Machine learning prediction algorithm to determine best performing routes in cognitive radio networks

By

Mukonyezi Isaac
SEP15/COMP/0642U
Option-Computer Networks

Supervisor
Johnson Mwebaze (PHD)
UTAMU

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DECLARATION

I, Mukonyezi Isaac declare that the work in this proposal is original and has never been used before in any university or institution as an academic requirement.

Mukonyezi Isaac

Signature……………………………….. Date…………………….………….

Supervisor: Dr. Johnson Mwebaze (PhD)

Signature……………………………….. Date…………………….………….

Contents

Abstract

Intelligent Routing will influence the general performance of a communication network's outturn and potency. Routing methods are needed to adapt to dynamical network hundreds and completely different topologies. Learning from the network setting, so as to optimally adapt the network settings, is a necessary demand for providing efficient communication services in such environments. Cognitive networks are capable of learning and reasoning and they energetically adapt to varied network conditions so as to optimize end-to-end performance and utilize network resources. In this proposed work we'll focus on machine learning in routing themes that features routing awareness and routing reconfiguration.

1. Introduction

1.1 Background

The Cognitive Radio Network is an innovative software defined radio technique considered to be one of the promising technologies to improve the utilization of the congested RF spectrum. Adopting CR is motivated by the fact that a large portion of the radio spectrum is underutilized most of the time. In CR networks, a secondary system/users can share spectrum bands with the licensed primary system/users, either on an interference-free basis or on an interference-tolerant basis.

By definition, a Cognitive Radio is an "intelligent communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind: highly reliable communication whenever and wherever needed and efficient utilization of the radio spectrum." [1].

Cognitive Radio technology is based on the fact that the licensed users (also named primary users, PUs) are not always using their spectrum bands; CR brings new radio types—cognitive radios—that should firstly, identify the existing spectrum holes, and secondly, utilize them in a flexible manner, according to an access medium scheme.

CRs have also been proposed for a wide range of applications including Internet of Things, 5G wireless networks and smart grid communications. CR promises to dramatically improve spectrum access, capacity, and link performance while also incorporating the needs and the context of the user. CRs are increasingly being viewed as an essential component of next-generation wireless networks.

1.2 Problem Statement

Conventional network forwards packets using routing algorithms and detect failures after packets are lost. Due to the cognitive nature of CRNs there is an opportunity to know the status of every node in the network, so it doesn't send data using a route that cannot deliver the packet and in the long run preventing congestion.

Previous similar works have focused mainly on simulation of machine-learning and AI techniques to problems of spectrum sensing, power control, and adaptive modulation in CRNs [2]. Future cognitive networks will require greater architectural support from fully ‘cognitive routing protocols’ that will seamlessly incorporate AI-based techniques such as learning, planning, and reasoning in their design. Inference, reasoning, modeling and prediction cognitive tasks that future cognitive routing protocols must incorporate have been explored and incorporated in this research work [3]. Using this awareness they can adjust their operation to match current and near future network conditions. A Cognitive Network aims to be proactive, so that it can predict most of the usual use cases before they occur and adapt to those beforehand. In any case a Cognitive Network learns from every situation it encounters and uses that information for future cases. The main goal of a Cognitive Network is to increase network efficiency and performance. The important aspect of a cognitive network is that it optimizes data communication for the whole network between the sender and the receiver to meet the required end-to-end goals of users of the network.

While spectrum sensing techniques and spectrum sharing solutions are two important aspects that have received the attention of the CRN community, routing in CRNs remains an important yet unexplored aspect.

Several routing metrics were proposed; Assuming full spectrum knowledge, such as throughput maximizing protocols, delay minimizing protocols, route stability maximizing protocols and route maintenance minimizing protocols. These metrics will be used to collect data concerning the quality of the routes and the data will be used to model the prediction algorithm.

1.3 Objectives

1.3.1 General Objective:

To develop and evaluate a machine learning algorithm that uses predictive analytics to determine best performing routes in a cognitive radio network.

1.3.2 Specific Objectives:

a) Provide CR capabilities at the different network layers such as sensing, PU detection, channel hand-off and decision making.
b) Simulate the performance of routing level protocol metrics using the NS-3 environment
c) Develop the learning the machine learning algorithm, train and test the algorithm.
d) Release of the full source code, with additional guides on how to compile and run trial examples.

1.4 Research questions

a) What are the cognitive routing tasks in Cognitive Radio Networks

b) What are the current routing protocols in cognitive radio networks and the performance evaluation metrics that can be used for machine learning

c) What are the best decision, planning and learning techniques to use at the network level?

d) Can the proposed simulation framework be tested and verified for implementation?

