. ATTRIBUTES AND TASKS OF COGNITIVE RADIO

To explore the efficient utilization methods of radio spectrum, the term *spectrum holes* is defined in [2] as the spectrum band that allocated to the primary users which are unused at specific time and location. The spectrum efficiency could be tremendously improved if a secondary user (cognitive user) can access the spectrum holes. Thus, the main aim for CR is to exploit the spectrum holes. To achieve such goal, a CR is expected to have following properties [6]:

1) Observation: Collect information of the RF environment.
2) Reconfiguration: Adjust the radio parameters.

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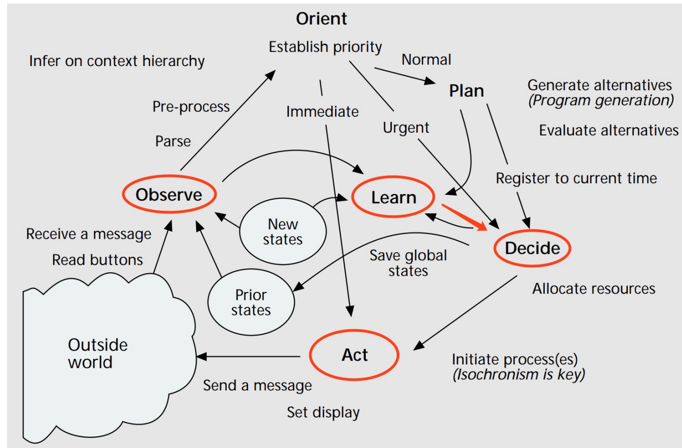

Fig. 1. The cognition cycle of an autonomous cognitive radio [1]. The original cycle in this reference hasn't point out the influence of learning on decision process, where [7] suggested decision is made based on learnt knowledge and observation.

3) Cognition: Understand the information from observation and capability of the radio (awareness), make decisions on actions (reasoning) as well as learn the relationship between action and performance of the CR (learning).

This set of properties contribute to the scheme of CR, which defined as cognitive cycle [1] as shown in Fig.

For the property of reconfiguration, a CR requires SDR to perform such task, and it also needs artificial techniques like machine learning (ML) for the implementation of cognition. There are three main tasks for cognitive radio [2]:

1) Radio-scene analysis, which includes spectrum hole perception and interference estimation.
2) Channel identification, which includes channel state information (CSI) and transmitter channel capacity estimation.
3) Tx power control and dynamic spectrum management.

The former two tasks are mainly achieved in the receiver and the third is carried out in the transmitter.

III. CR EMPLOYED MACHINE LEARNING TECHNIQUES

To perform its cognitive tasks, a CR should be aware of its RF environment, where learning techniques can be applied to estimate the wireless channel characteristics and to determine the specific coding rate that is required to achieve a certain error rate. Moreover, problems become more complicated in the case of cognitive radio networks (CRNs) where CRs try to learning and adjust their policy simultaneously [3].

Despite the numerous ML techniques, there are three main categories: supervised learning, unsupervised learning and reinforcement learning. One important criteria of whether an

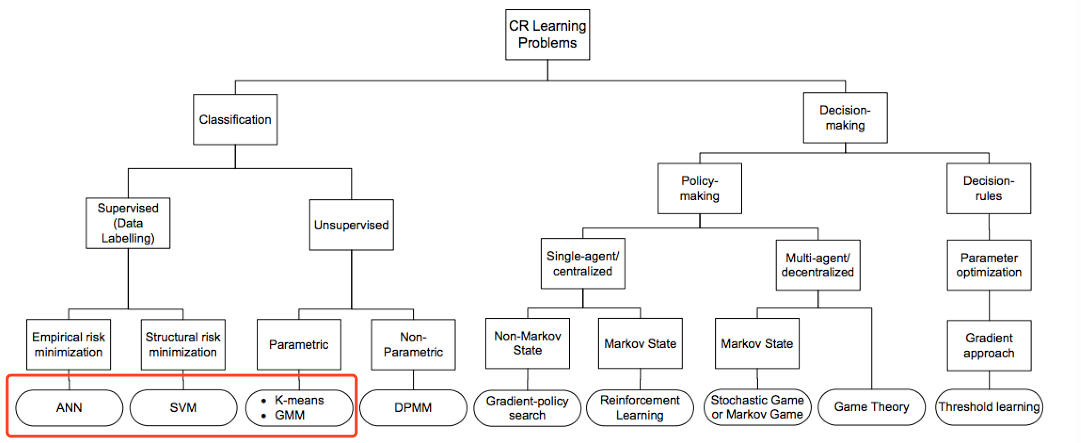

Fig. 2. Typical problems in cognitive radio and their corresponding learning algorithms [3].

learning algorithm is supervised or unsupervised is the training set have target vector or not. According to [8], for supervised learning, the training process is based on the minimization of a loss function whereas there is no target vector for unsupervised learning. The goal is to find pattern or groups in the training set which is called clustering (i.e. K-means) or to find the distribution within the data, which is called density estimation (i.e. Gaussian Mixture Models (GMM)). Reinforcement learning is a technique learning what to do, that is, learning to map a situation observed by the interaction between agents and environment to maximize a reward function.

A. Learning issue in CR

From the perspective of machine learning, and according to previously introduced tasks of CR, learning problems can be classified as [3]:

1) Feature classification: spectrum hole detection, signal classification, etc.
2) Decision-making: Parameters modification, adaptive modulation, power control, etc.

It is crucial that allocating different tasks with appropriate learning algorithms. Fig.&LCognitiveCycle&MLummarized various state-of-the-art machine learning techniques with respect to CR learning problems. Supervised learning may be the best choice if CRs have prior knowledge about the environment. And unsupervised learning may the best choice for CR which operating in alien RF environment, under which case, autonomous unsupervised learning algorithms permit exploring the environment parameters and self-adapting without any prior knowledge.

