Spectrum Availability Prediction in Cognitive Aerospace Communications: A Deep Learning Perspective

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Outline

- ❑Introduction
- ❑System Model
- ❑Spectrum Availability Prediction
- ❑Performance Evaluation
- ❑Conclusion

Introduction

- Cognitive Radio (CR) can release the spectrum resource
- Aerospace communications are requiring larger bandwidth—CR is the promising solution
- Previous works developed complicated spectrum sensing schemes—energy and time consuming
- Machine Learning are applied to optimize the sensing policy:
  - Reinforcement Learning method
  - SVM for primary user classification

Our Method

- We proposed a deep learning approach
- Long Short-Term Memory network
- Using spatio-temporal domain information to predict more channels' availability

System Model

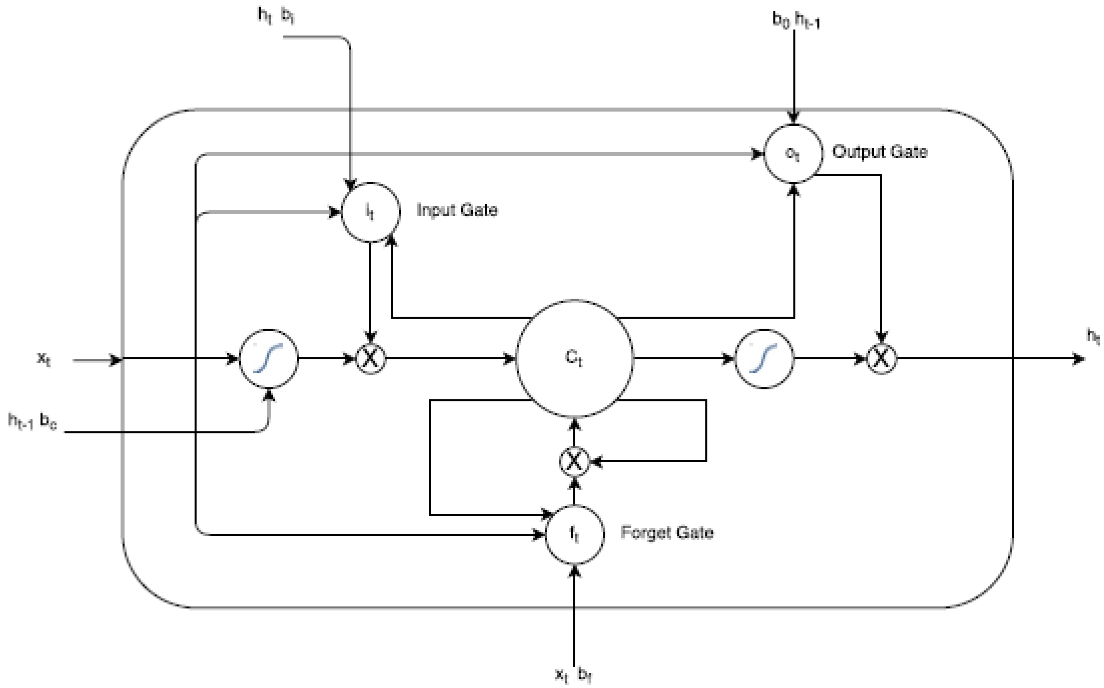
- Multi-hot vector to denote the channels' availability
  - "1" stands for the corresponding channel is occupied
  - "0" means the corresponding channel is available to use (SU)

Spectrum Availability Prediction

- Long Short-Term Memory network: A special kind of RNN
- RNN can theoretically well deal with temporally correlated data but not a good choice for long-term dependency data
- LSTM addresses this problem with special architecture

