Optimization of Machine Learning Parameters for Spectrum Survey Analysis

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Abstract— This paper shows preliminary results of the optimization of machine learning parameters for cognitive radio application by brutal force calculations. We were analyzing frequency occupancy data of the huge measurement campaign of the spectrum background. For these date there are two possible states. Firstly, limited frequency band is occupied (detected signal level is above the threshold) by the other frequency signal — there will be an interference for our system for this frequency band. Secondly, the frequency band is free of any other wireless radiation. These true/false data are analyzed in a context of the cognitive radio by the reinforcement learning and simple learning. Each channel received a score from the learning algorithm given by weighting function. The quality of the output scores is discussed in this paper according to the learning algorithm parameters and optional learning time.

1. INTRODUCTION

In the modern wireless communication there is nearly no idle frequency spectrum capacity. The most suitable frequency bands are already allocated or sold out. The newly incoming wireless system has to be moved to higher frequency bands or to share spectrum with existing system. Nowadays two main approaches of spectrums sharing [1, 2] are discussed. The first one is called the underlay spectrum sharing which is using the limited radiation power to minimize interference with existing systems like UWB technology. The second one is called overlay spectrum which is sharing technique using utilization of the unused spectrum parts of the particular frequency band. All of these techniques are applied in cognitive radio system for spectrum allocation [2]. In this paper we are focusing mainly on the frequency spectrum data evaluation based on the real measurement [3], which is used predominantly for overlay spectrum sharing. Firstly, the occupied parts of the frequency spectrum need to be detected and the threshold level needs to be set up [4]. Afterwards, the measured frequency points are mapped into the channels of the particular examined service. This paper targets the machine learning algorithms for channel assignment in cognitive radio.

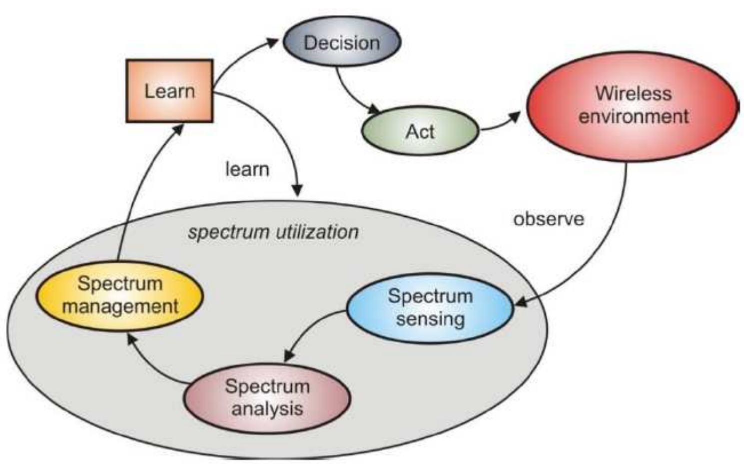

Figure 1: Cognitive cycle.

2. REASONS FOR MACHINE LEARNING

Generally, machine learning is the science how to get computers acting without being programmed. Machine learning influences our lives by many ways. It has given us by self-driving cars, effective web search and many other applications. Machine learning is so pervasive today that you probably use it dozens of times a day without knowing it. For wireless communication learning starts to be popular to solve cognitive system problems, such as dynamic spectrum sharing. Cognitive radio systems are sensing its own surroundings and aware it. It needs to adapt to the environment with its system (modulation) and transmission (radiation frequency, radiation power) to the environment as it is given by cognitive cycle Fig. 1 [5, 6].

Machine learning is an innovative tool how to apply learning mechanism to cognitive radio [7, 8]. In our case, we are trying to learn, which channel is the best for transmission [4] based on real data. We passed huge measurement campaign to collect spectrum information from various scenarios (indoor and outdoor) and various time tom cover the differences in different wireless traffic over the day.

2.1. Reinforcement Learning

Reinforcement learning is type of the machine learning to maximize a numerical reward output. The agent is not told which actions to take, as in most forms of machine learning, but instead must discover which of his actions yield the most reward. In the most interesting and challenging cases, actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards. These two characteristics Ctest and trial- search and delayed reward are the two most important distinguishing features of reinforcement learning. In our case, we will be evaluating the scores of the wireless channel of the particular system. The weighting function (1) is given by:

$$WR_{ch} = W_{ch,t-1} + RP, \tag{1}$$

where WR_{ch} stands for weight value of particular channel ch. $W_{ch,t-1}$ stands for the weight value for particular in previous learning step and RP symbolizes reward/punishment value for this step.

It is clear that RP function need to be carefully selected. The general form is presented as (2).

$$RP = \sum\nolimits_{i=1}^{S_W} P_i + R_i = \sum\nolimits_{i=1}^{S_W} \left(\sum\nolimits_{y_i}^{n_i} C_P^n - \sum\nolimits_{z_i}^{m_i} C_R^m \right), \tag{2}$$

where SW is size of the sliding window in data processing ($SW = 1$ when no sliding window used). C_P is constant values used as PUISHMENT and C_R stands for constant value for REWARD. All these values are discussed in results part of this paper. It is obvious that due to negative value of the reward WR can reach negative values. Indexes m_i, m, n_i, n will be discussed later.

For our purposes for cognitive radio we use negative logic — so we are counting punishment of each channel. The lowest score is the best channel from the frequency data perspective.

