RL-NCS: Reinforcement Learning Based Data-driven Approach for Adaptive Non-Uniform Compressed Sensing

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1. Objective

- **Goal:** Achieving adaptive non-uniform compressed sensing (NCS) for time-varying signals by designing optimal sensing pattern at each time step.
- **Approach:** Reinforcement Learning (RL) and LSTM.
- **Main characteristics of RL-NCS**
  - ✓ Learns the dynamic nature of a compressed sensing system.
  - ✓ Adaptively designs the measurement matrix such that the coefficients in the region of interest (ROI) are recovered with higher accuracy
  - ✓ Has the flexibility to choose from different sensing mechanisms where each mechanism designs the measurement matrix in a specific way

2. Non-Uniform Compressed Sensing

Compressed sensing: To under sample and retrieve a sparse signal x.

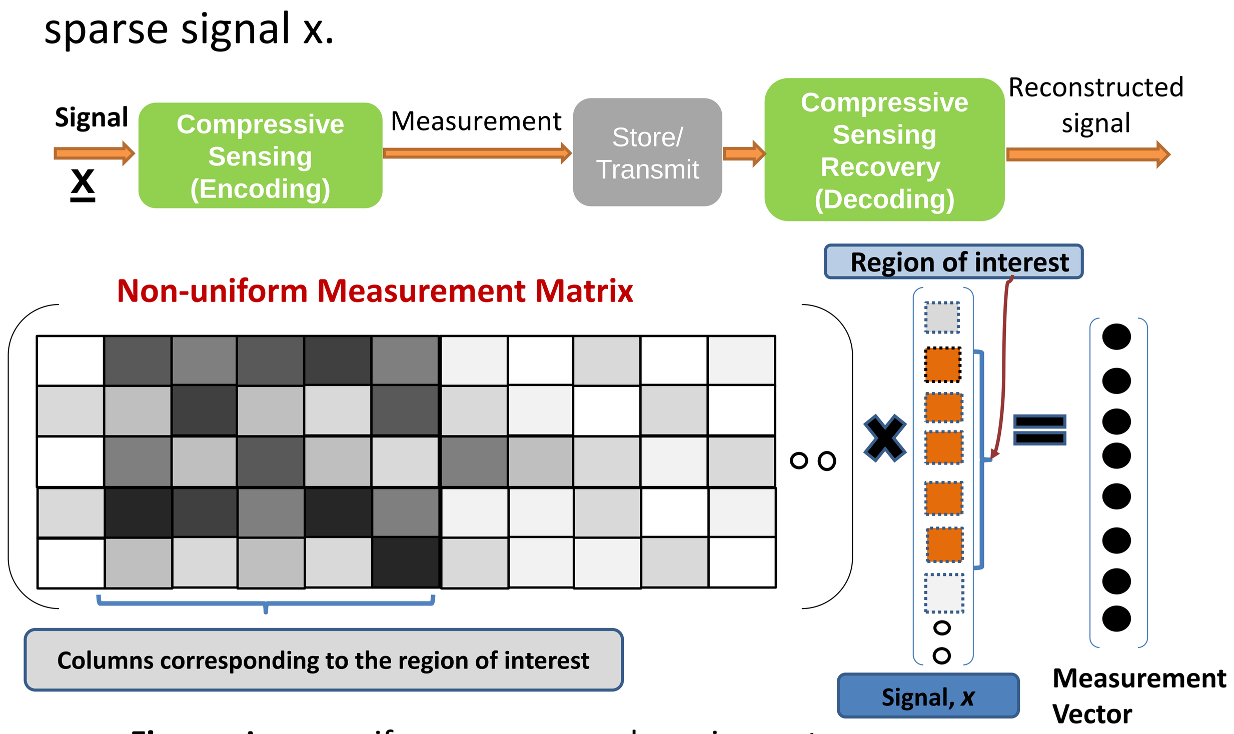


Figure: A non-uniform compressed sensing system.

3. Adaptive NCS

A system where region of interest (ROI) changes over time.

