Spectrum Occupancy Prediction Using Machine Learning

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Workshop 9:
Spectrum Sharing for the Digital Ecosystem Towards 6G

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Acknowledgement

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TRUSTED AUTONOMOUS SYSTEMS
DEFENCE CRC

Distributed aUtonomous Spectrum managemenT

DUST

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Australian Government
Department of Defence
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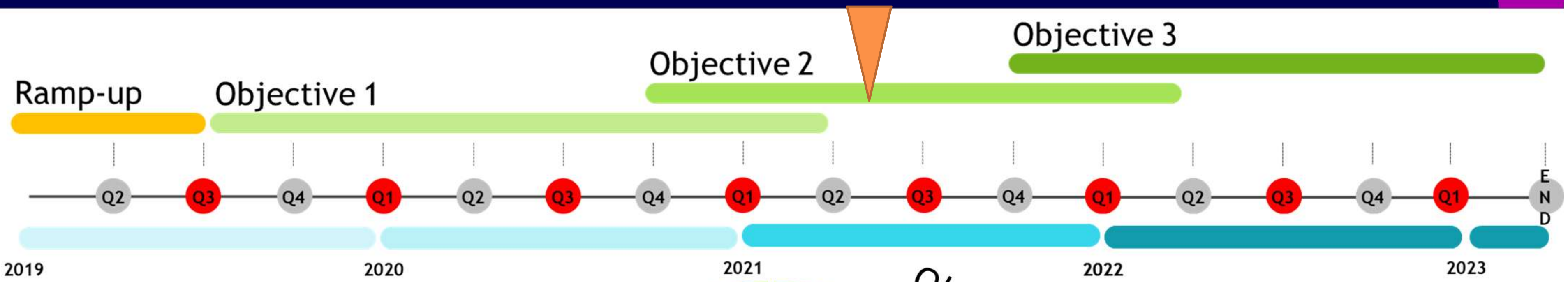
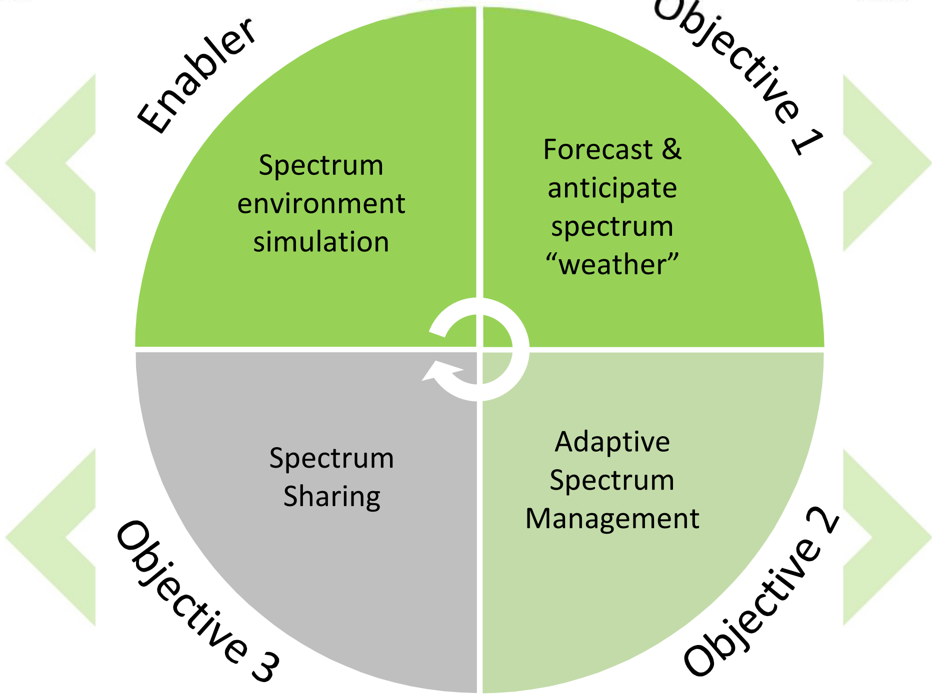


- Enabling simulation
- Outputs: high density, low fidelity spectral event data

- Machine Learning (ML)
- Order of magnitude performance improvement over published alternatives



- Trusted peer to peer spectrum assignment
- Spectrum sharing through fine grained resource trading

- Artificial Intelligence (AI)
- Near real-time
- Adaptive, distributed spectrum planning & management