Spectrum Availability Prediction

❖LSTM Memory Cell



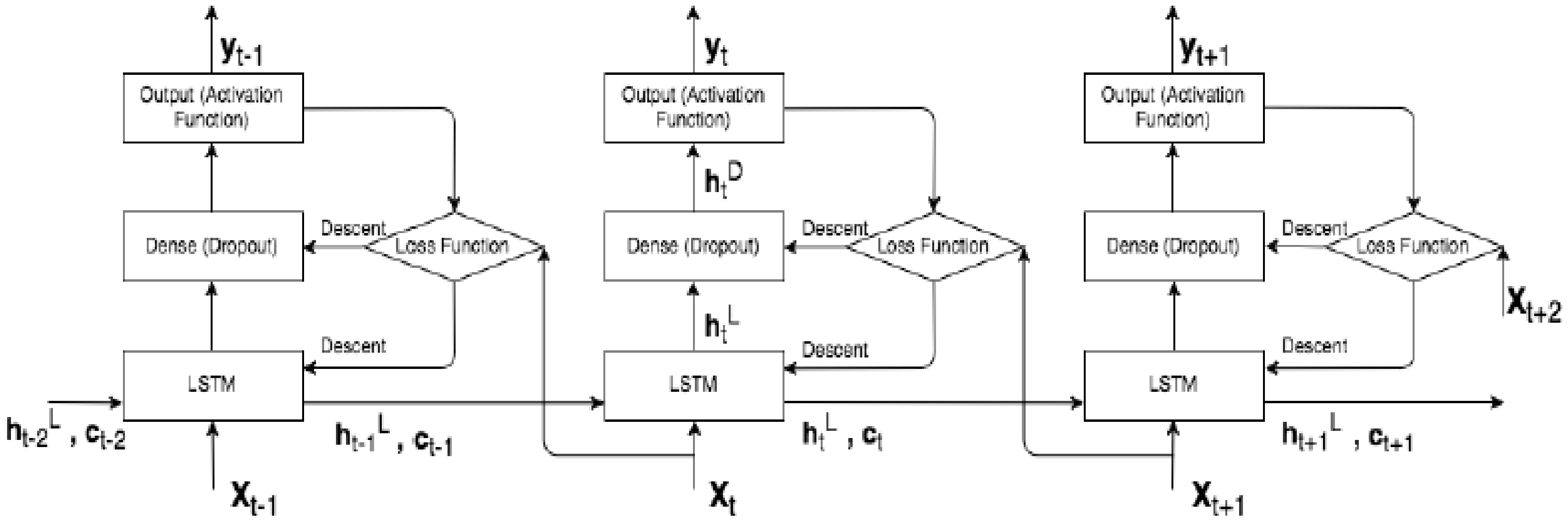
Spectrum Availability Prediction

❖LSTM Memory Cell

$$
\begin{aligned}
\mathbf{i}_t &= \sigma(\mathbf{W}_{ix}\mathbf{x}_t + \mathbf{W}_{ih}\mathbf{h}_{t-1} + \mathbf{W}_{ic}\mathbf{c}_{t-1} + \mathbf{b}_i) \\
\mathbf{f}_t &= \sigma(\mathbf{W}_{fx}\mathbf{x}_t + \mathbf{W}_{fh}\mathbf{h}_{t-1} + \mathbf{W}_{fc}\mathbf{c}_{t-1} + \mathbf{b}_f) \\
\mathbf{c}_t &= \mathbf{f}_t \circ \mathbf{c}_{t-1} + \mathbf{i}_t \circ \phi(\mathbf{W}_{cx}\mathbf{x}_t + \mathbf{W}_{ch}\mathbf{h}_{t-1} + \mathbf{b}_c) \\
\mathbf{o}_t &= \sigma(\mathbf{W}_{ox}\mathbf{x}_t + \mathbf{W}_{oh}\mathbf{h}_{t-1} + \mathbf{W}_{oc}\mathbf{c}_t + \mathbf{b}_o) \\
\mathbf{h}_t &= \mathbf{o}_t \circ \phi(\mathbf{c}_t)
\end{aligned}
$$