1.5 Research plan

We will study the current work in routing for cognitive radio networks and then using both analytical modelling and simulation, we will test and evaluate the machine learning model as applied to the network level routing.

1.6 Anticipated Outcomes

1. A machine learning algorithm to support cognitive routing tasks through the use of predictive analytics.

1.7 Motivation

Cognitive Radio (CR) is one of the many long term developments that are currently taking place in the area of telecommunications. The need to develop cognitive radios has emerged after it was recognized that the adaptation on network changes would utilize the radio spectrum, communication and speed throughout the network. This has led to the need of development of efficient routing protocols that incorporate machine learning techniques that can achieve the purpose and thus the need to test and evaluate their performance.

CRs would also benefit in the development of several applications such as cooperative networks, dynamic spectrum access, intelligent transport systems, public safety systems, 5G networks, and smart grid communications [3].

1.8 Significance/ Justification of Study

This research work aims at supporting the work of producing better designs of routing protocols which leverage the power of machine learning that can enhance PU protection while at the same time providing full utilization of the spectrum. With the emergence of 5G technology, cognitive radios will be the main tool to aid communication in an environment of ever increasing demand for higher data rates and increased spectrum utilization. Thus the need of an agile machine learning framework that can be used to test and evaluate routing protocols that support artificial intelligence through the implementation of machine learning techniques.

1.9 Research Contribution

An NS-3 based simulation framework that will be used to test and evaluate routing protocols that support for machine learning using Bayesian Networks techniques. The framework will offer Application Programming Interfaces to offer support to the research community to add to this work and also to accommodate integration with upper layers of the protocol stack. This framework will enable researchers quickly test and evaluate their routing protocols that support for AI through machine learning implementation.

2. Literature Review

2.1 Introduction

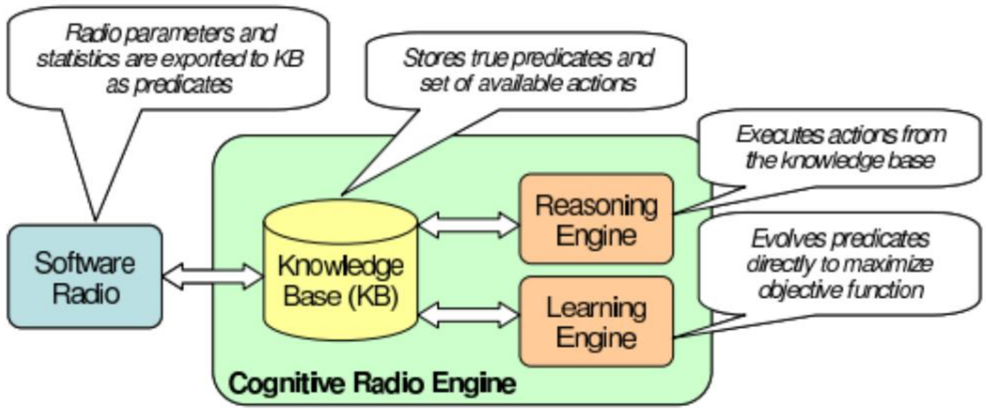

Figure 1: Components within a cognitive radio

In the beginning the radio implemented consisted only of a software radio (see Fig. 1), which is programmed to transmit and receive waveforms. The cognitive radio is considered as an extension to the software radio, this extension is also the cognitive engine, composed of a knowledge base, reasoning engine and a learning engine, and these components enable software modifications according to the network state. The engine generates conclusions upon information in the knowledge base, however these information are based on reasoning and learning techniques. The reasoning engine could be defined as artificial intelligence to take decisions. The learning engine is responsible for manipulating knowledge gathered from experiences. Finally we can deduce that there is a coupling among knowledge, learning and reasoning.

2.2 Cognitive Radio Technology

Cognitive radio includes four main functional blocks

i) Spectrum Sensing

ii) Spectrum Management

iii) Spectrum Sharing and

iv) Spectrum Mobility

Spectrum Sensing will determine the spectrum availability and the presence of the licensed users (also known as primary users). Spectrum management will predict how long the spectrum holes are going to remain open for use of the unlicensed users (also called the secondary users or CR users). Spectrum

Sharing is meant to allocate the spectrum holes equitably among the secondary users bearing in mind the usage cost. Spectrum Mobility is to ensure and maintain the seamless communication requirements during the transition to lighter spectrum. The spectrum sensing function is the most crucial to establish a cognitive radio network. There are some techniques used for spectrum sensing, which are; Primary transmitter detection, cooperative detection and interference detection. The reason that spectrum sensing is the most crucial task is that there are many uncertainties connected while picking up the signals to find the holes in the band like Channel Uncertainty, Noise Uncertainty, Sensing Interference Limit, etc. So, these uncertainties need to be addressed while solving the problem that is spectrum sensing in cognitive radio networks.