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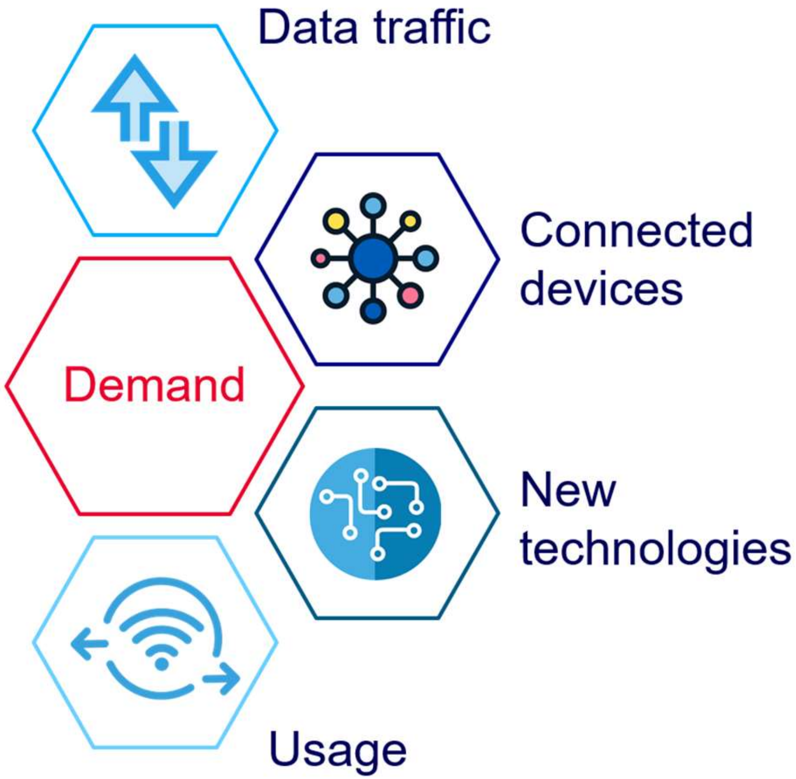
Overview

- Motivation
- Background to Prediction
- Dynamic Spectrum Sharing
    - Without and with prediction
- Spectrum occupancy prediction
    - Bayesian prediction
    - LSTM based prediction
    - Rapid learning
    - Prediction performance
- Concluding remarks

Motivation

Radio Spectrum

Motivation



Inadequate spectrum management policies

Spectrum scarcity, wastage

Opportunistic usage through Dynamic Spectrum Access (DSA) and Cognitive Radios

Performs cognitive functions for opportunistic access

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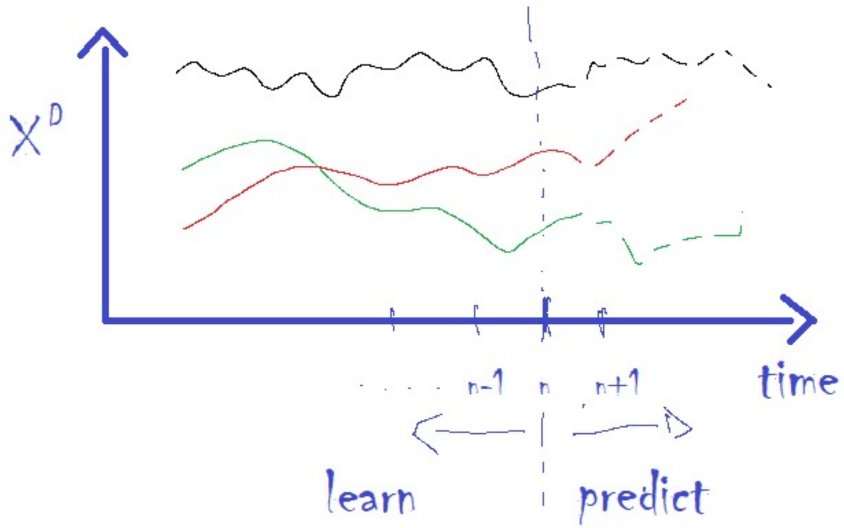
Prediction or Predictive Analysis



- **Learn**, from what we know from the past
  - Training over a dimension of D of some process $X^D(n-1, n-2, ..)$**,** where n denotes the current time step
  - Set/tune yourself to generate a likely value for the same process for the future $\hat{X}^D(n, n+1..)$
- **Prediction**, and forecasting the future
  - Generate $\hat{X}^D(n, n+1..)$

Prediction: Some key aspects

- **Performance,** of prediction (the predictor) is mostly measured in terms of
  - Prediction error, can be defined as the expected value of an error function $\phi(.)$ for the difference between the predicted value and the actual value,

$$\mathcal{E}_D = \mathrm{E}\left[\phi(X^D - \hat{X}^D)\right]$$

- **Capability,** of a predictor is defined with respect to;
  - The prediction error $\mathcal{E}_D$
  - Complexity (computational) and the time to learn/train and predict
- **Data correlation,** is crucial to successfully predict
  - Higher the correlation better the prediction outcome, that is lower $\mathcal{E}_D$
  - Independent events (i.e. no correlation) cannot be predicted

