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Deep Learning Meets Cognitive Radio: Predicting Future Steps

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Abstract—Learning the channel occupancy patterns to reuse the underutilised spectrum frequencies without interfering with the incumbent is a promising approach to overcome the spectrum limitations. In this work we proposed a Deep Learning (DL) approach to learn the channel occupancy model and predict its availability in the next time slots. Our results show that the proposed DL approach outperforms existing works by 5%. We also show that our proposed DL approach predicts the availability of channels accurately for more than one time slot.

Index Terms—Cognitive radio, deep learning, channel occupancy models

I. INTRODUCTION

Spectrum limitations have always been one of the challenges of wireless and cellular communications. To overcome this challenge, different approaches and technologies have been proposed and used in different communication standards. Some considered using higher frequencies, e.g. using millimeter Wave (mmWave) in 5G [1], while others focused on techniques for more efficiently using the spectrum, e.g. network densification and Multiple Input Multiple Output (MIMO) has been used in Long Term Evolution (LTE), and using massive MIMO in 5G. All these techniques are very useful; however, they have their own challenges. For instance mmWave and densification (small cell) can only cover short ranges, and MIMO-based techniques need more complex transmitters using more power. These challenges make these techniques unsuitable for applications like Internet of Things (IoT).

Dynamic Spectrum Access (DSA) and Cognitive Radio (CR) have been investigated as methods for enhancing spectrum usage efficiency by enabling spectrum sharing. Among different forms of DSA, multi-level (hierarchical) spectrum exploitation has attracted more attention, specifically for the use in 5G in the form of cognitive and cooperative spectrum sharing [2]. In [3] the authors provide a long list of CR-based spectrum sharing applications for 5G, including Device-to-Device (D2D) and unlicensed LTE. In all these spectrum sharing approaches awareness of the environment is a key issue in which Machine Learning (ML) plays an important role.

One of the main challenges of hierarchical spectrum sharing is finding the transmission opportunities in the shared spectrum when the licensed user (a.k.a Primary User (PU)) is not active. Different approaches like spectrum sensing and querying a spectrum occupancy data base [4] have been proposed in the literature.

To find the underlying structure and patterns in spectrum usage that can be used to predict the availability of frequency

channels well in advance in time, various ML and deep learning based techniques have been proposed. However, most ML-based works on hierarchical spectrum sharing have focused on and studied channel occupancy models then and used ML-approaches to predict the availability of the spectrum in next time slot. Ding et al. in [5] provide a comprehensive survey of the aforementioned approaches.

In [6], the authors compare the performance of multiple supervised and unsupervised learning algorithms in terms of classification accuracy. The authors also propose a new algorithm by combining support vector machines and the firefly algorithm. The algorithms have been compared over 8 channels with different power levels. A periodic pattern mining approach has been proposed in [7] to predict spectrum availability. The authors tested their proposed method on WiFi and personal communication service data sets. The authors of [8] used multi-armed bandit aggregation learning techniques to deal with the learning of multiple spectrum channels' activities. The authors compared their approach with different multi-arm bandit approaches in the literature and on different distributions for PU activities.

We proposed a Markov-based learning model to select a channel with the highest probability of being unoccupied in [9]. Our results in comparison with neural networks and conventional hidden Markov models showed that the proposed method performs equally with those, while being much less computationally intensive. A version of the proposed learning technique has been implemented in [10] on Ettus Research¹ Universal Software Radio Platforms (USRPs).

In [11] and [12] we proposed a theoretical limit for the predictability of channel occupancy, and evaluated the performance of our Markov-based and reinforcement learning algorithms. Moving a step forward in [13], we used the spectrum predictability limit and duty cycle to allocate fungible sets of channels to unlicensed users. This two step learning approach provides a level of fairness among Secondary Users (SUs) and gives them the freedom of choosing their own learning approach.

In recent years, the deep learning paradigm has become one of the dominant forms of machine learning for computer vision and natural language processing tasks, consistently outperforming other techniques on a wide range of problems [14], [15]. A key benefit of deep learning algorithms over conventional machine learning algorithms is that they can learn features of importance from the data rather than relying on

¹www.ettus.com

complex feature engineering steps. DL has attracted attention of the wireless communications community and has been used in CR networks for spectrum sharing and management. In [16], the authors propose a DL-based message passing algorithm to solve an NP-hard energy and spectral efficiency maximization problem in underlying CR networks. Automatic modulation detection in CR networks is another application of DL which has been investigated in [17].