2.3 Reasoning

The reasoning output is simply an intelligent answer to set of questions or problems based on environment observation and network objectives. The result of the reasoning highly depends on the knowledge base and how accurate is the data measured or the environment observed. The more it is accurate the better the reasoning output will be, leading to better decision making.

2.3.1 Reasoning Types

There are different types of reasoning used in the cognitive networks nowadays. The reasoning type to be used depends on the network and the environment in which it will be used. The following are some of these types.

2.3.1.1 Proactive

The proactive reasoning is used in a wireless environment that is not time sensitive which means that the network characteristic and topology does not change constantly and rapidly, this allows the reasoning output to be more accurate and reliable.

The proactive technique takes place after a problem occurs and is usually combined with centralized and the sequential reasoning. In other words the relationship between the actions should be taken and the output is closely observed and examined to generate an optimal reasoning output.

2.3.1.2 Reactive

On the other hand, reactive reasoning is more suitable in a dynamic wireless environment where the network characteristics changes rapidly and the environment in this case is time sensitive.

The reactive technique take place when a problem is predicted and is used as it shortens the time needed for reasoning, it does not rely on the past actions or knowledge it uses the available information and act upon the expected results of certain actions.
Examples in which reactive reasoning approach is used is in cognitive ad-hoc networks and cognitive cellular networks as they are highly dynamic wireless environments.

2.4 Learning in cognitive radio networks

Learning in cognitive radios has recently gained a lot of interest in the literature. In this section, artificial intelligence and machine learning are introduced as well as a survey of the state-of-the-art achievements in applying learning techniques in cognitive radio networks.

The approach of learning is modifying a nodes behavior through training, while ongoing different network conditions or the ability to create knowledge from this experience to take it into consideration in the future. The process of learning must be powerful enough to enrich the knowledge base from its past actions, consequently increasing the efficiency of the reasoning.

Learning mechanisms could be divided to subgroups of unsupervised or supervised learning techniques. Corresponding to learning by reinforcement and instruction, respectively.

2.4.1 Supervised Learning

On the contrary supervised learning needs prior information or to be in certain familiar environments. In this section we discuss some supervised learning techniques applied in cognitive networks.

2.4.1.1 Q-Routing

Q-Learning is a reinforcement learning algorithm that is able to learn an optimal sequence of actions in an environment which maximizes rewards received from the environment. Q-Routing is an adaptation from Q-Learning that is able to distributively route packets in a network.

2.4.1.2 The Bayesian Learning Algorithm approach

Bayesian analysis accords significant importance to the prior distribution which is supposed to represent knowledge about unknown parameters before the data becomes available. While it is a common assumption that the agent has no prior knowledge about what it is trying to learn, this is not an accurate reflection of reality in many cases. Frequently, an agent will have some prior information, and the learning process should ideally exploit this available information. Bayesian learning can be viewed as a form of uncertain reasoning from observations [4].

Bayesian learning is used to calculate the probability of each hypothesis, given the data, and to make predictions on that basis. It has been shown that the true hypothesis eventually dominates in Bayesian prediction [5]. Bayesian analysis is appealing since it provides a mathematical formulation of how previous knowledge can be incorporated with fresh evidence to create new knowledge. However, choosing the right prior distribution is not trivial and an incorrect assumption can skew the inference. It is for this reason that some statisticians feel uneasy about the use of prior distributions fearing that it may distort "what the data are trying to say." [6]. We can model the prior distribution to prior knowledge or use a 'noninformative' prior to model ignorance about prior information. Bayesian networks can be used for computing how much a set of mutually exclusive prior events contributes to a posterior condition, which can be a prior to yet another posterior, and so on. Bayesian networks can be used for reasoning and for tracing chain of conditional causation back from the final condition to the initial causes [5]

Bayesian approach is based on probabilistic learning. It provides exact inferences which do not rely on large sample approximations with simple interpretations. Bayesian inference estimates a full probability model and allows prior knowledge and results to be used in the current model. Bayesian inference has a statistical decision to facilitate decision-making, it includes uncertainty in the probability model, yielding more realistic predictions. The Bayesian approach does not face over fitting since it uses observed data only.