2.2. Simple Learning

On the one hand, reinforcement learning bring huge dynamic in the results, but on the other hand, there is also inconclusive results. From this reason we tried more basic learning mechanism. The most basic one is the counting the spectrum events occurrences (detected level over the threshold) for particular channel. As it is proved, this algorithm bring us simplification and surprisingly shortened learning times comparing to reinforcement learning. The weighting function is given by (3).

$$\begin{array}{ll} WI_{ch} = W_{ch,t-1} + P & \\ P = 1, & \text{when interference detected,} \\ P = 0, & \text{eslewhere} \end{array} \tag{3}$$

3. SIMULATION RESULTS

To compare results we firstly need to define comparable parameters. Firstly, we are focused on credibility of the simulations. The credibility it the comparison between the order of the channels based on the scores from the learning after the 5 minutes learning time (the lowest score the best channel) and the order of the channels by the scores given by the simple learning (interference count) over the whole data set. The same procedure was repeated 100 with the random starts of the learning sequence over the whole data set. The sufficient credibility performance is more than 80%. Getting significantly higher agreement is nearly impossible, because the difference between channel's scores should be very low. Secondly, the learning time is very important. The duration of the agent's successfully training is crucial for future application. The minimal learning time was found by changing the learning duration and comparing the channels order with total interference count channels order.

The simulations were performed for LTE system parameters, which is a modern cellular communication standard. Channel bandwidth we choose 3 MHz in LTE band #3, uplink (1710 MHz–1785 MHz).

The first set of results presented in Table 1 describing the average credibility for 100 random 5 minutes long parts of the measurement data (48 hours samples). The upper index N in last 3 rows in Table 1 presented the situation when are indexes m and n from (3). These indexes takes into account consecutive frequency samples in the same state (used frequency, free frequency point). We are counting the number of the same consecutive samples (y_i, z_i) resulting to the value m and n respectively. We assume that increasing number of the consecutive is representing quality of the channel. Single sparking interference is not such dangerous as continuous interference in particular channel. On the other hand, the frequency band without interference for long time is perspective

Table 1: The credibility results for different settings.

C_P [-]	C_R [-]	Credibility [%] without SW	Credibility [%] $SW = 2$	Credibility [%] $SW = 5$
1	1	50	51	51
2	5	78	79	79
5	10	75	75	74
10	10	55	56	57
2^N	5^N	81	83	87
5^N	10^N	74	78	79
10^N	10^N	71	72	74
1	0	85	-	-

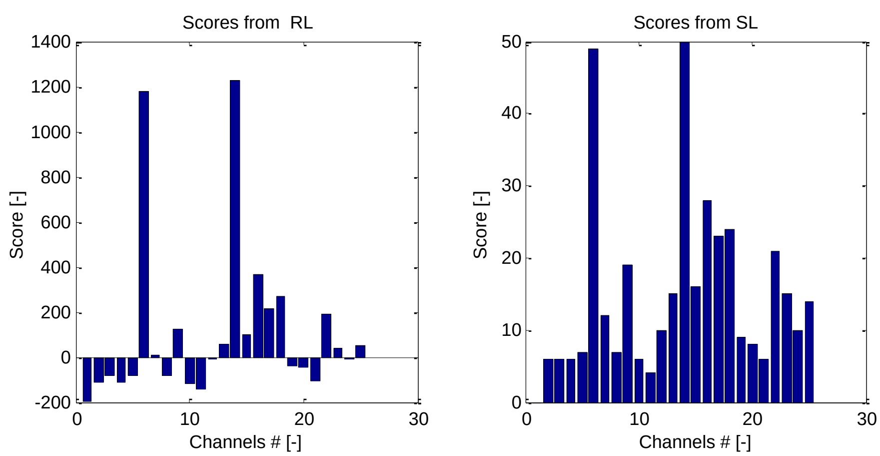

Figure 2: The output from the reinforcement learning (RL) and simple learning (SL) for 5 minutes learning tim.

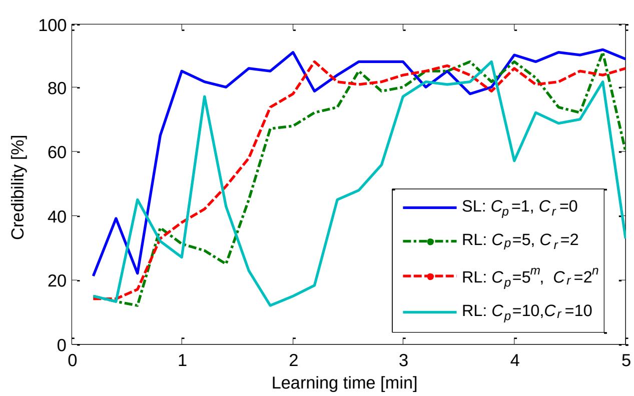

Figure 3: Learning time investigation for simple learning (SL) and reinforcement learning (RL).

for radio transmission — gain higher reward.

The last row in Table 1 is output from simple learning. It is obvious that it provides very high credibility with very low costs.

Finally, the learning time investigation is presented in Fig. 3. It is obvious that simple learning needed the shortest time to reach sufficient credibility (average of the 100 random starts for investigated time over the whole data file).

4. CONCLUSIONS

Recently, machine learning was proved as useful tool for representing learning part of the cognitive radio. It was presented, that reinforcement learning providing high dynamic results. The system using reinforcement learning needed longer learning times to provide credible results than simple learning. Simple learning provides sufficient result after 1 minute (6 time samples). Reinforcement learning provided results with same credibility after 2 minutes, but it is better for long-term channel sensing because of the reward feature — healing the channel. The wireless channel should improve its score after short-term interference. The optimal reward and punishment constants for presented learning algorithm were 5 for punishment and 2 for reward respectively. The further research should be divided into two groups. The best channel searching — based on the selected learning parameters we are able to find the best channel for transmission. Due to continuous spectrum sensing, we are able to update the channel scores. Secondly, rapid channel assignment should find its application for emergency networks. Our radio comes to the unknown environment and we need to choose interference less frequency band for communications.

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