Spectrum availability prediction has also benefited from DL. In [18], the authors perform channel availability prediction for cognitive aerospace communications. They used a three layer DL model on spectrum sensing data collected by the Shared Spectrum company² in New York City and Vienna to predict the presence/absence of PUs in 26 channels. Piasana et al. in [19] and [20] used DL for prediction of spectrum availability in the IEEE DySPAN spectrum challenge. The system that they have implemented on Ettus Research USRPs achieved high data rate transmission and low interference with PUs over $4 \times 2.5\text{MHz}$ channels. A DL approach with long short-term memory has been proposed in [21] to predict spectrum availability directly from the power spectral density. The authors tested their proposed method on terrestrial and satellite communication data.

All the aforementioned approaches try to predict only one step ahead and do not consider the effect of channel occupancy on future time slots. In this paper we will focus on this feature. Being able to predict how long a channel will be available reduces channel switching costs and helps the CR to select the channel more efficiently.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this work, similar to most of the existing works in the literature, we consider K channels in our wireless band. Depending on the sensing and transmission time frame [22], the time is quantised into timeslots with a fixed length. In each of the channels and at each timeslot, the presence of the PU is denoted with a 1 and its absence is denoted with a 0. We assume that the sensing is ideal, meaning that the effects of noise, missed detection, and false alarms are considered to be negligible.

We consider that the K channels are licensed to one network (PU) and only one unlicensed network (SU) observes these channels for opportunistic use. The SU observes and learns each of these channels individually. Our proposed DL approach learns the activities on each channel and predicts the availability of the channel for the next time slot. The SU then selects the channel with the highest probability of being free at the next time slot. Furthermore, our DL approach predicts the availability of the channels in the time slots after next. In this case, if the accuracy is high enough, the SU will be able to reduce the sensing frequency and in some cases select the channel with the highest probability of being free in the next t time slots.

A. Impact of licensed network behaviour

As mentioned in [11] and [13] the behaviour of PU has a significant impact in predictability of each channel. Additionally, as considered in many previous works, the usage level

of the channel a.k.a the Duty Cycle (DC) plays a significant role. Basically if the channel is only used 30% of the time, a random guess of channel being free (i.e. only predicting the channel being free) has an accuracy level of 0.7. In other words, the level of random chance will be 70% and therefore the learning algorithm must have an accuracy higher than that 70%.

In various DCs, the behaviour of the user can be completely random or have a pattern. The more random the behaviour becomes, the less predictable it will be. Let's say that we show the behaviour of the PU on each channel as a two state Markov Chain where p_{ij} denotes the probability of moving from state i to state j ; here $i, j \in \{1, 2\}$. This two state Markov chain (X) will have a stationary distribution denoted by $\delta = [\delta_0 \delta_1]$. The predictability/randomness of the PU's behaviour can be quantified using the normalized Lempel-Ziv (LZ) complexity [11] which for an ergodic source equals the entropy rate of the source [11].

$$h(X) = - \sum_{ij} \delta_i p_{ij} \log p_{ij}. \quad (1)$$

In our analysis we study the performance of the algorithms and compare them based on their performance on channels with different DC and LZ complexity values. As we showed in [11], LZ complexity of real measurement data can also be accurately measured when there are more than 1000 samples. Therefore, both DC and LZ complexity can be used for synthetic and real measurement data.

III. DEEP LEARNING

Over the last five years deep learning has seen rapid development and successful adoption across a wide range of computer vision and natural language processing tasks due to consistently outperforming other methods [14], [15]. A key advantage of deep learning approaches such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) is their capability for end-to-end learning without the need for complex feature extraction steps.

More recently there has been increasing interest in the ability of deep learning models - particularly RNNs - to model and learn from sequence data [23]. Unlike traditional machine learning approaches, which assume that the input variables comprising a sequence are independent of each other, RNNs can capture the dynamic temporal behaviour of an input sequence by retaining and utilising information about what has happened in previous time-steps. This allows them to "remember" information about the entire input sequence.