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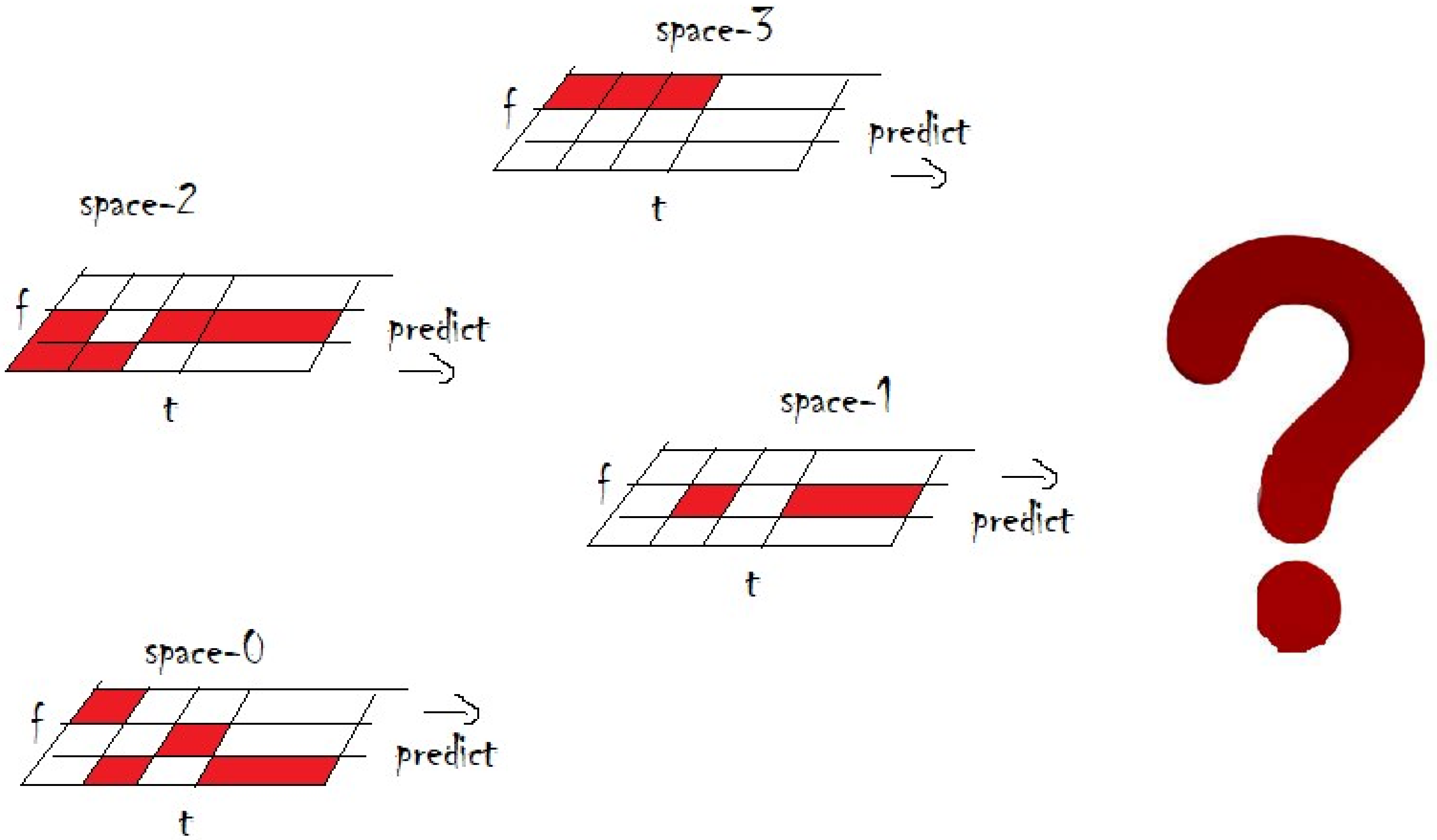