2.5 Cognitive Routing Tasks in CRNs

Previous work on routing in multi-hop wireless networks can be noted for the most part for the lack of learning from environment. Most of the classical wireless routing protocols tend to use instantaneous online parameters and do not utilize environment history and learn from it to predict about links and parameters that are more likely to result in better quality routes. These protocols also do not learn about parameter history and therefore cannot prioritize higher-quality links over links of poor quality. While primitive protocols such as AODV, DSDV, and DSR have typically relied on basic metrics such as hop count or delay, other metrics were developed for wireless networks over time such as those that targeted: maximizing throughput [7], minimizing interference [8], load balancing [9], and choosing more reliable links [10]. Since metrics designed for traditional wireless networks do not sufficiently capture the time-varying spectrum availability found in CRNs, some recent works have proposed more nuanced spectrum aware routing metrics [11] [12] [13] [7] [14].

As noted earlier, although CRN routing protocols do mostly incorporate spectrum-awareness into their design, future cognitive networks will require greater architectural support from fully 'cognitive routing protocols' that will seamlessly incorporate AI-based techniques such as learning, planning, and reasoning in their design.

Some inference and reasoning and modeling and prediction cognitive tasks that future cognitive routing protocols must incorporate are described.

2.5.1 Inference and Reasoning Tasks

Reasoning is an important aspect of CRN behavior and is necessary for cognitive behavior. Knowledge can be represented using an ontology which provides shared vocabulary useful for modeling a domain, e.g., it can be used to model the type of objects and concepts existing in a system or domain, and their mutual relationship and properties [15]. A rule based system can make use of a knowledge base and some means of inference through an inference engine.

It is also possible to reason by analogy. This involves the transferring of knowledge from a past analogous situation to another similar present situation. Case-based reasoning (CBR) is a well-known kind of analogy making which has been exploited in CRN research [16]. In case-based reasoning a database of existing cases is maintained and used to draw conclusions about new cases. The CBR reasoning method can utilize procedures like pattern matching and various statistical techniques to find which historical case to relate to the current case.

Fuzzy logic is another tool that is useful for reasoning in systems and situations having inherent uncertainty or ambiguity. Since complete environmental knowledge is difficult, or even impossible, to obtain in CRNs. Fuzzy logic is a natural fit to the CRN environment where there is limited or no information about certain environment factors.

2.5.2 Modeling, Prediction, and Learning Tasks

Future cognitive routing protocols can benefit from the following tasks: i) channel quality modeling and prediction, ii) PU activity modeling and prediction, and iii) detecting and mitigating selfish behavior. We will discuss these in turn next under their respective headings.

2.5.2.1 Channel quality modeling and prediction

[17] Proposed using HMM to model the wireless channel online with the HMM being trained using a genetic algorithm, techniques for modeling wireless network channel using Markov models are presented along with techniques for efficient estimation of Markov model parameters (including the number of states) to aid in reproducing and/or forecasting channel statistics accurately. In another work, Xing et al. have proposed to perform channel quality prediction using Bayesian inference [18]. Channel estimation problem has also been addressed in which the use of particle filters, rooted in Bayesian estimation, were proposed as a device for tracking statistical variations in a wireless channel. Using the Bayesian-based cognitive engine for learning how various channel's quality status affects performance and thereby dynamically selecting a channel that improves performance. The dynamic selection of channels has an obvious implication for network-layer functionality and the routing algorithm for such networks should be able to keep up with the channel changes so that best performing routes are selected.

2.5.2.1 Spectrum occupancy modeling

A satisfactory model of spectrum occupancy (or, of spectrum white spaces) should incorporate: i) states of the channel along with their transition behavior, and ii) the sojourn time or the time duration the system resides in each of the states.

Since many DSA environments (e.g., contention based protocols such as IEEE 802.11) do not have a slotted structure, it is more appropriate to use a continuous-time (CT) model. A CT model that is especially relevant to DSA, and one that is popularly used for modeling spectrum occupancy, is the semi- Markov model (SMM) which generalizes the concept of CT Markov chains (CTMCs).

It has been posited that for practical purposes of analyzing DSA/ CRNs, a simple two-state semi-Markov ON-OFF model is adequate for modeling spectrum usage. The OFF state represents an idle channel, while the ON state indicates a busy channel not available for opportunistic access, with the length of ON and OFF periods being random variables (RVs) following some specified distribution [19].