A prime factor limiting the application of vanilla RNN models has been the increasing difficulty in training such model as the temporal span of the input sequence increases. This is due to the gradients of the weights either decaying or exploding as errors are backpropagated through time [24]. However, the Long Short Term Memory (LSTM) recurrent neural network architecture introduced in [25] overcomes many of these difficulties in training networks by providing a direct path through the network known as the memory state. This joins multiple LSTM cells that are processing data from different time-steps whilst controlling how much information

²<http://www.sharedspectrum.com/>

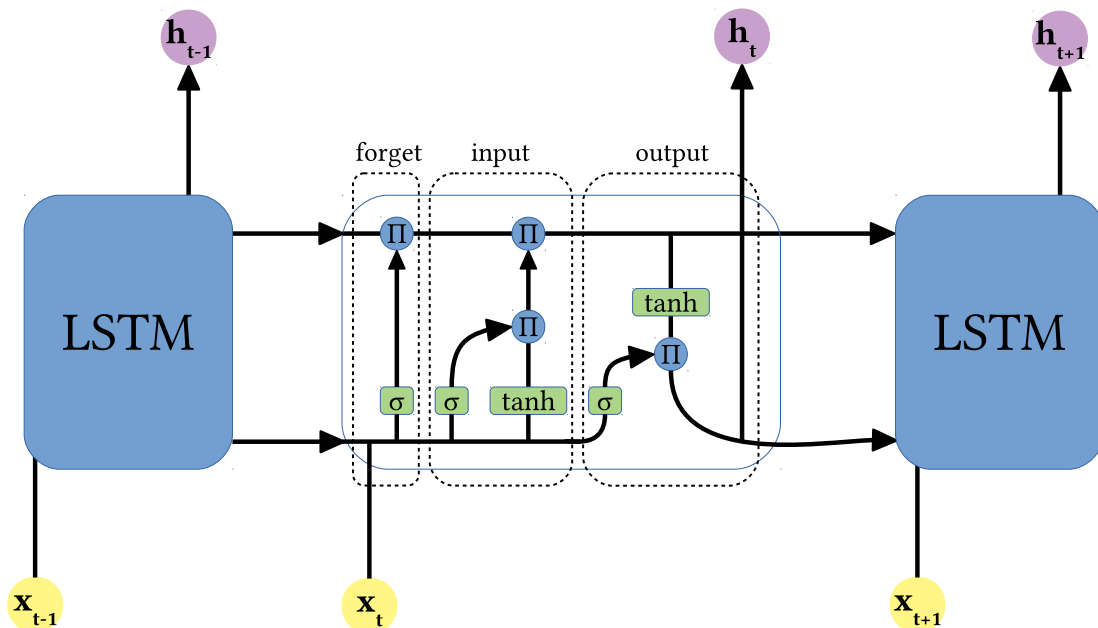


Fig. 1. LSTM architecture

is added to and retained by the memory state using a gating mechanism. Figure 1 shows this LSTM architecture.

This gating mechanism consists of three gates that regulate the addition or removal of information from the memory state of the LSTM network:

- 1) The **forget gate** which controls how much of the previous state the LSTM should remember.
- 2) The **input gate** which controls how much new information the LSTM should add to its memory.
- 3) The **output gate** which controls how much of the memory we are going to use in the output of the state at the current time step.

LSTM based network architectures have recently seen increasing use in time-series forecasting applications [26] and often outperform conventional methods such as Autoregressive Moving Average (ARMA) and Nonlinear Autoregressive Exogenous (NARX) models due to their ability to capture the nonlinear dynamics of a system in the presence of complex, noisy, and high dimensional data sets [27]. In this work, we propose using an LSTM based model to forecast channel occupancy in a opportunistic channel access scenario. Using this approach we can make accurate predictions under a range of operating loads for not only the next time-slot, but for several time-slots ahead.

IV. SIMULATION RESULTS AND DISCUSSIONS

In our simulations we use synthetic and real data sets. The synthetic data is generated using a two-stage Markov chain with known DC and LZ complexity. We test our proposed method over exactly the same type of generated data in [11]. In figure 2 we compare the prediction accuracy of DL with [11] over channels with stationary distribution of $\delta = [0.50.5]$, having the probability of being free $p_f = 1 - 0.5^K$. Here K is the number of channels. As mentioned channels with same DC can have different complexities. The blue line in the figure

is where the channels are completely random ($h(X) = 1$), and basically no prediction can be made. For the other two tests we used channels with lower complexity and created data for red and green results using $\begin{pmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{pmatrix}$ and $\begin{pmatrix} 0.95 & 0.05 \\ 0.05 & 0.95 \end{pmatrix}$, respectively.