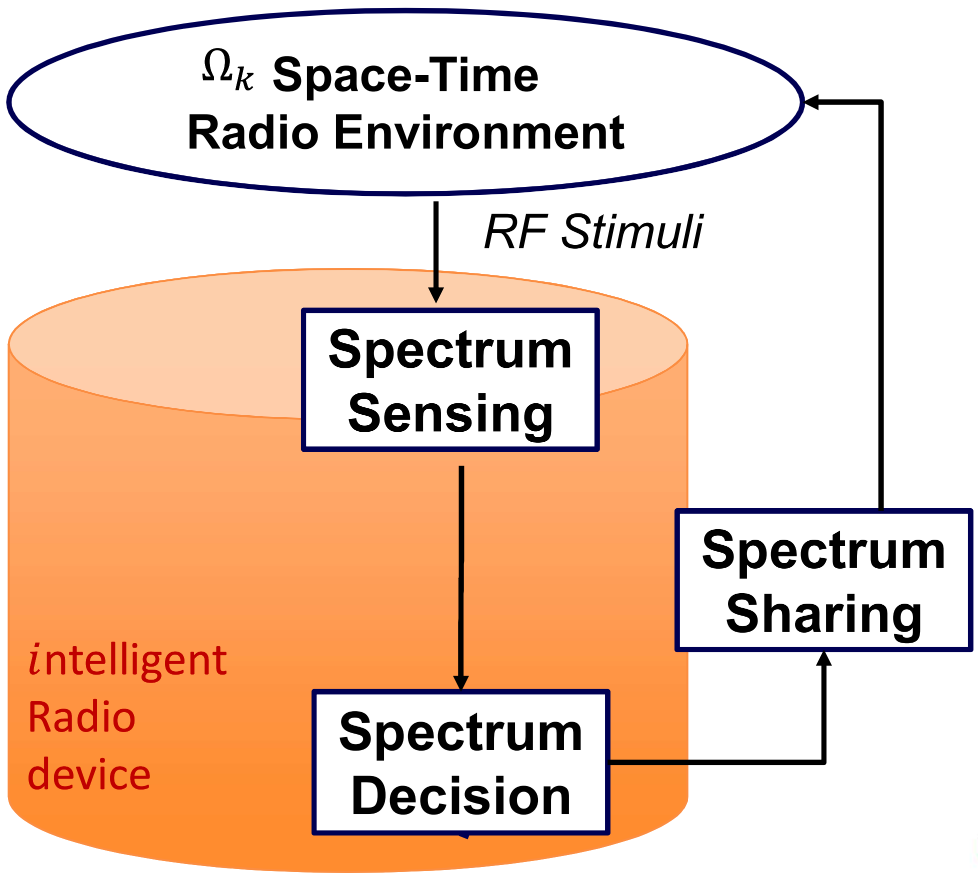
Spectrum Prediction over Space-Time



