THE UNIVERSITY OF SYDNEY

Mobile Bayesian Spectrum Learning for Heterogeneous Networks

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Motivation

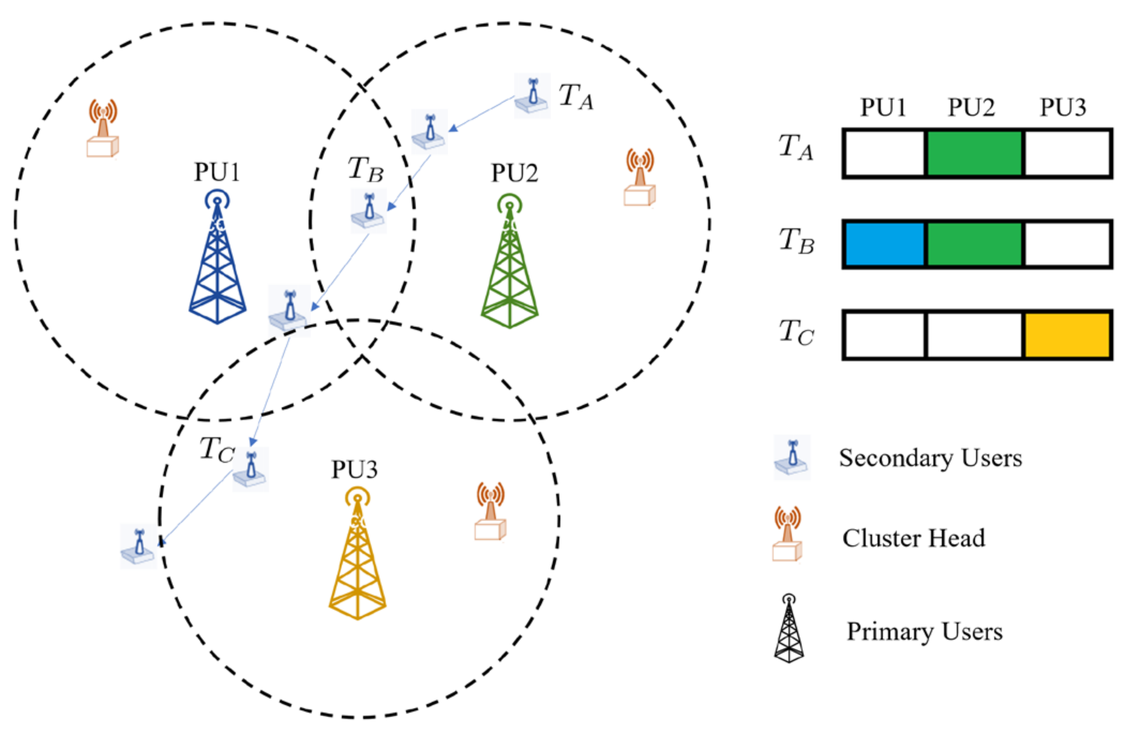
Spectrum sensing in large-scale heterogeneous cognitive radio networks (CRNs) is very challenging.

- Traditional methods require a large number of static secondary users (SUs).

To tackle this problem, we exploit the mobility of multiple SUs to simultaneously collect spectrum sensing data.

We propose a novel non-parametric Bayesian learning model, referred to as beta process hidden Markov model (BP-HMM), to capture the spatial-temporal correlation in the collected spectrum data. Bayesian inference is carried out to establish the global spectrum picture.

System Model



- *N PUs and M mobile Sus*
- *Organized into a cluster topology*
- *Relatively small SUs' Velocity*

Cooperative Spectrum sensing

1. Each CH runs the proposed algorithm and exchanges information in the form of sufficient statistics and other parameters
2. CHs transmit the local results to a fusion center

Spectrum sensing data collected by SU

At sensing index i, the sensing sample for the l-th ($1 \le l \le L$) sub-band obtained by the m-th SU can be expressed as

$$x_l^m[i] = \begin{cases} n_l^m[i] & \mathcal{H}_0^{(l)}, \\ \sqrt{\gamma_l^m} s_l^m[i] + n_l^m[i] & \mathcal{H}_1^{(l)}. \end{cases}$$

With additive while Gaussian noise and assumption of s_l^m being a complex Gaussian distribution, the sensing sample can be further written as

$$x_l^m[i] \sim \mathcal{CN}(0, \gamma_l^m + \sigma_n^2).$$

As SUs are sampling L sub-bands simultaneously, the final sample is a $L \times 2$ dimension observation following multivariate Gaussian distribution.

Conclusion

- A non-parametric Bayesian learning based mobile CSS scheme was proposed for spectrum sensing in heterogeneous CRNs. This novel scheme significantly outperforms the traditional methods.