For a single-agent CR, reinforcement learning is a good choice for CR operating under Markov process [9], which will be introduced in the following section. The degree of freedom will be significantly increased when it comes to CRNs, the complex training process and considerably increased convergence time become the key issue.

Besides, regardless of what learning technique been employed, feature extraction lies at the heart of training a learning machine. Conventional signal classification schemes employ signal properties such as amplitude, frequency, and phase information to approach signal classification problems, which is time-consuming and baseband representation are required. Whereas, [10] utilizes the cyclostationary signal feature, which is highly efficient, to solve such problem.

B. Artificial Neural Network

Artificial neural network (ANN) is a supervised learning algorithm, which does expect the prior knowledge of the observed environment. It is a promising technique for its adjustable architecture, remarkable nonlinear fitting and transfer learning properties for various tasks like convolutional neural network (CNN) for image classification, recurrent neural network (RNN) for sequence data with sequential information. [11] proposed an ANN scheme assisting CR to predict the data rate of selected radio parameters. And [12] uses ANN to perform spectrum prediction for CR.

The architecture of a basic Artificial Neural Network (ANN) includes an input layer, a hidden layer, and an output layer [13]. Neurons communicate with each other by a weighted connection with bias. The sum of weighted outputs at each neuron is injected to a nonlinear activation function to get the output. There are several activation functions (i.e. ReLU, Sigmod) and the choice usually related to the problem to be solved.

Generally, the ANN is trained by gradient descent. Since mostly ANN has more than one hidden layer, then, it is time-consuming to calculate the gradient for each neuron even employed back-propagation (BP) algorithm to reduce the complexity of gradient descent. However, it can be optimized by transfer learning. The definition of transfer learning is given in [14], given a source domain $\mathcal{D}_S$ and learning task $\mathcal{T}_S$ and a target domain $\mathcal{D}_T$ and learning task $\mathcal{T}_T$, transfer learning helps to improve the training of target function $f_T(\cdot)$ in $\mathcal{D}_T$ utilizing the knowledge of $\mathcal{D}_S$ and $\mathcal{T}_S$. Then, learning machine can be pre-trained based on previous knowledge of the RF environment before deploying.

C. Support Vector Machine for classification

Support Vector Machine, sometimes called maximum margin classifier, is a famous supervised learning algorithm which used to solve classification problems. Basically, it can only solve binary classifications, but with some tricks (i.e. One-versus-One or One-versus-All), it can also handle multi-classification problems. Recently, SVM has been used for signal classification in cognitive radios [15]. It is a promising technique to solve classification problem for it maximum margin characteristic.

D. Reinforcement learning for decision-making

As noticed, reinforcement learning (RL) permits an agent/ learning machine to learn by interacting with the environment [16] without any prior knowledge, which is the key advantage of such technique because the nature of the radio frequency environment is unknown. Thus, this technique empowers the agent to learn without supervision. According to Fig.1, the decision-making process in CR is a process that enables CR to interact with the environment and such process can be improved by learning, thus making RL a promising choice for this task. RL has been used for dynamic spectrum access in cognitive radio network (CRN) [17].

For each state s_i, a reinforcement learning machine have an action a_i based on the actor/ policy $\pi_\theta(s)$, and got a reward from the environment r_i. The interaction process between learning machine and environment can be considered as a Markov decision process (MDP), where the state s_{t+1} only determined by previous state s_t and action a_t:

$$p(s_{t+1}|s_t, a_t, s_{t-1}, a_{t-1}, ..., s_0, a_0) = p(s_{t+1}|s_t, a_t) \quad (1)$$

For a given policy $\pi_\theta(s)$ and a given terminal state s_T, the trajectory of MDP is defined as $\tau = \{s_0, a_0, s_1, a_1, ..., s_T, a_T\}$. The cumulative reward $R(\tau) = \sum_{n=1}^{T} r_n$ is what the training method need to maximize. And for those without terminal state, especially the case for cognitive radio, discounted future reward is defined as $R(\tau) = \sum_{n=t}^{T} \gamma^{n-t} r_n$. Generally, the cumulative reward $R(\tau)$ is a conditional random variable of policy π_θ. The aim for training is to maximize the reward expection $\overline{R}_\theta$. However, conditional probability density function $p(\tau|\theta)$ is unreachable, where we use Monte Carlo method to approximate $\overline{R}_\theta$ by sampling. There are two ways in solving the problem under the assumption of Markov state, policy gradient and Q-learning. And gradient policy search is proposed for non-Markov state environment.

IV. Conclusion

As a promising technique of opportunistic spectrum access, the scheme and tasks of cognitive radio have been present. Besides, this review characteristic the learning problem in CR to achieve the understanding-by-building goal, which can be greatly assisted by machine learning technique due to their inherent learning by observing property.

Besides, some promising learning technique like ANN, SVM, and reinforcement learning have been introduced to solve the supervised and unsupervised learning problems in familiar and alien RF environment, which technique can be used to solve different tasks with respect superiorities. The main considerations for the application of ML to CR in the future are the convergence time, implementation complexity and robustness of the system. Despite the fact that there do have an increasing number of applications of ML to cognitive radio but such applications are still not complete and have tremendous potential to be explored. What's more, feature extraction always significantly contributes to the accuracy and efficiency of learning machine regardless of which algorithm been employed.

Apart from ML technique, under the circumstance of cognitive radio networks, game theory provides analytical tools to acquire interaction among users and makes such problem analytically tractable, which should be considered in the future work.

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