Dynamic Spectrum Sharing

Without prediction

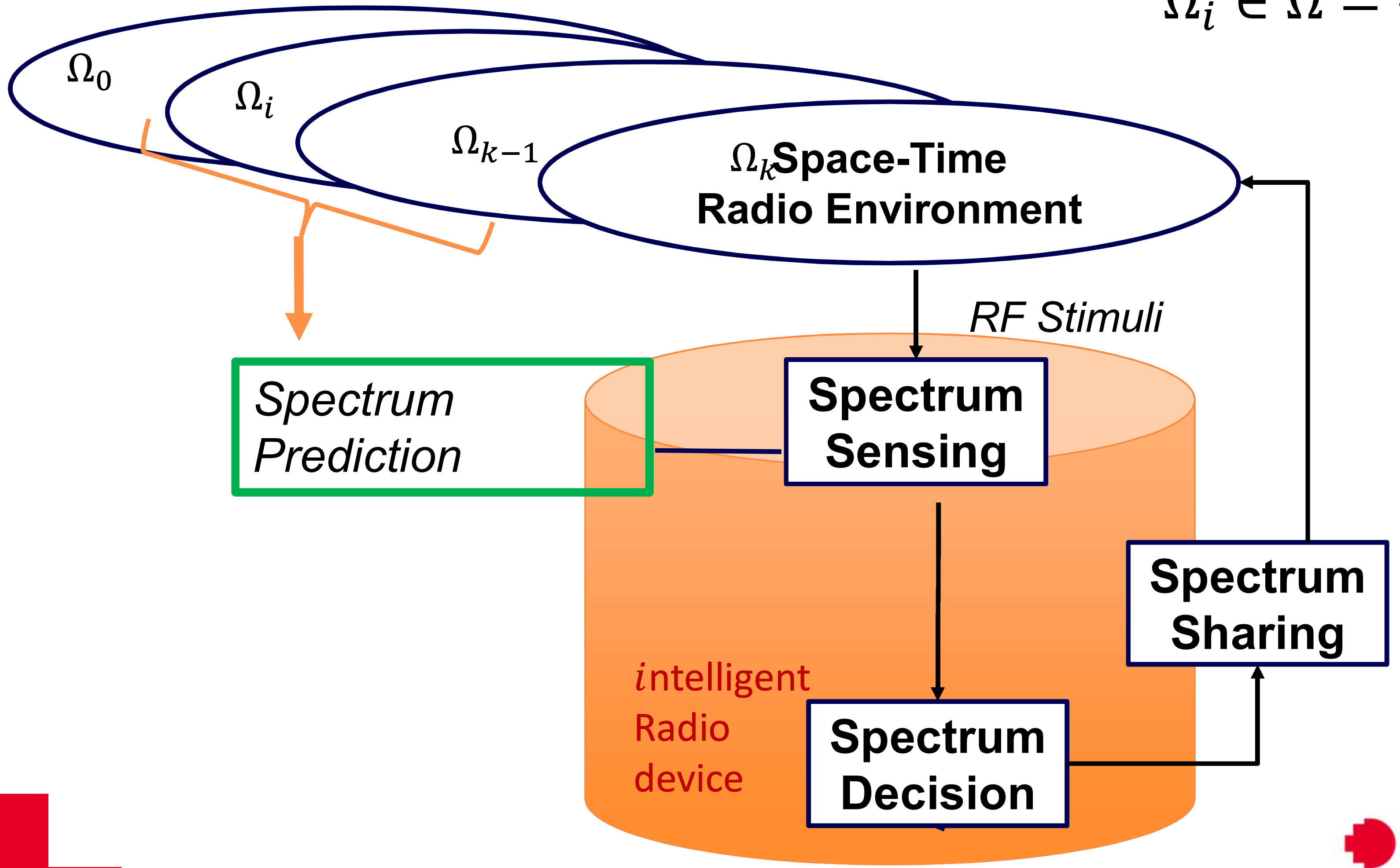
$$\Omega_i \in \Omega = \{t, s, f\}$$



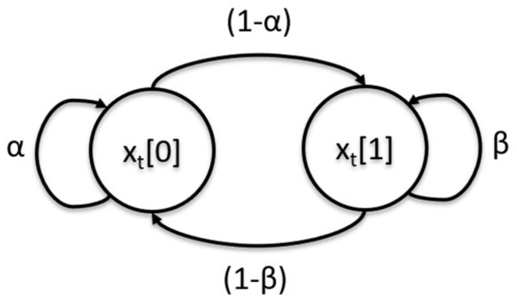
Dynamic Spectrum Sharing

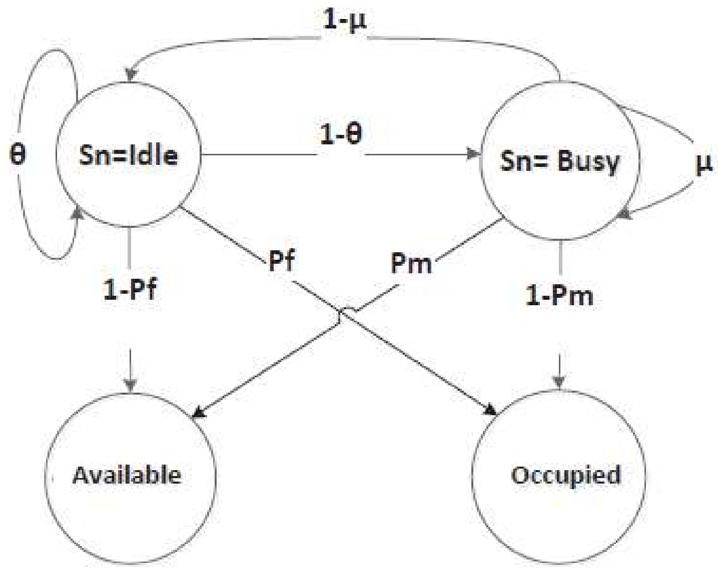
With prediction

$$\Omega_i \in \Omega = \{t, s, f\}$$



Spectrum Prediction Techniques





- **Occupancy Model;**
  - 2-State Markov
  - 4-State HMM
- **Prediction Methods (presented here)**
  - Bayesian prediction
  - Cooperative prediction
  - LSTM prediction

Bayesian Spectrum Prediction [1]

- Use Bayesian principle to predict the next state given the observations ***O***

$$\mathbf{P}(\check{s}_{n+1}|\mathbf{O}^n) = \sum_{s_n=i} \mathbf{P}(s_{n+1}|s_n)\mathbf{P}(\check{s}_n|\mathbf{O}^n) \quad : i \in \{1,2\}$$