2.5.2.2 PU activity modeling and prediction

In DSA CRN networks, being the licensed incumbent user, a primary user (PU) has prioritized access to the wireless spectrum. Therefore, on the arrival of a PU, a SU must either vacate the relevant channel by switching to another channel or by terminating its connection; alternatively, the PU must reduce its transmission power to ensure that PU does not face any interference. Since the arrivals of PU are non-deterministic, and random from the point-of-view of a SU, frequent PU arrivals can lead to frequent temporal connection losses for secondary users thereby seriously impacting its performance. However, a PU can probabilistically model the arrival process and traffic pattern of PU and avoid the channels that will be claimed by PU with a high probability. This can help reduce the temporal connection loss faced by SUs and potential interference faced by PUs due to any delays in vacation of channel by SUs.

A cognitive radio that manages to learn the behavioral patterns of a primary user by modeling it can optimize its performance by exploiting the learned model. For example, a SU can exploit information, potentially gleaned from spectrum sensing data, and select white spaces (that emerge due to absence of PUs) that tend to be longer lived at certain times of day and at certain locations. Knowing something about PU patterns can also be helpful for advanced planning when a SU has to decide the channel to switch to on the arrival of a PU [20].

A number of techniques have been proposed for spectrum prediction including techniques that are: a) HMM based, b) NN based, Bayesian inference based, moving-average based, autoregressive-model based, and static-neighbor-graph based (which is able to incorporate PU mobility pattern) [18].

2.5.2.3 Detection of Selfish Behavior

Network-layer behavior entails both the problems of routing and forwarding. In wireless networks, selfish behavior can manifest itself when nodes engage in unsocial behavior—i.e., they utilize the network resources but do not pay back the favor by providing necessary services to the other network nodes. For correct network behavior, it is important that such behavior be arrested. The following papers have addressed the problems of identifying and mitigating selfish network behavior [21] [22]. This problem has been studied through the tools provided by game theory in [23].

2.6 Routing Protocols for CRNs

Routing protocols for wireless ad hoc networks can be classified into reactive and proactive protocols [24]. Reactive protocols build on-demand paths between the source and destination nodes only when needed. In proactive protocols, each node maintains fresh routing tables for all destinations, by means of periodic distribution of information (e.g. link state) throughout the network. Therefore, proactive protocols reduce path acquisition time compared to reactive ones, but at the same time exhibit very slow reaction to network dynamics, such as nodes' mobility [24]. In CRNs, the dynamic spectrum allocation determines that each wireless link may experience different conditions over time, as a function of the interference of PUs, available bandwidth, and so on. For this reason, we focus our attention on reactive protocols, and we consider two approaches for route formation over CRNs:

- Single-path routing. We consider the AODV routing protocol, which discovers a single path between a source and a destination node.
- Multi-path Routing. We consider the AOMDV routing protocol, which discovers multiple paths between a source and a destination node. The discovered paths can be node disjoint, i.e. they have no nodes in common, or link-disjoint, i.e. they have no links in common.

2.7 Simulation Packages

Cognitive Radio Cognitive Network (CRCN) [15] is a simulation framework designed for ns-2 that provides multi/single radio and multi-channel support per node. It provides APIs that return information, such as the current noise or traffic conditions at a given channel, and provides a mechanism for channel handoff. CogNS [25] is another extension for ns-2 that allows one network interface per node that is able to sense PU activity, and defer to another free channel based on a proposed spectrum decision algorithm. Nodes created in this environment cannot incorporate multiple radios per node. [26]Provides a CR simulation extension for OMNeT++ [27]. It provides support for multiple interfaces per node, and is focused on evaluating CR MAC layer protocols. [28] Is a simulator written in C++ for CR networks.

2.8 Evaluation Metrics

A wide variety of routing protocols have been proposed for CRNs and these routing protocols have used a diverse set of routing metrics and objectives: e.g., throughput maximizing protocols [29] [30] [11] [31], route-stability maximizing protocols [32] delay minimizing protocols [33] [34] [12] and route-maintenance minimizing protocols [13] [7].

The most commonly used approach in literature is to incorporate these metrics into some variant of a reactive or an on-demand routing protocol to avoid the overhead of managing dynamic topologies proactively. With dynamic spectrum access (DSA) being envisioned as a prime application of CRNs, it is important for routing protocols for CRNs to incorporate PU traffic dynamics into its design. Some of the CRN routing protocols have conspicuously not catered to PU dynamics in their design [29] [31] [34], although more recent work [30] [11] [33] [7] have importantly incorporated PU awareness.