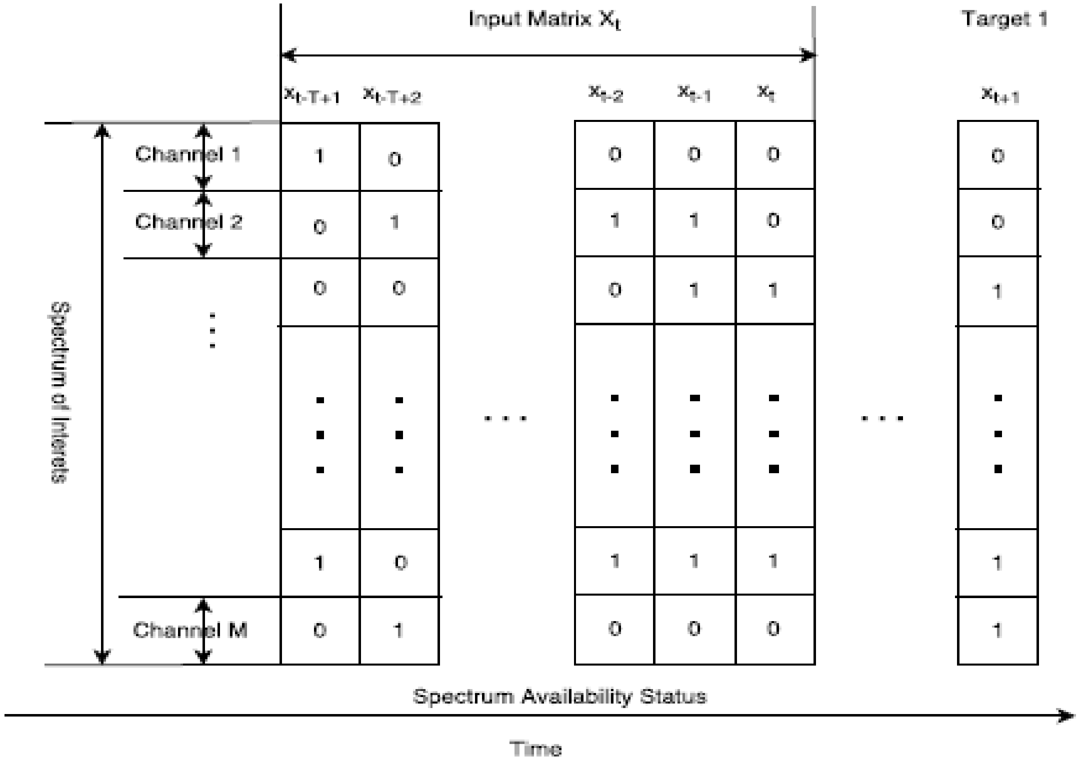
Spectrum Availability Prediction

❖Network Layers



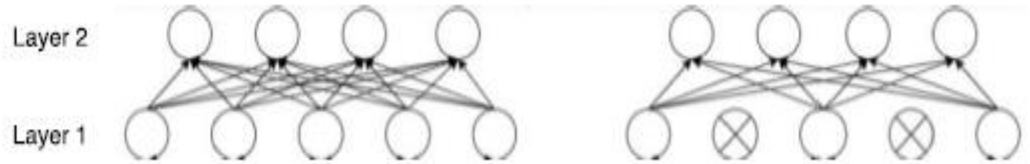
Spectrum Availability Prediction

- Input Matrix



Spectrum Availability Prediction

❖ Dense Layer with Dropout



Spectrum Availability Prediction

❖ Output Layer Activation Function: Softmax

$$\mathrm{y_t^m} = \frac{e^{\mathbf{z^m}}}{\sum_{i=1}^{M} e^{\mathbf{z^i}}}, \text{for } m = 1, \ldots, M$$

Spectrum Availability Prediction

- Loss Function: Cross-entropy

$$\xi(\mathrm{x_{t+1}}, \mathrm{y_t}) = -\sum_{i=1}^{M} \mathrm{x^i_{t+1}} \log \mathrm{y^i_t}$$

