

Analysis of Spectrum Occupancy using Naïve Bayesian Classifier

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Abstract: This work evaluates spectrum occupancy in cognitive radio network (CRN) based on naïve Bayesian classifier (NBC). It considers OFDM based users as primary users (PU) and 64-QAM based user as secondary user (SU). The motivation for this work is the classification problem in spectrum sensing, wherein it becomes important for secondary users (SUs) to sense free channel and use it for its own transmission/reception purpose given PU or SU are not present for effective utilization of spectrum that eventually leads to increased network throughput. Data were collected as constellation points of OFDM and 64-QAM at transmission power of -10dBm (0.1mw). Our proposed evaluation can be applied to D2D communication in next-generation heterogeneous network, where devices are considered as SUs and cellular based users are considered as PU. The complete architecture can be considered as decentralized network, where devices (SU) can use channel upon confirming the channel not being occupied by any other PU or SUs, this is believed to increase throughput of SUs. NBC is considered because it considers all features independent and gives good model for classification in future.

I. INTRODUCTION

Cognitive radio (CR) has emerged as path-breaking solution to mitigate the scarcity of radio spectrum. CR refers to an intelligent wireless communication devices, which senses EM environment and dynamically adjusts its radio operating parameters. Therefore, it allows opportunistic access of spectrum/frequency band allocated to PU, whenever PU is not involved in any kind of transmission or reception. Once CR device detects unavailability of PU, it uses the channel for its own transmission or reception, until PU is not detected. The moment PU is detected, SU stops all activities and senses other vacant channel, and this in turn leads to effective utilization of network resources.

Machine learning is a tool to make machine/devices learn through experiences (past recorded data). ML uses these past recorded data to build a model by making some kind correlation among them. The model built can be used to predict both the continuous values and discrete values.

This paper evaluates spectrum occupancy in CRN based on past recorded constellation points, NBC is trained on those data to build a model to make future prediction given constellation points.

In [1], the authors develop a Bayesian learning model which they refer as 'beta process sticky hidden Markov model' (BP-SHMM), for capturing the spatial temporal

correlation of the collected spectrum data and also develop a new algorithm which will predict the spectrum availability thereby enabling a newly available SU to immediately access the unoccupied channel without sensing, this will ultimately save time required for sensing and allow SU to use channel as soon as it wants to transmit.

In [2] authors coins new term known as 'end-to-end learning from spectrum data'-newly coined term for complicated wireless signal identification technique in spectrum monitoring applications based on deep neural networks. End-to-end learning allows 1) To learn features from simple wireless signal representations which do not require any design of hand-crafted expert like features 2) Also train wireless signal classifiers in one end-to-end step which will eliminate the need for complex multi-stage machine learning processing pipelines.

In [3], the authors discuss about machine learning technique which is used for prediction algorithm in D2D scenario is considered, having multiple elements/devices that receive data from controller, which requires the accurate on-the-fly estimation of the remaining transmission time, i.e., the Estimated Time of Arrival (ETA). This kind of information is important when the devices need to take decision whether they need to continue transmission or stop.

Authors in [4] consider CR-based Het-Net where cognitive D2D pairs and cellular users coexists and cellular users are the primary users while D2D pairs are secondary users. The results shows that the centralized algorithm based on GA outperform the semi-distributed algorithm based on stackelberg game.

In [5], the authors Spectrum occupancy in CRN using different machine learning technique is analyzed. Comparison in terms of computational time and classification accuracy is performed. SVM combining with fire fly algorithm outperformed others.

Authors in [6] Learning based power control method for spectrum sharing in CRN is developed. Set of sensor nodes are spatially deployed to collect RSS information at different locations. SU can use this information to adjust its transmission power after few rounds of interaction with PU.

This work enables detection of both PU and SU which makes SU transmit/receive without interference of other SU.

II. METHODOLOGY

NBC is probabilistic classifier based on Bayes theorem, which has strong (naïve) independence assumptions between the features. NBC assume that the value of a particular feature is independent of the value of any other feature, given the class variable.

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For instance to classify whether channel is occupied by PU or not based on constellation and magnitude, NBC considers both these features to contribute independently to the probability if channel is occupied by PU.

In context of this work Bayes Theorem may be written as

$$P(1/X) = p(X/1) P(1). \quad (1)$$

$P(1/X)$ = Probability of primary user being present given features, $P(X/1)$ = Likelihood of features given PU is present, $P(1)$ = prior probability.

Equation 1 corresponds to probability of spectrum being occupied by PU, given the features constellation points and magnitude.

Also,

$$P(0/X) = p(X/0) P(0). \quad (2)$$

$P(0/X)$ = Probability of secondary user being present given features, $P(X/0)$ = Likelihood of features given SU is present, $P(0)$ = prior probability.

Equation 2 corresponds to probability of spectrum being occupied by SU, given the features constellation points and magnitude.

III.SYSTEM MODEL

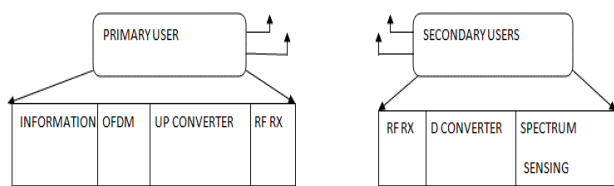


Figure 1: Primary user and secondary users in a heterogeneous network

In this model it has been assumed that only one PU is present and many SUs in a small geographical area, this is similar to heterogeneous network where cellular based user is PU and nearby devices are SUs.