[35] Have conducted a detailed performance evaluation of three representative CRN routing protocols: SAMER [11] , Coolest Path [36] and CRP [12] using both simulations (on the NS2 simulator) and an empirical evaluation (on a testbed of 6 node testbed based on USRP2 platform). The three protocols evaluated all have different design objectives. SAMER aims mainly at finding the highest throughput path while considering both the PU/ SU activities and the link quality. Coolest Path is designed to prefer paths that more stable since it prefers path with the highest spectrum availability. CRP is designed to either find a path with minimum end-to-end delay along with satisfactory PU protection, or to offer more complete protection to PU receivers at the cost of some performance degradation to SUs. Due to the randomness of PU activity these protocols and their metrics falter due to the need of SUs to vacate the channels at the arrival of Pus.

2.9 Research Gap

When planning the deployment of CR networks or testing a new protocol, researchers face uphill challenges given the challenging environment in which these networks operate, it is important for CRs to learn from the previous network conditions, predict and act, and not just depend on instantaneous parameters hence the need to incorporate machine learning techniques. The CRs must quickly determine which licensed channels are available, and make use of this spectrum before the PU reclaims it. Accurate protocol operation is critical, as any prolonged use of the channel raises concerns of interfering with the activities of the PUs. This concern directly translates to meticulous testing of the protocol or networking concept in a controlled environment. Given the costs of purchasing multiple software defined radios and deploying them in a city, which will serve as the hardware building blocks of CR enabled smart city network, and the time investment in writing and deploying code in them, accurate computer simulation often becomes the methodology of choice. While several commercial simulators exist, such as OPNET, which can capably simulate heterogeneous networks, our focus in this work remains on improvements for open-source use.

The work proposed is focused on providing the first cognitive radio extension that incorporates machine learning techniques to the network simulator 3 [16] or ns-3 to learn and perform predictions in reactive routing, which is a discrete event driven simulator. It is suitable for large scale simulations, which reflect better the practical, city-wide deployments. Moreover, ns-3 simulator is poised to replace its widely popular predecessor, network simulator 2 or ns-2 as it provides several advantages:

(i) it has a new core written in C++, (ii) it is geared for wireless communications, (iii) it offers mobility schemes that are crucial for realizing vehicular networks that will play a role in smart cities, (iv) it has an organized modular architecture that is expandable, (v) it includes intuitive and extensive documentation via the html Doxygen [37] interface, and (vi) the same ns-3 code can be easily adapted to work in real devices [16].

Additionally, several more accurate highway mobility extensions such as [4] can also be incorporated in the simulation scenarios, thereby reflecting the road layouts that actually exist. Despite the clear superiority of this new simulation platform, ns-3 lacks implementation support for CR networks. To bridge this gap, several changes have been catered for in various network layers in ns-3 [38].

3. Proposed Methodology

3.1 Introduction

In this section, we detail the needed changes to each layer of the protocol stack for a given CR node in ns-3. Figure 2 depicts an overview of these changes. As can be seen, the proposed CR extension exposes several APIs and listeners to all the networking layers. We also make use of ns-3 tagging feature. The method to 'tag' a packet with some information helps to determine that packet's internal routing in a given node, thereby avoiding the costly overhead that would ensue if said information was to be integrated into the packet's header instead.

1) All layers up to the transport layer: No changes are proposed to these layers. However, all the Spectrum Manager's APIs and listeners are exposed to these layers so a network researcher working on a CR application, for example, can make use of the CR features of the node by calling the respective APIs in the Spectrum Manager.

2) Transport layer: Our framework modifies this layer so that any packet that is generated here will be tagged as a DATA packet. This information will be processed by the lower layers to determine the correct routing of such packets. This change affects all transport layer protocols defined in the simulator such as TCP, UDP, and potentially any new transport protocol that a researcher might be interested in implementing.

3) Network layer: For CRs to work in an ad-hoc topology, some information must be exchanged between neighboring nodes to determine listening channel of each member of the network. We extend the information carried in the packets of the AODV protocol to include the current listening channel of each node, as the packet traverse through the paths details of the state of path like congestion met, queuing delays, PU activity and SU activity detection rates are sent back to the source to update the knowledge of the machine on the state of paths, which will improve on the prediction for the routes in the future.. This information will be passed along with every HELLO, RREQ and RREP messages. Every packet that is generated by AODV is tagged as CTRL or control packet.

4) Link and physical layers: A CR node may define any number of these cognitive interfaces. Each interface constitutes of three separate MAC-PHY layers; the first is for communicating control packet information on a common control channel. For example AODV and ARP messages will be communicated over such an interface. We call this interface the CTRL interface. The second is used to transmit data messages to neighboring nodes (TX).