Performance Evaluation

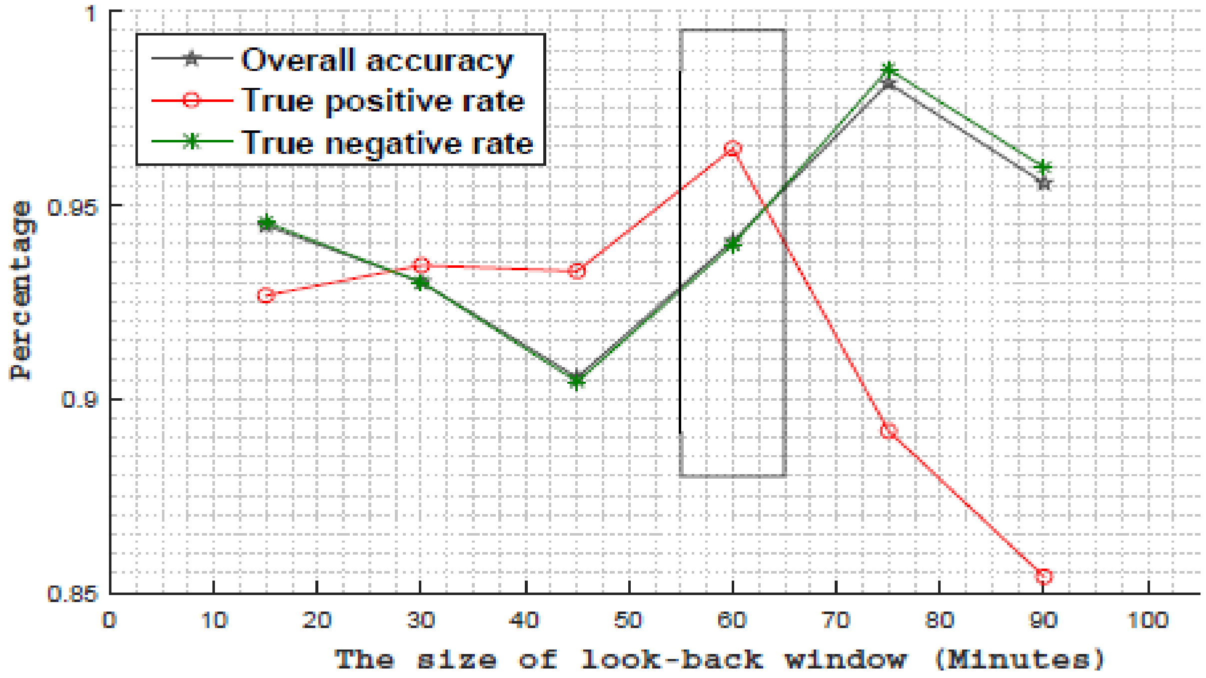
- ❖ Simulation Data: 3MHz to 5.4MHz
- ❖ 26 Channels
- ❖ Busy or Idle: -100dbm
- ❖ NYC and Vienna (Share Spectrum Company)

Performance Evaluation

- Network Setting
- 128 nodes in LSTM layer
- Three layers in dense network: 512, 256, 128 nodes
- Output: 26 nodes