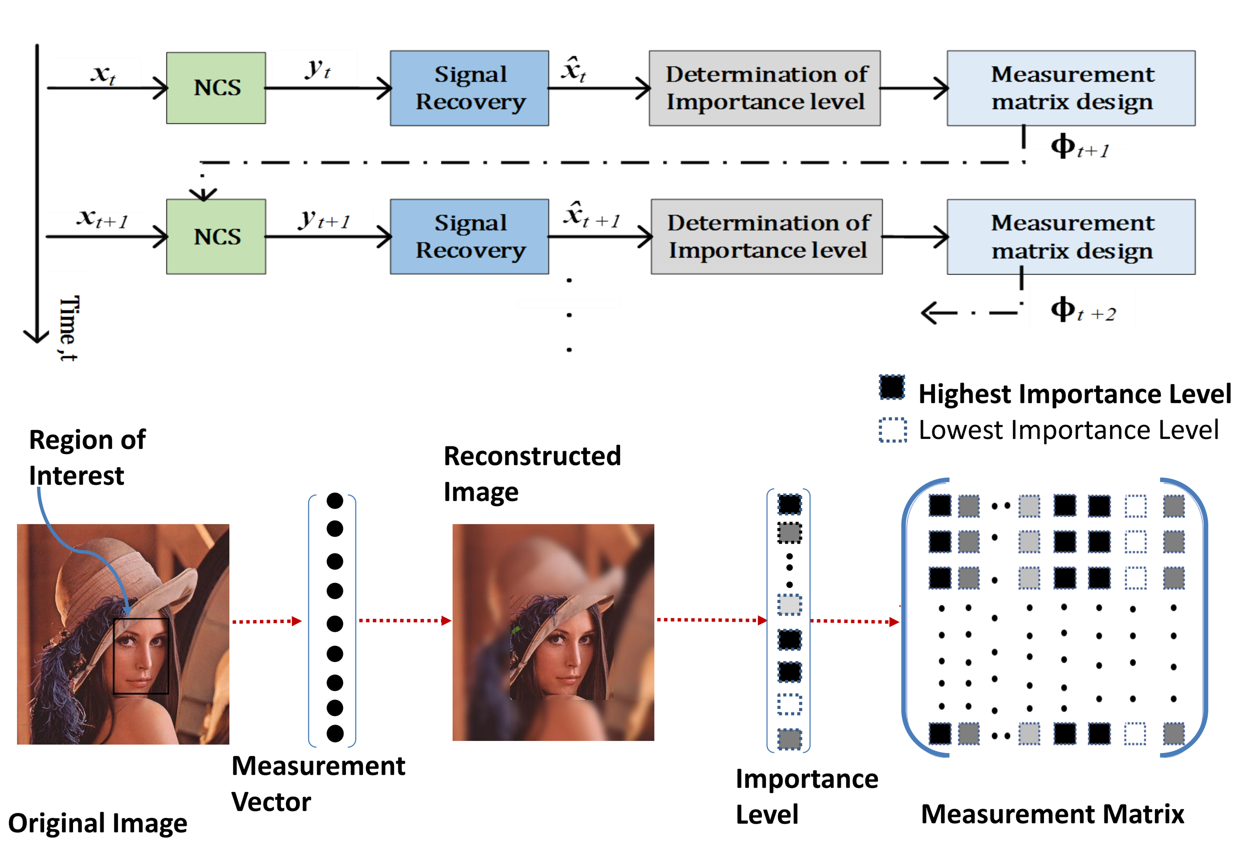


Figure: Adaptive time varying Non-uniform Compressed Sensing System

- Importance level of each signal coefficients needs to be determined.
- Adaptive design of the measurement matrix needs to be achieved.
- ROI coefficients needs to be reconstructed with less error.

4. Mechanisms for Inference

- **Long Short-Term memory (LSTM):** shows effectiveness at finding the time correlation in a sequence of signals. So, LSTM can be used for predicting the next step ROI (Importance level).
- **Direct:** For slowly changing signals, we can keep the ROI same for next step.
- **Decision Problem**: we need to take a decision which mechanism should we choose to determine the next step ROI.
- **Solution:** Reinforcement Learning.