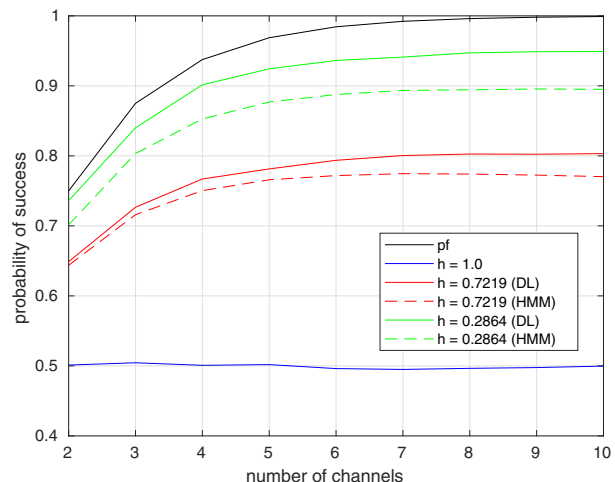


Fig. 2. Probability of success of the proposed DL approach versus the Hidden Markov Model process-based learning algorithm as a function of the number of channels. Each curve refers to combinations of different numbers of channels characterized by the same DC and different values of entropy rate h .

In Figure 2 we compared the performance of our proposed DL with the presented Markov chain-based approach in [9] and show that the proposed DL clearly outperforms the Markov chain-based approach.

In addition to better performance, our proposed DL is able to accurately predict multiple future steps. This means that the decision making algorithm can also consider minimizing the channel switching when there is a cost on that. An example of

that would be switching to an idle channel on another band. This knowledge can also be used when there are multiple CRs and choosing which channel to test and occupy first is important.

In figures 3 and 4 we present the accuracy of the proposed DL in predicting the availability of a channel for more than one time slot ahead. Figure 3 presents the scenario where all the channels have the LZ complexity of 0.72 (first matrix, red line in figure 2). As expected the prediction of more steps ahead have lower accuracy; however, the probability of selecting an idle channel two step ahead is more than 70% and for up to five steps ahead is above 60%.

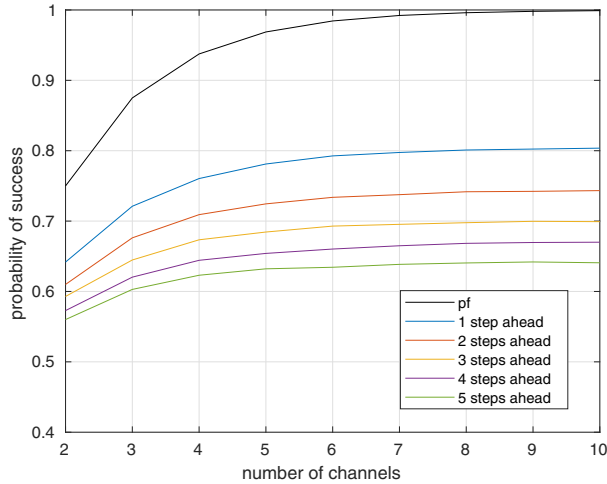


Fig. 3. Probability of success beyond one time slot of the proposed DL approach as a function of the number of channels. Each curve refers to probability of success for a number of time slots ahead. The channels are characterized by the same DC and entropy rate of $h = 0.72$.

In figure 4 we present the future steps channel selection results for channels with lower complexity. In this figure the DCs of the channels are still 50%, but their complexity is lower, i.e. $h = 0.28$ (second matrix, green line in figure 2). The results show that the probability of success in selecting an idle channel reaches 90% for two steps ahead and 80% in sets of 4 channels, respectively. These results show that the proposed DL is capable of accurately selecting the idle channels in the scenarios with synthetic data.

We also tested our proposed algorithm over real data too. Following similar works in the literature, we run our DL over the Rheinisch-Westfalische Technische Hochschule (RWTH) Aachen University data set [28]. In this data set, the power spectral density (PSD) is recorded across several bands. In this work, similar to [9], we use the data collected over the 2.4-GHz ISM and GSM 1800 bands. Moreover, we consider all the channels with $DC \in [0.3, 0.8]$. In our simulations we created bundles of $K = 4$ channels and the DL algorithm selects the channel that it believes will be free with the highest probability. We show its success rate with probability of success P_{suc} .