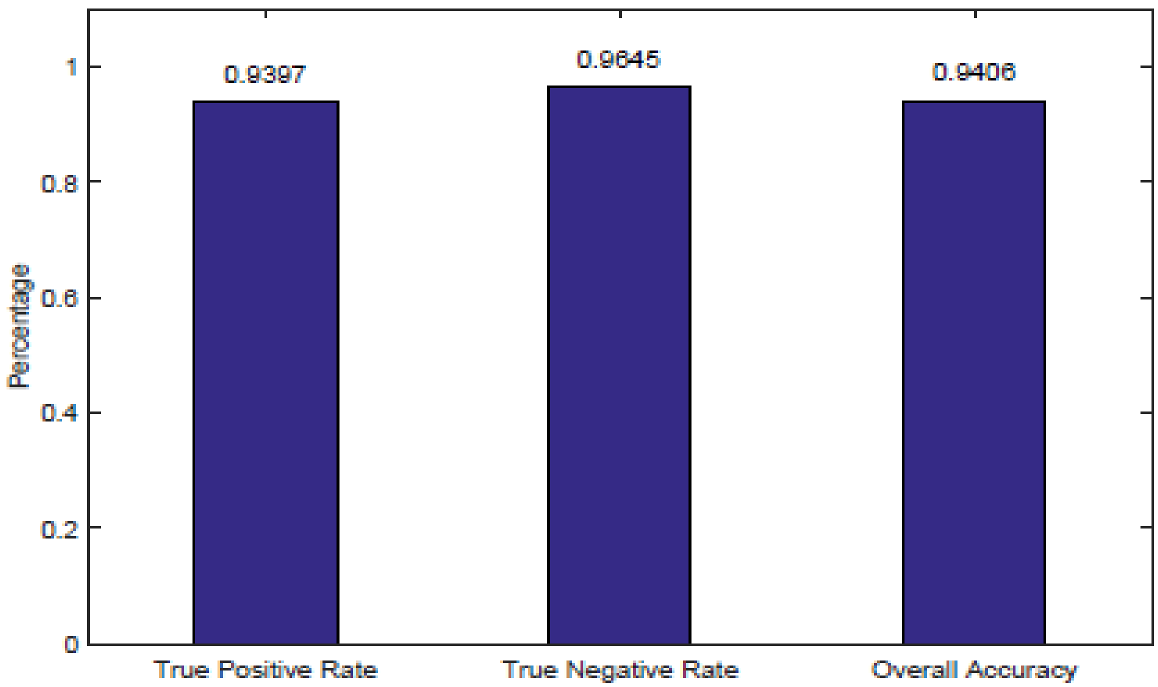
Performance Evaluation

- ❖ Look back window setting: 15, 30, 45, 60, 75, 90 (Min)