5. Reinforcement Learning (RL)

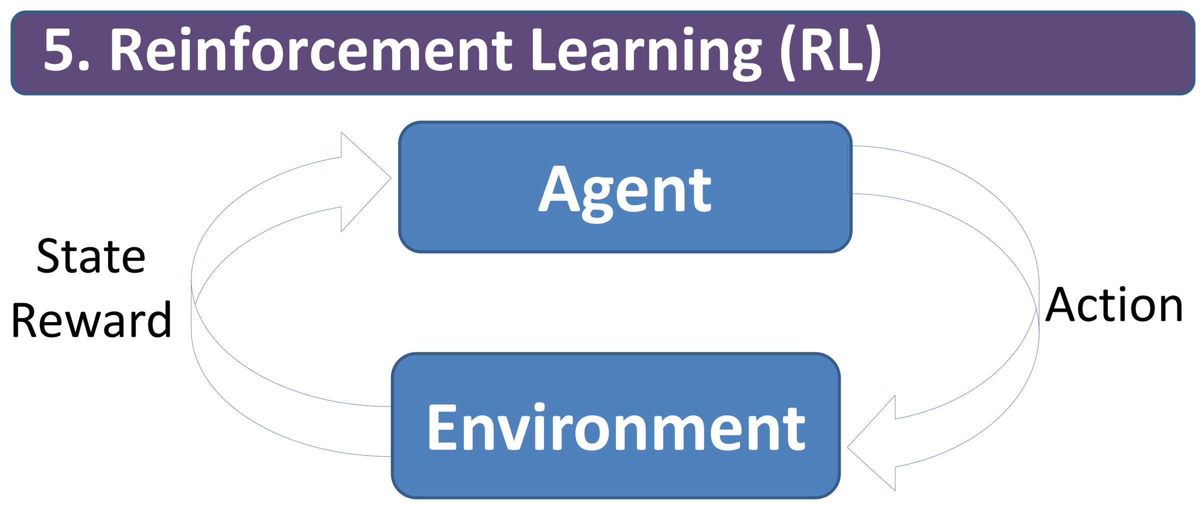
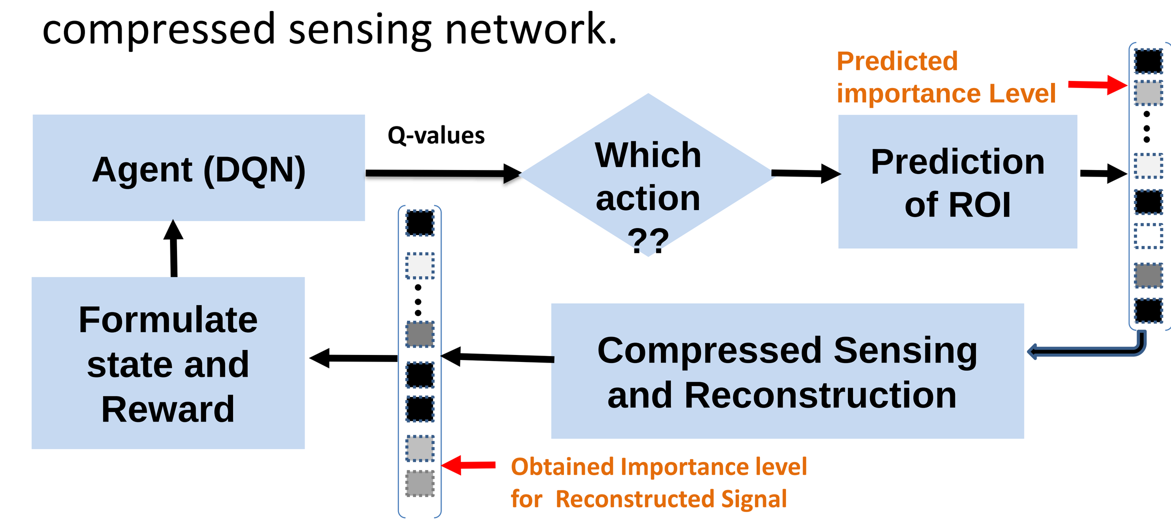


Figure: Reinforcement Learning Framework.

- A time-varying compressed sensing network (e.g. Wireless Sensor Network) is formulated as a RL environment.
- An agent will choose the suitable mechanism for inference.
- The state and reward for the agent comes from the compressed sensing network.