The transmission, sensing times, and probability of detection error can all be defined using the ns-3 attribute system. We will also emphasize that the Cognitive Interface makes all these new calls through the Spectrum Manager block. The tagging mechanism that was discussed earlier in the transport and network layers are used here to determine which interface a packet should be sent on.

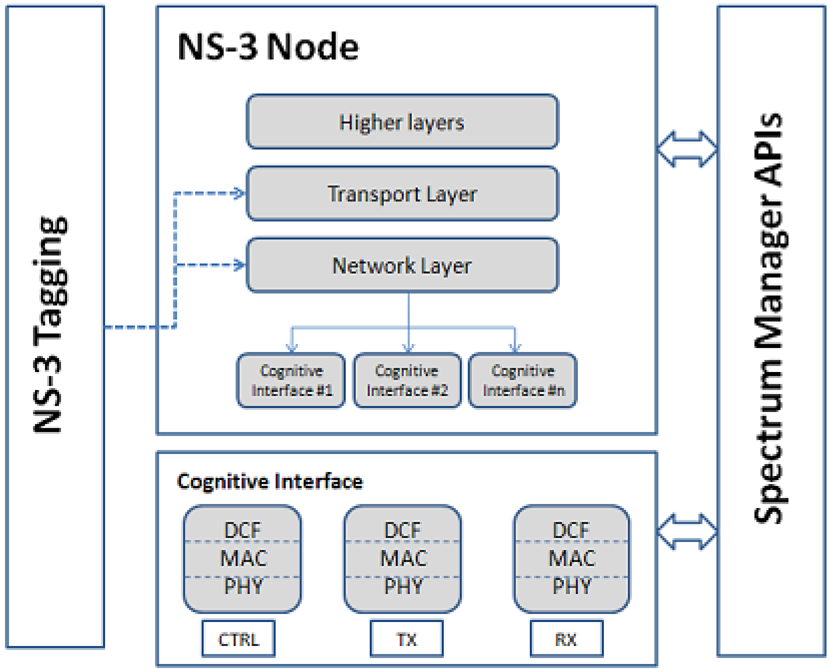

Figure 2: Layered Architecture of an NS-3 CR Node

The TX Distributed Coordination Function (DCF) will also be modified to store queued packets into different MAC queues based on the channel that they should be transmitted on. This will help the TX interface select which packets to transmit when it switches spectrum. At the physical layer (PHY), a new sensing state will be added. The functionality of the sensing state is similar to that of the hand-off state where the PHY layer instructs the DCF to halt dequeueing from the respective MAC queue, while the sensing or hand-off operation is ongoing. The sensing and hand-off times can be defined using the ns-3 attribute system. The sensing state in the PHY layer uses the Spectrum Manager APIs which query the PU Database (See Figure 2) to determine PU activity. Note that the PHY layer can switch between any number of defined channels. These channels can have a different frequency, propagation path loss and delay models, as defined by the default ns-3 simulation environment.

3.2 Learning

In this section, we introduce the steps of our learning framework. The figure below presents a high level overview of the steps involved, with the four key steps listed as follows:

1. First, we select the features to be used in training and classification;

2. Then, we instrument every node in the network to track these features and their corresponding labels which are periodically collected;

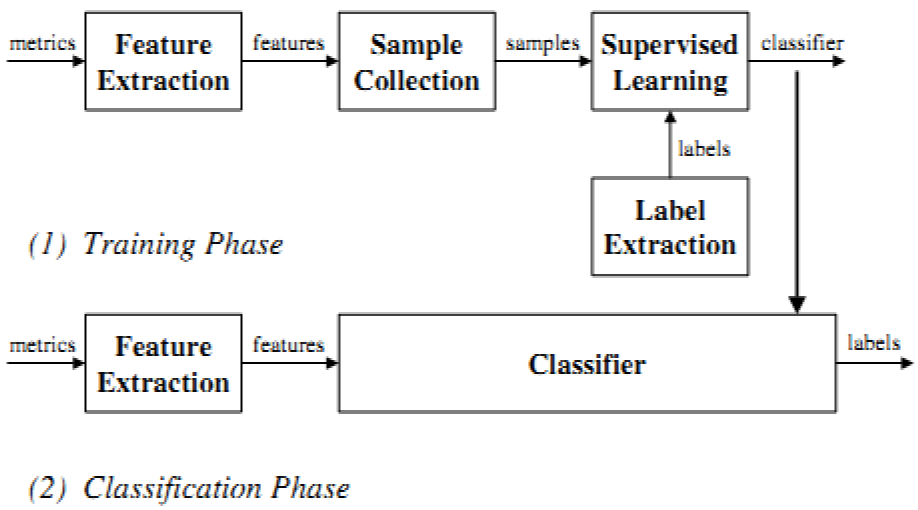

Figure 3: The Learning Process

3. Next, we use the labeled data to perform training at in the machine learning classifier;

4. Finally, we instruct the nodes in the network to use the classifier for differentiating between high quality and low quality links at runtime for real deployment.