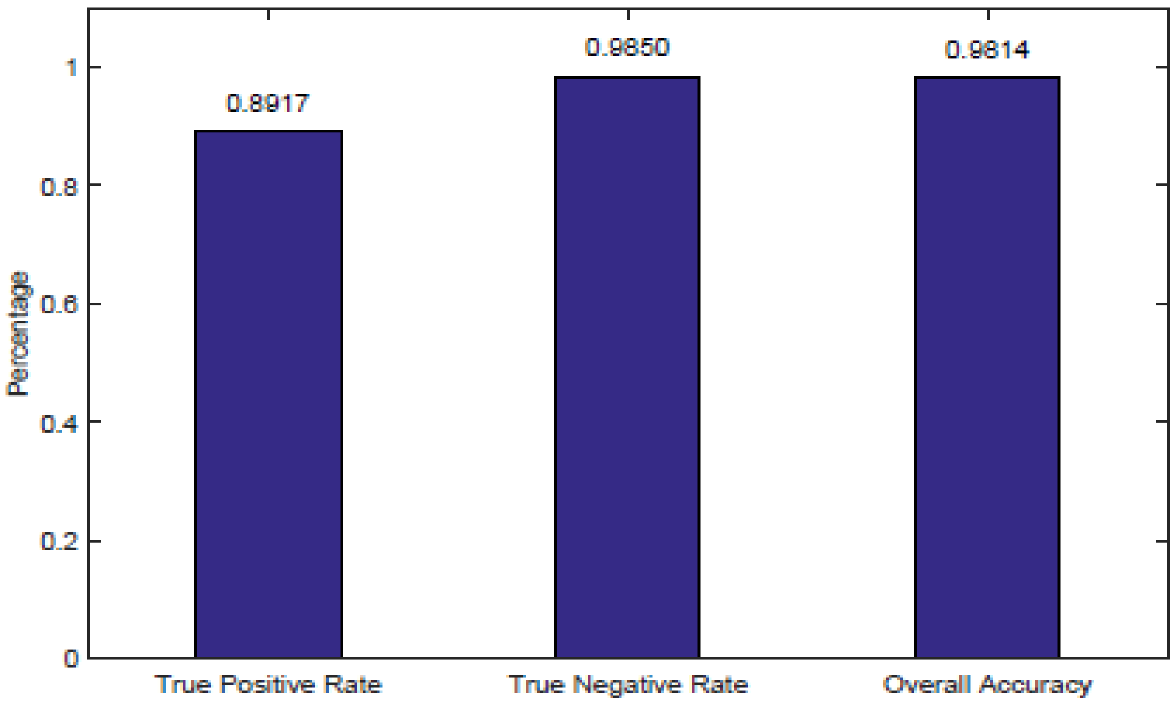
Performance Evaluation

❖Look back window setting: 60 minutes



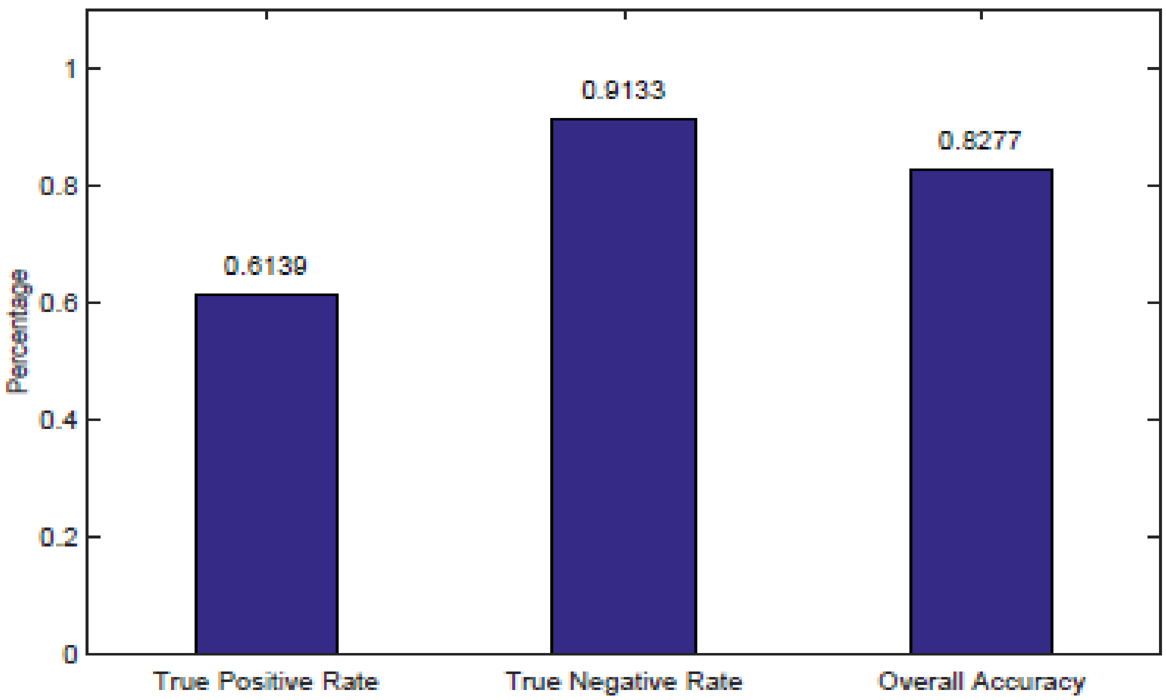
Performance Evaluation

❖ Look back window setting: 75 minutes



Performance Evaluation

- Three-layer ANN prediction model with 512, 256,128 nodes



Conclusion

- We employed the LSTM network for a better prediction method
- We utilized the spatio-temporal correlation of the channels by taking advantage of the LSTM network for a more efficient prediction (more than one channel)
- We got a higher accuracy in prediction simulation

Thank You!