6. Details of RL-NCS Architecture

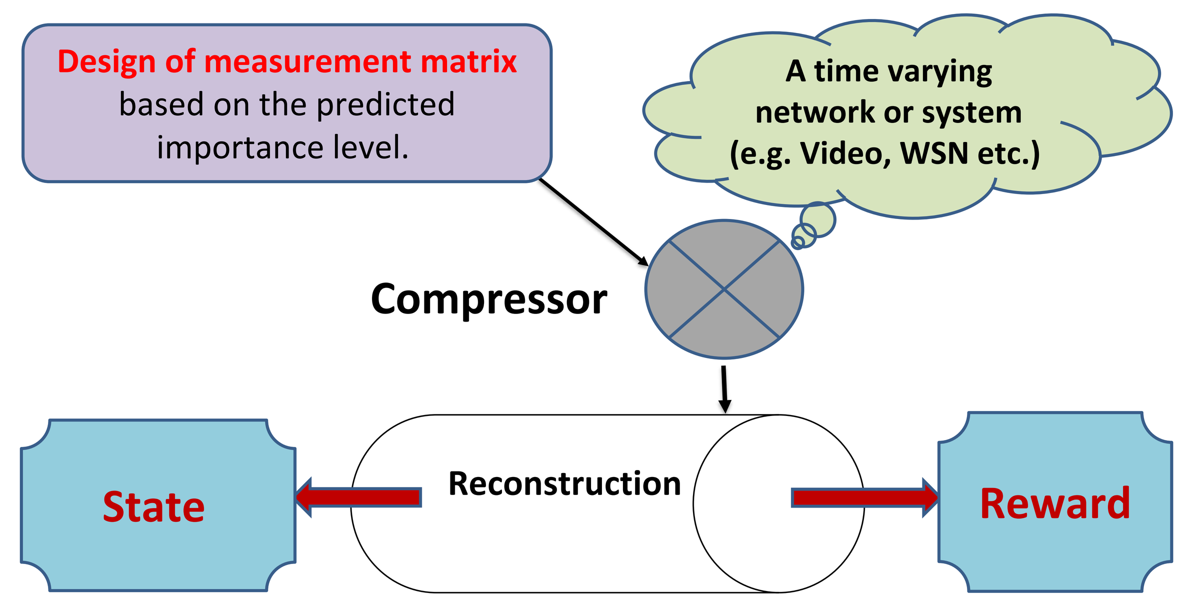


Figure: Operations that take place inside the CS environment.