3.2.1 Feature Extraction and Output Labeling

The first step in supervised learning extracts input features and labels output. This step requires domain knowledge to produce high-quality, and well-prepared data. In wireless sensor networks, we favor local features (within one- hop) that can be collected without expensive communications. This is because cognitive networks are very resource constrained and it is desirable and necessary to impose as little overhead as possible. As pointed out in previous studies, link delivery probability (or link quality) is determined by many factors, including wireless channel conditions, such as internode separation, fast fading and slow fading, the traffic pattern in the network and local traffic load of each node, etc.

3.2.2 Output labeling

Output labeling is the process of classifying sample outputs using domain knowledge. Supervised learning algorithms need to use labels to determine what category the input feature vector is assigned. There are many ways to label link quality, the first one uses a binary model that predicts a link either good or bad. The second one uses a multi-class model and can predict a set of classes of link quality. These categories can be used to distinguish link quality in a finer granularity than using the binary model.

3.2.3 Sample Collection

To perform offline training, we collect samples from cognitive nodes and stored in files which will be sent to the classifier which is configured as the machine learning algorithm.

3.2.4 Offline Training

Our learning and validation experiment will be performed using a Bayesian network classifier, a standard machine learning algorithm. As with most data-intensive machine learning algorithms, it is important to avoid having the classifier memorize, or over fit, the training data. We use cross validation and tree pruning to reduce such effects. Cross validation is a standard method to estimate classification accuracy over unseen data. We will use 10-fold cross validation in our experiments. The available data will be divided into ten equal-sized blocks. Nine of the blocks will be randomly chosen and used for training the classifier, with the remaining block used for validation. This process will be repeated 10 times to give a reliable measure of classification accuracy

3.3 Study Requirement

The environment where the next set of evaluations is con- ducted is an Ubuntu Linux 64-bit distribution with Linux kernel v3.1.5. The CPU is an Intel Core i5 clocked at 2.80 GHz. All simulations will be performed on a single thread/core. The installed RAM has a total capacity of 8 GB. In the simulations, the nodes will perform sensing and data transmission in intervals of 100ms and 1s, respectively. The CR interface channel switching delay is set to 20μs. The wifi MAC standard is set to 802.1g with a rate of 54 Mbps. We will use a total number of 1 channels that the PUs and CR users can switch to.

3.3.1 CR network configuration and simulation setup

The simulation setup and CR network configuration parameters are as follows, 25 nodes will be placed randomly with a random uniform distribution in a 500 m × 500 m field. Each CR node has a single radio transceiver and can access to 1 channels. Each wireless channel has 2Mbps bandwidth. Two-ray ground model is set as propagation model of CR nodes. Host CR nodes will use TCP Reno as transport protocol. The AODV and AOMDV protocol will be used by CR nodes as routing protocol.

3.4 Performance Parameters for Evaluation

In this section, we propose how we will perform the evaluation of the end-to-end protocols over CR routing layer protocols.

3.4.1 Routing layer

We consider two metrics for the performance analysis:

1. Throughput maximization: In CR networks it's important to use routes that will provide the most available capacity to enable efficient and effective end to end communication. To use routes with the highest available data rates.

2. Route stability maximization: due to the inherent nature of CR networks, SUs have to be assured of what stable routes can be used in communication due to the limitation of the existence of PU activity.

3. Delay minimization: We also want to discover how can routing protocols using a variant of machine learning be able to detect routes that provide for minimal delays.

4. Route discovery frequency. This is the average number of route discovery procedures generated by the source node, for each second. A route discovery is initiated when a source node broadcasts a route request message (RREQ), containing the address of the destination node. It provides an indicator of the stability of the route discovered by the routing protocol.

5. Packet delivery ratio (PDR). This is the ratio of packets which are received by the destination node, over the number of packets sent by the source. It provides an indicator of end-to-end delivery capabilities of the routing protocol.

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