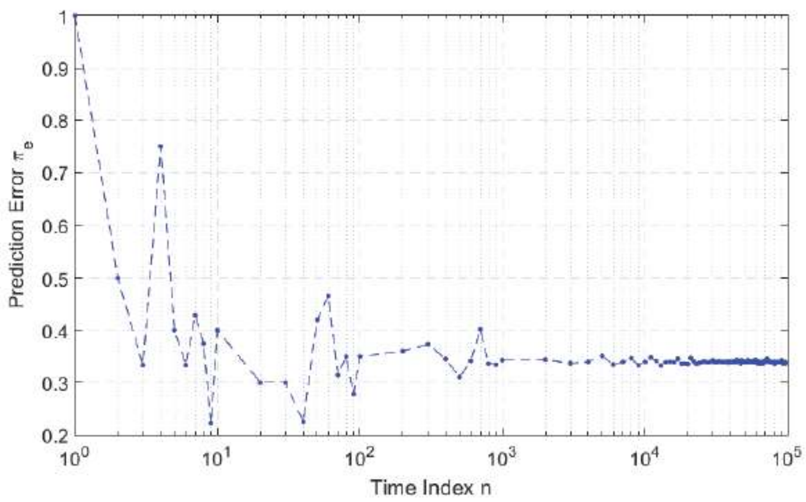


Fig. Prediction Error as a function of observation sequence length

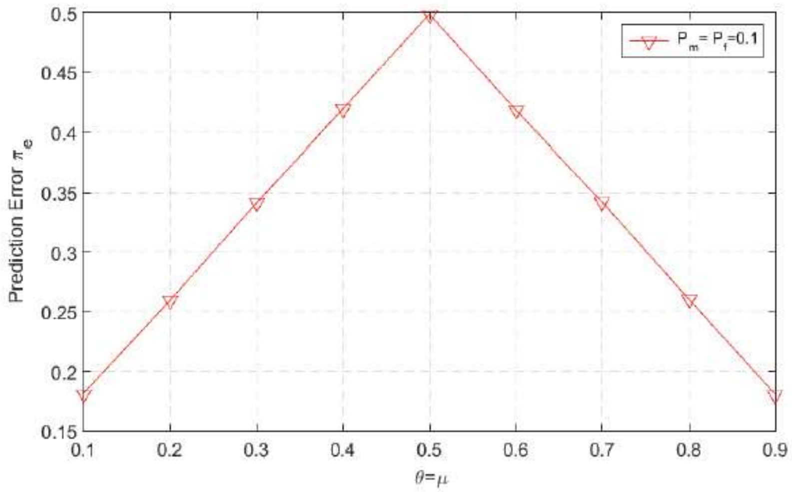


Fig. Prediction Error Vs probability to remain in specific state, Equal Stationary Distribution case

Cooperative Spectrum Prediction [2,3]

- Use multiple radios to predict the next state of the spectrum by fusing individual predictions

$$U_n^T = \bigwedge\{d_n^1, d_n^2, ...d_n^N\}$$

Fusion function can be hard or soft

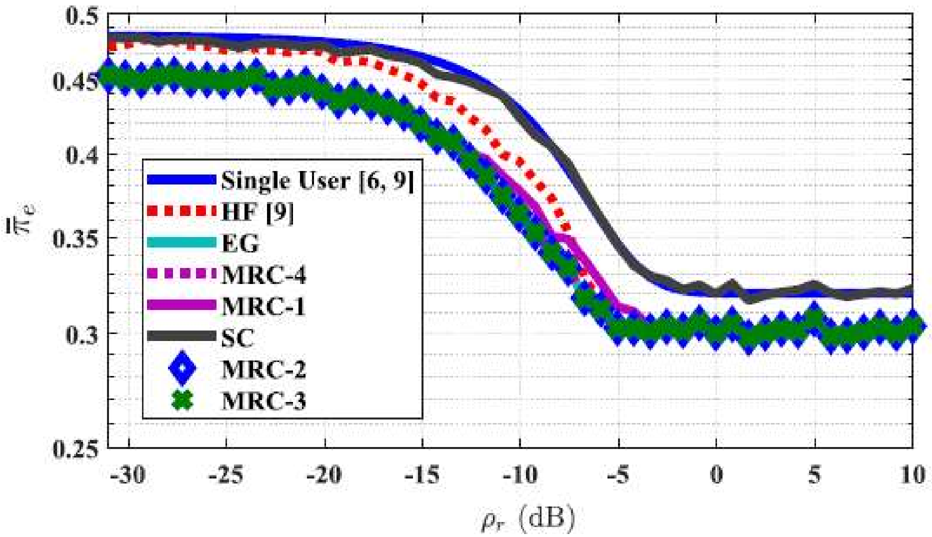
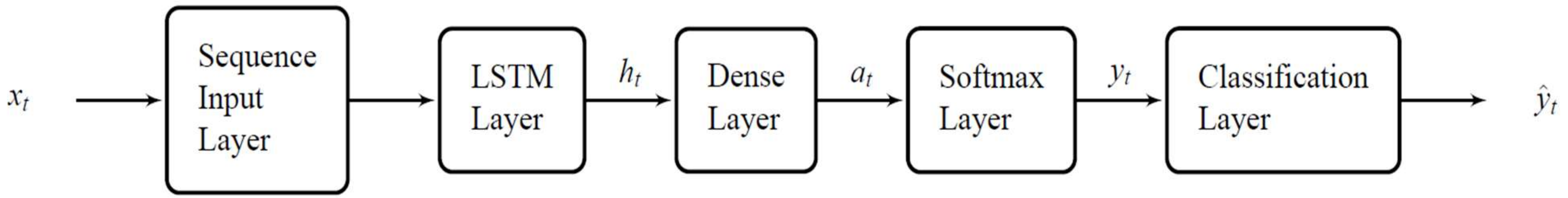


Fig. Comparing the soft fusion mean prediction error for 15 SUs.