Let Y_s be the sample being sensed by the SU, which is taken as data for classification of channel.

$$Y_s = h_{ps} P_{pu} X_p + \sum_{i=1}^N h_{ss} (1 - P_{pu}) X_s + n. \quad (3)$$

Here, h_{ps} = channel occupied by PU, P_{pu} (probability that PU is present) = 1, when channel is occupied PU and 0 when SU is present. X_p , X_s are PU and SU transmission respectively. It is assumed that there is one PU and n numbers of SUs. If SU (devices) senses channel to be occupied by PU then equation (3) becomes

$$Y_s = h_{ps} X_p + n. \quad (4)$$

If channel is occupied by SU, then

$$Y_s = \sum_{i=1}^N h_{ss} X_s + n. \quad (5)$$

Y_s is used by the model to classify whether channel is occupied by PU or SU.

IV.RESULTS

All the results achieved are based on specification given below.

Parameters	Specification
Modulation (PU)	OFDM
Modulation (SU)	64-QAM
Transmission power	-10dBm(0.1mw)
Frequency	2GHz
Distance between PU and SU	0m
Training data size	80

Test data size	20
Features (Independent variable)	(i) Constellation Points. (ii) Magnitude
Parameters set for NBC function	None

Here configuration and setup of transmitter and receiver were considered same to capture data, transmit power was kept at worst possible level of -10dBm (0.1mw).

The confusion matrix was found to be CM,

$$\begin{bmatrix} 9 & 0 \\ 0 & 11 \end{bmatrix}$$

Where A_{ij} represents i_{th} row and j_{th} column. A_{11} = prediction for number of SUs present given SU is present. A_{12} = prediction for number of SUs present given PU is present, A_{21} = prediction for number of SUs present given PU is present, A_{22} = prediction for number of PUs present given PU is present, which tells that it does 20 correct prediction and 0 wrong prediction on set of 20 test data (out of which PU are present on 11 and SU are present on 9).

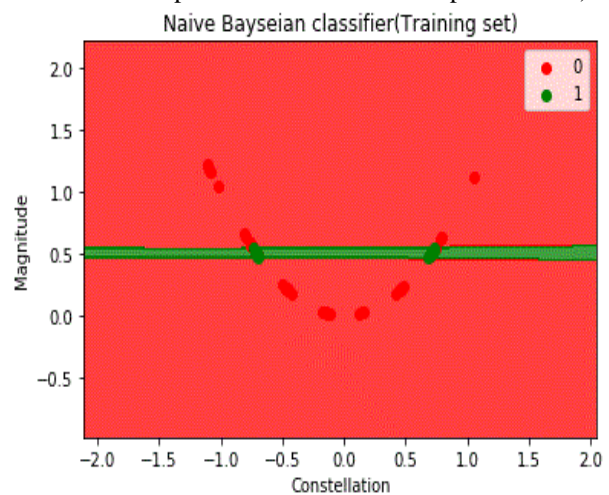


Figure 2: Naïve Bayesian classifier on training set

On the above figure NBC is applied based on the training data, NBC builds a model (decision region), where red region depicts presence of SU and green the presence of PU. NBC uses this model to classify test set or future data. Any point lying on red region will be treated as SU users and vice versa for all future prediction.

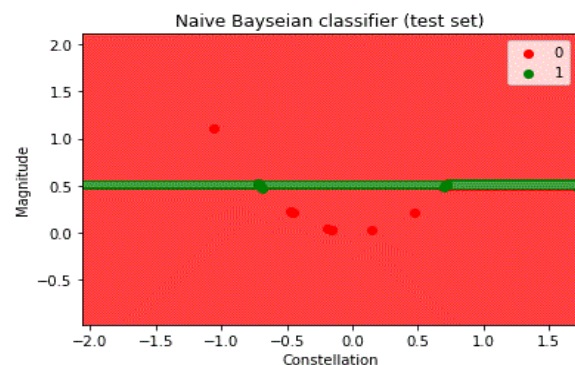


Figure 3: Naïve Bayesian classifier on test set

Based on model build by NBC, it is used to classify test set. As it can be clearly seen the model predicting perfectly for all data in test set also depicted by confusion matrix.

To calculate precision and recall:

$$\text{Precision (P)} = \text{TA} / (\text{TA} + \text{FA}) \quad (6)$$

$$\text{Recall(R)} = \text{TA} / (\text{TA} + \text{FB}) \quad (7)$$

$$\text{Accuracy (A)} = (\text{TA} + \text{TB}) / (\text{TA} + \text{TB} + \text{FA} + \text{FB}) \quad (8)$$

Where, we have the parameters as, True class A (TA), False class A (FA), True class B (TB), False class B (FB). Let the class A be presence of PU and class B be presence of SU.

Here, TA = 11, FA = 0, TB = 9, FB = 0. Substituting these values we get: P = 1, R = 1, A = 1.

All the performance matrices are ideal, since configuration and setup were considered to be same for Transmitter and receiver. In future the analysis of occupancy of spectrum can be studied with other machine learning algorithms such as SVM, KNN and under different setups and configuration (keeping some distance between PU and SU, and at different frequencies) to visualize the real-time effects.

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