Non-parametric Bayesian Learning

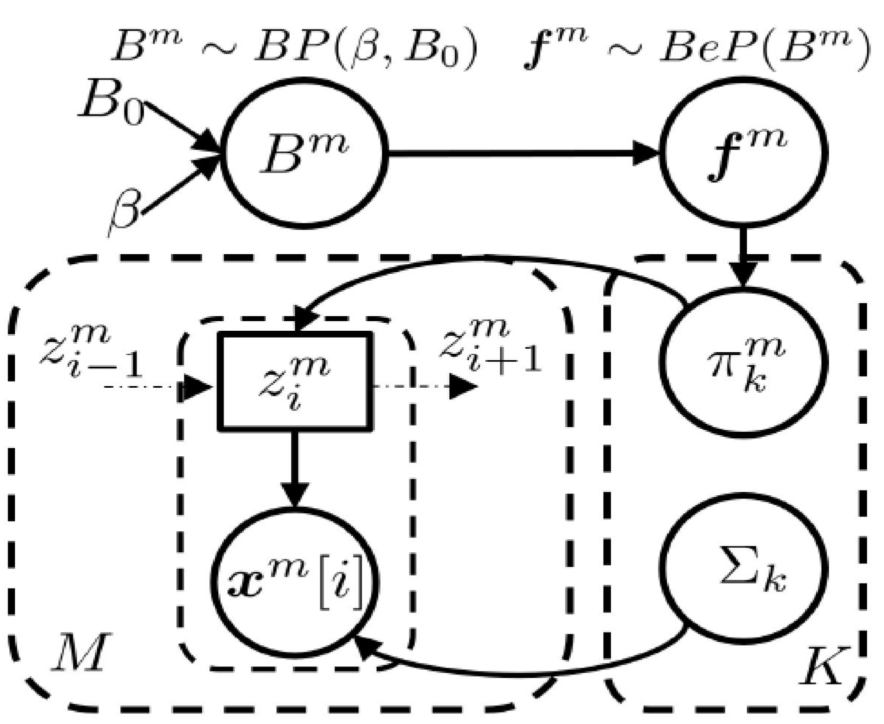
Beta-process hidden Markov Model (BP-HMM)

Hidden Markov Model

- To discover the latent statistical correlation within single SU's time series data, where a sticky parameter is introduced to reflect the slow spectrum state transition

Beta Process

- To replace the set of conditional finite mixture models in the HMM



$$B^m | B_0, \beta \sim BP(\beta, B_0),$$

$$\boldsymbol{f}^m | B^m \sim BeP(B^m),$$

$$\boldsymbol{\pi}^m \sim Dir([\gamma, ..., \gamma, \gamma + \kappa, \gamma, \gamma]) \odot \boldsymbol{f}^m,$$

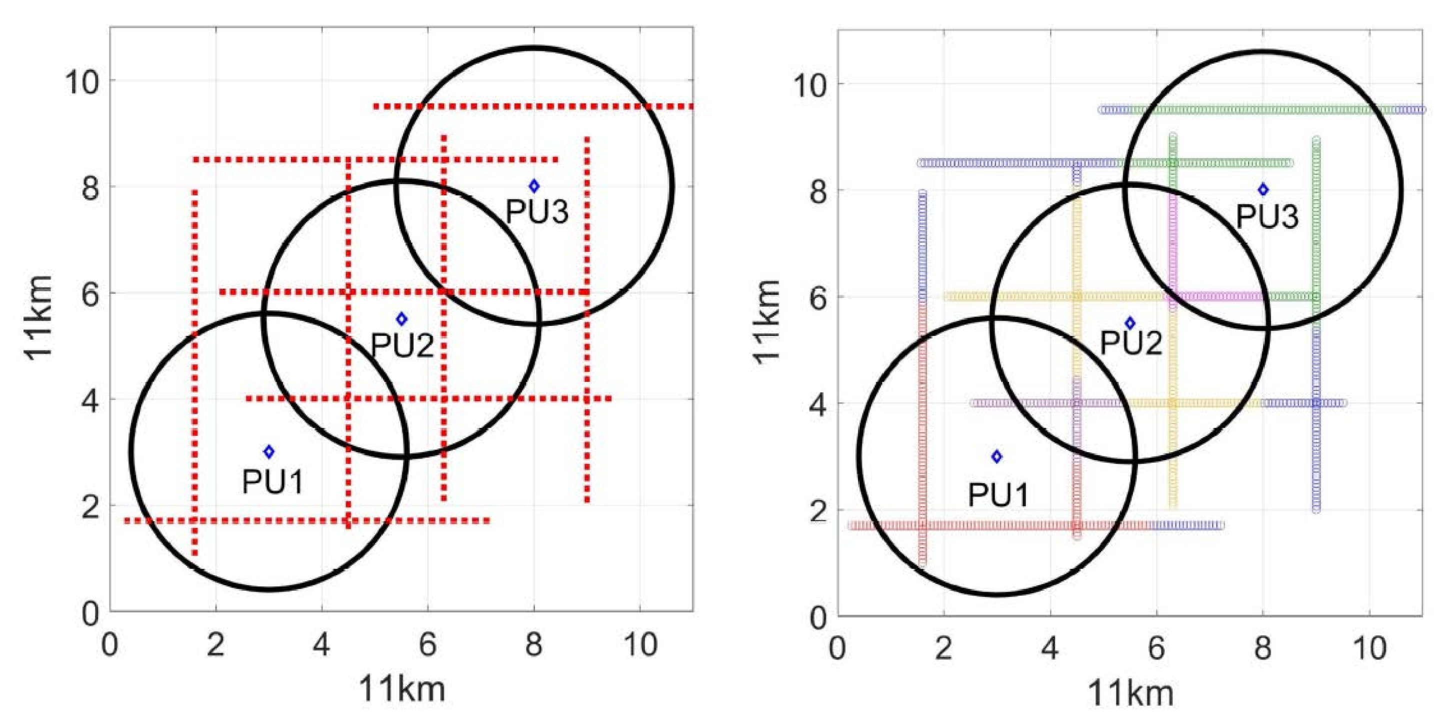
$$z_i^m | z_{i-1}^m, \boldsymbol{\pi}^m \sim Mult(\boldsymbol{\pi}_{z_{i-1}}^m),$$