Spectrum Prediction with LSTM [4,5]



- Fast training with LSTM
  - Using statistically modelled training parameters
  - Uses model parameters to set the training parameters
- Prediction Error
  - Theoretically characterising the error performance

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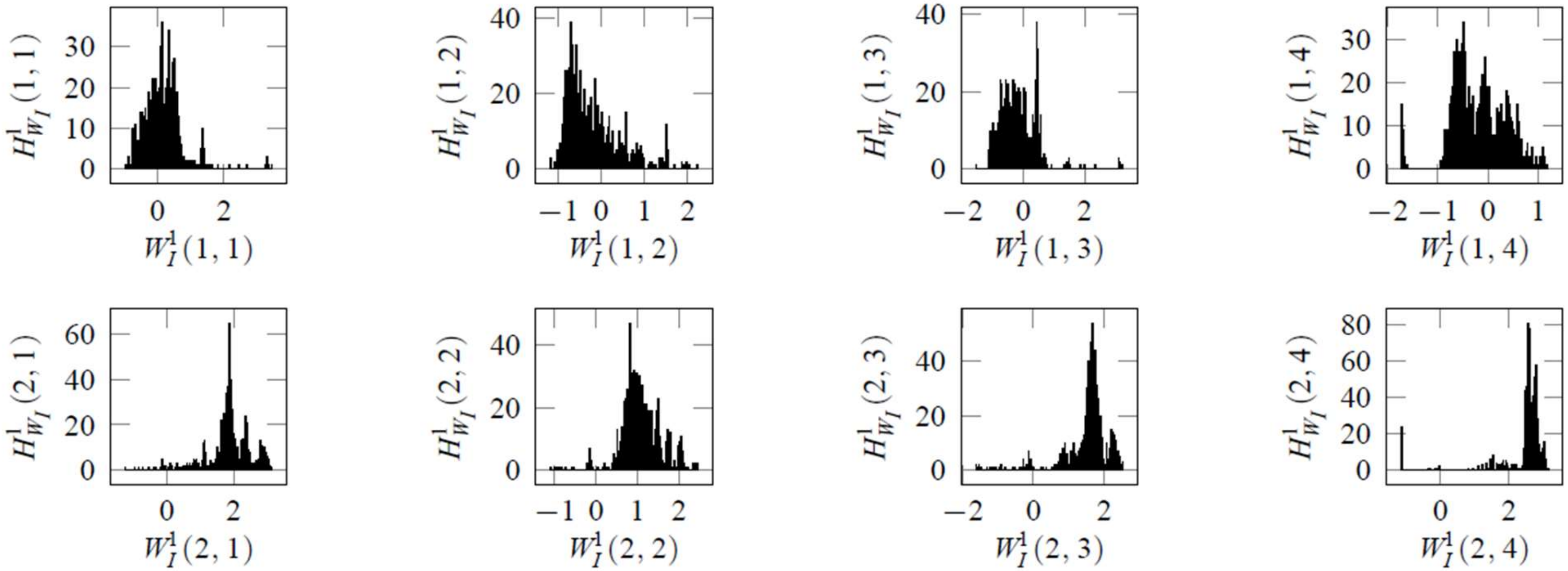
LSTM Learning: Statistical modelling [4]