Our results over 2.4 GHz ISM and GSM 1800 bands, figures 5 and 6, show that our proposed DL approach improves the probability of success (on average) by 5% (with worst case 3% and best case 7%) compared to existing methods in the literature [9].

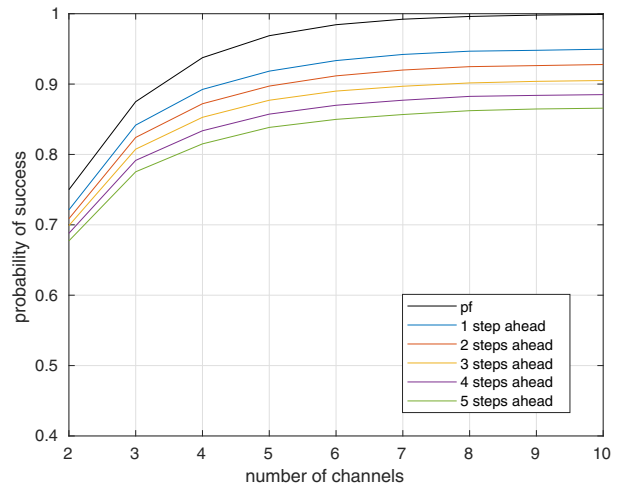


Fig. 4. Probability of success beyond one time slot of the proposed DL approach as a function of the number of channels. Each curve refers to probability of success for a number of time slots ahead. The channels are characterized by the same DC and entropy rate of $h = 0.28$.

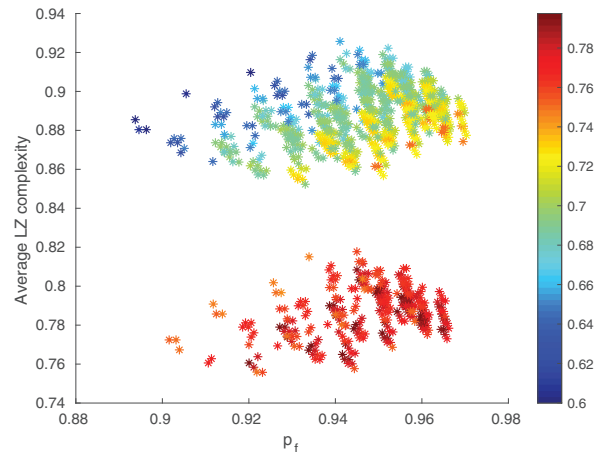


Fig. 5. Probability of success of the proposed DL algorithm as a function of the average LZ complexity and the probability of at least one free channel existing. Each point represents a particular instance of the DL applied to $K = 4$ channels of 2.4-GHz ISM band.

V. CONCLUSIONS

In this paper we presented a DL approach to learning channel activities and selecting a channel for transmission. Our results on synthetic and real data shows that our proposed approach outperforms the literature. Moreover, unlike existing techniques, our proposed DL can accurately select a free channel for more than one time slot ahead. Our results show that the selection accuracy is above 80% for up to 5 timeslots in low complexity channels, and above 70% for high complexity channels. The knowledge of future time slots will help us with the channel selection specifically for the cases that channel hopping has tuning costs. In our future works we will study this.

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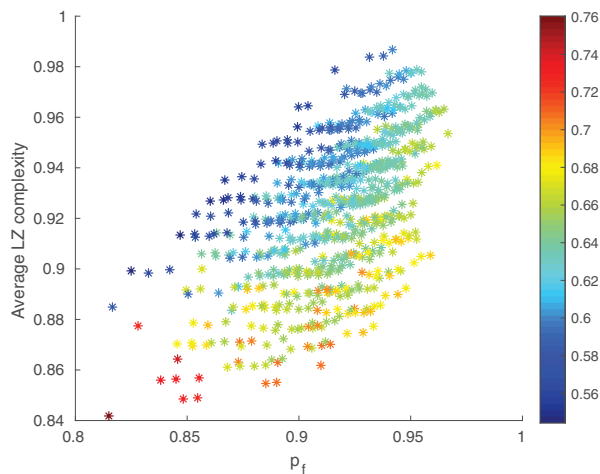


Fig. 6. Probability of success of the proposed DL algorithm as a function of the average LZ complexity and the probability of at least one free channel existing. Each point represents a particular instance of the DL applied to $K = 4$ channels of GSM 1800 band.

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