$$\boldsymbol{x}^m[i] | z_i^m, \Sigma \sim \mathcal{N}(0, \Sigma_{z_i^m}).$$

Bayesian Inference

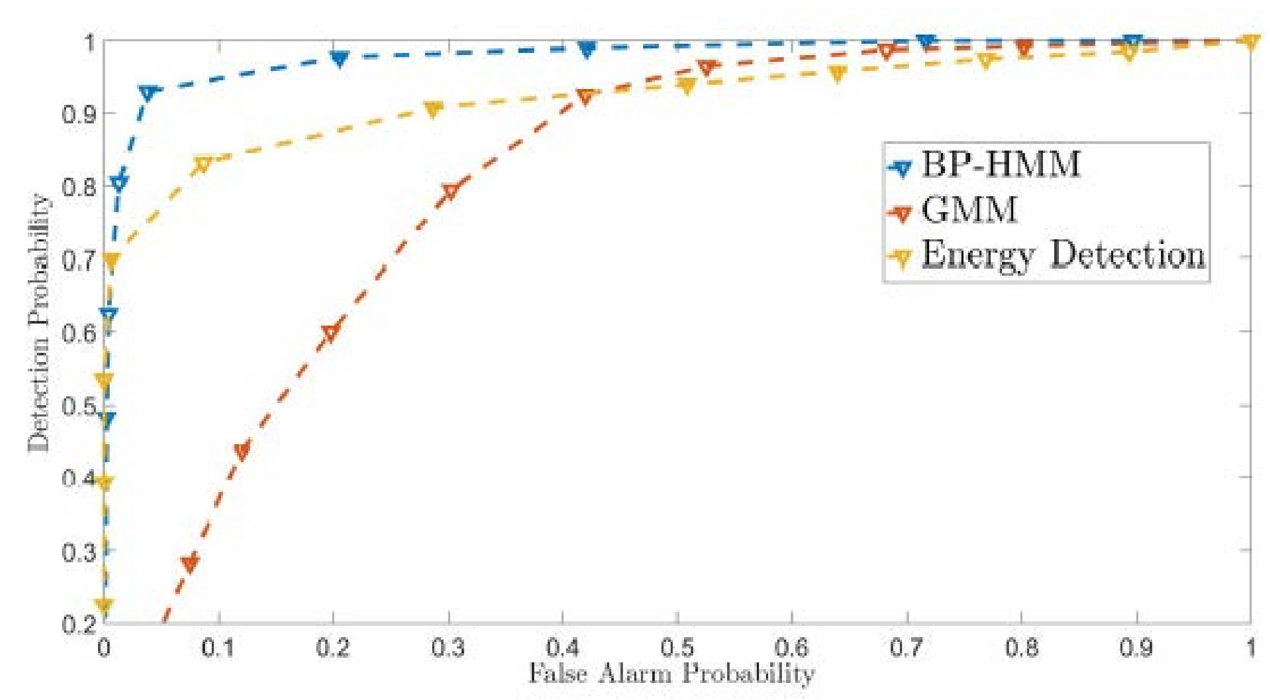
We adopt Markov chain monte Carlo (MCMC) sampling to infer the hidden state z_i^m. Specifically, Gibbs sampling and Metropolis-Hasting algorithm are considered. The core parameters in this model are $\{\mathbf{f}^m, \mathbf{z}^m, \theta\}$. After initializing these parameters, in each iteration, we update one variable with the other ones fixed.

Simulation Results



(a) CRN configuration (b) Classification Results

Classification results of a CRN configuration (N =3, M = 9)



ROC curve performance comparison with other algorithm under the same CRN setup