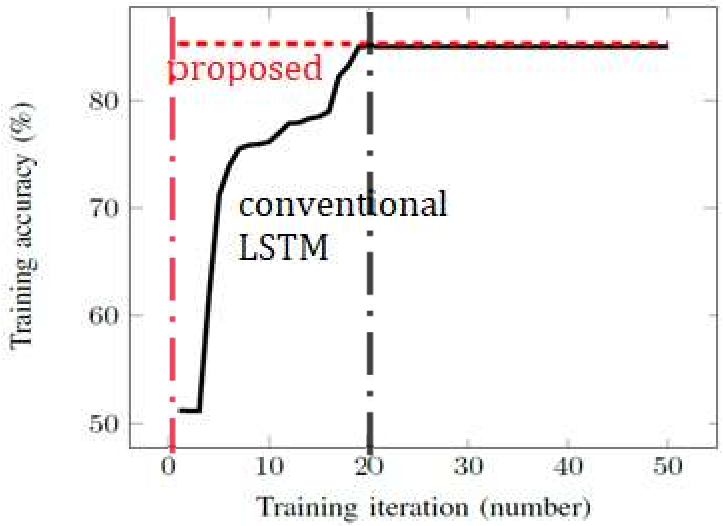


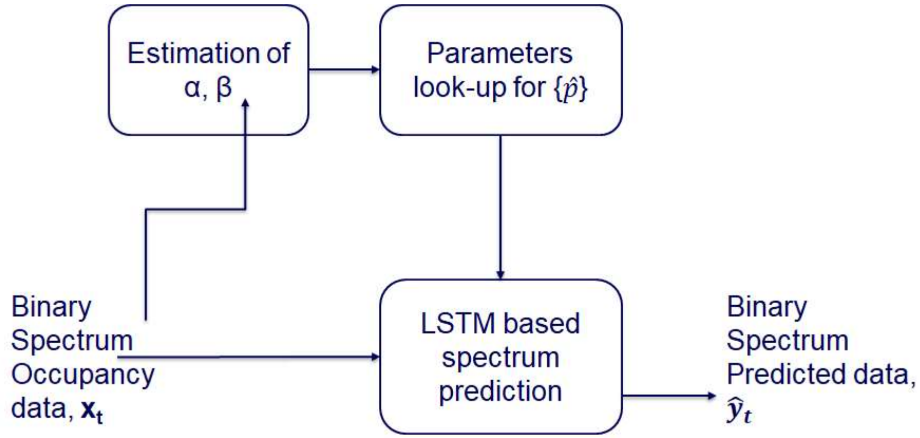
Histograms of input weight matrix of LSTM layer

- Proposed initialization strategy
  - Modes of the distribution are chosen as alternate initial values.

LSTM: Fast Learning [4]

The LSTM based method uses look-up table to match the tuning parameters to the input process (Markov input process in this example)





LSTM Prediction Performance [5]

- The pdfs of predicted scores are modelled as a mixture of truncated Gaussian distributions ($\lambda_T(.)$),

$$f_Y(y_t(i)|S_t) = \sum_{m=1}^{M} \theta_{im}\lambda_T(y_t(i); \upsilon_{im}, \delta_{im}, a, b)$$

- S_t – actual occupancy at time step t
  $y_t(i)$ – predicted score for class i at time step t
  θ – component proportions
  υ – means of the parent Gaussian components
  δ – standard deviation of the parent Gaussian components
  $[a, b]$ – truncation interval $[0,1]$

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LSTM Prediction Performance [5]

- We then derive the error probability of LSTM based prediction using the distributions of the scores
- The simulations and theory match very well

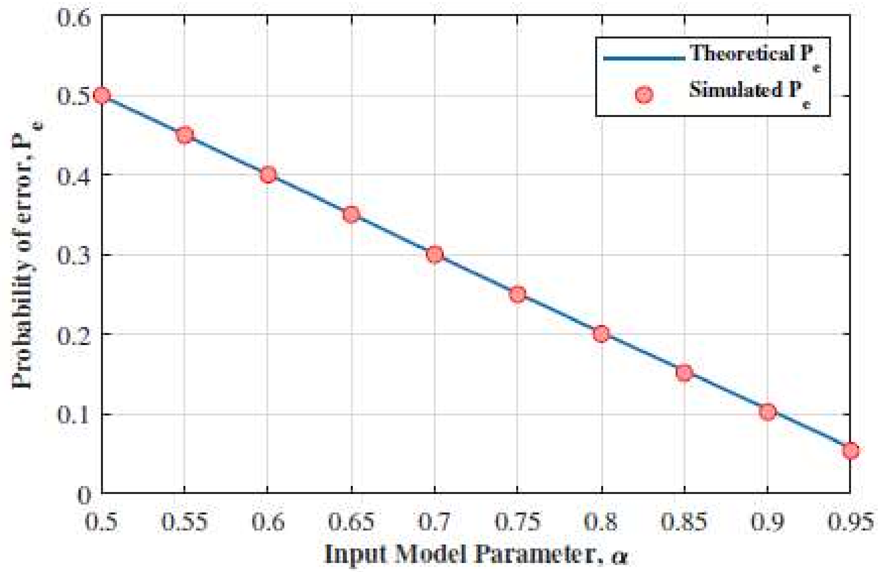

Fig. Probability of error for simulated data

Key References

1. H. Eltom, S. Kandeepan, B. Moran, and R. J. Evans, “Spectrum occupancy prediction using a hidden markov model,” in 2015 9th International Conference on Signal Processing and Communication Systems (ICSPCS), pp. 1–8, Dec 2015.
2. H. Eltom, S. Kandeepan, Ying Chang Liang, B. Moran, and R. J. Evans, “Hmm based cooperative spectrum occupancy prediction using hard fusion,” in 2016 IEEE International Conference on Communications Workshops (ICC), pp. 669–675, May 2016.
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4. N . Radhakrishnan, S. Kandeepan, An Improved Initialization Method for Fast Learning in Long Short-Term Memory based Markovian Spectrum Prediction, IEEE Transactions on Cognitive Communications and Networking, 2020
5. N. Radhakrishnan, et. al, Performance Analysis of Long Short-Term Memory-based Markovian Spectrum Prediction, **Submitted to the** IEEE Transactions on Cognitive Communications and Networking, Feb 2021

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Thank you