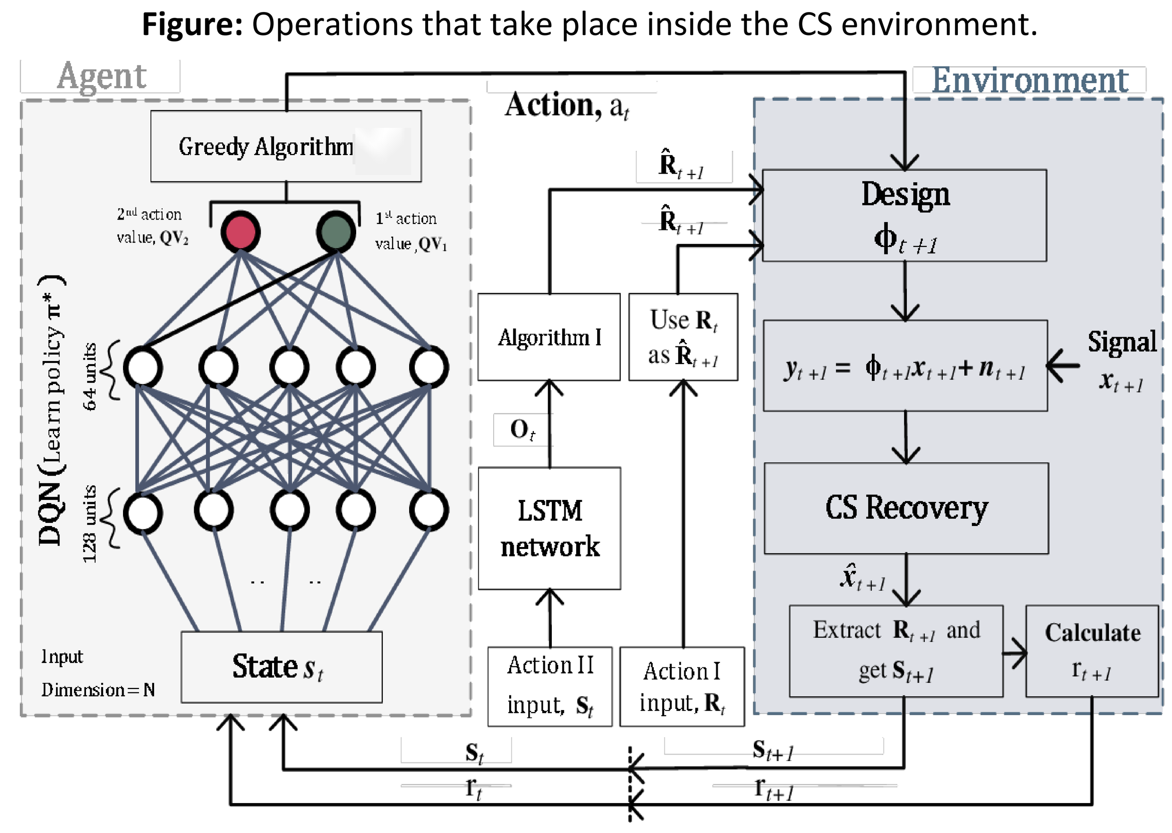
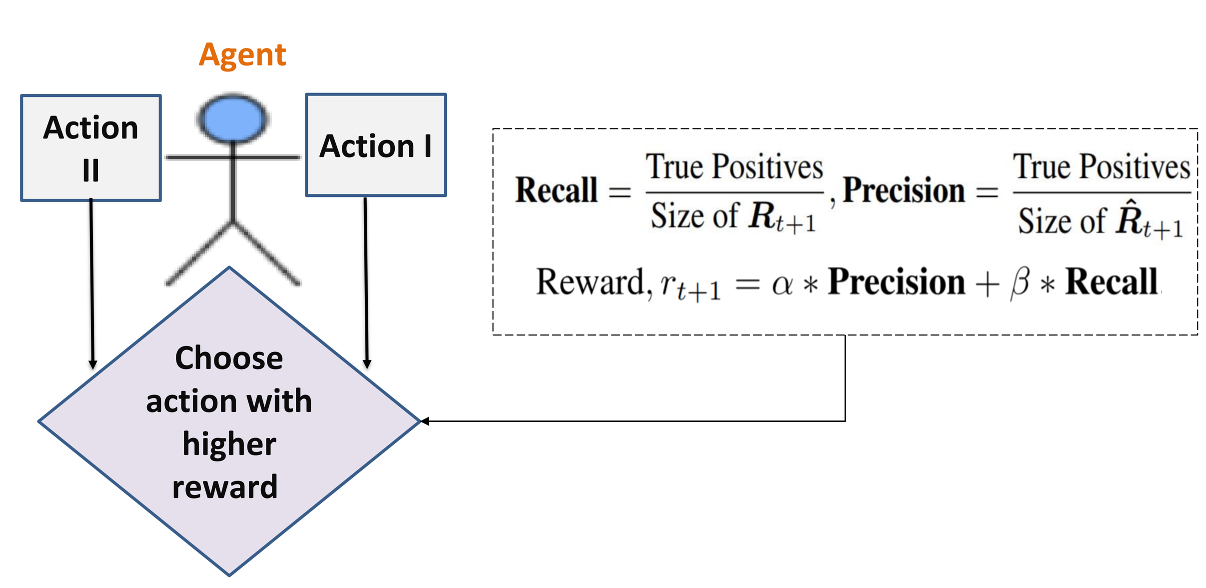


Figure: Complete RL-NCS Architecture



$$\text{Recall} = \frac{\text{True Positives}}{\text{Size of } R_{t+1}}, \text{Precision} = \frac{\text{True Positives}}{\text{Size of } \hat{R}_{t+1}}$$

$$\text{Reward}, r_{t+1} = \alpha * \textbf{Precision} + \beta * \textbf{Recall}$$

Figure: Process of choosing the right action.

Agent Objective: Determine whether the environment is changing fast or slow and act based on that.

Algorithm 1 Update Rule for ROI

- **Input:** $\hat{\boldsymbol{R}}_{t+1} = \{\}, \boldsymbol{I}_t, \boldsymbol{O}_t, Th_{up} \in [0,1]$ & $Th_{low} \in [0,1]$
- **for** steps $j \in \{1, 2, \dots N\}$ **do**
  - **if** $j \in \boldsymbol{R}_t$ & $\boldsymbol{O}_t^{(j)} \geq Th_{low}$ **do**
    - $\hat{\boldsymbol{R}}_{t+1} \leftarrow \hat{\boldsymbol{R}}_{t+1} \cup \{j\}$
  - **else if** $j \in \boldsymbol{I}_t$ & $\boldsymbol{O}_t^{(j)} \geq Th_{up}$ **do**
    - $\hat{\boldsymbol{R}}_{t+1} \leftarrow \hat{\boldsymbol{R}}_{t+1} \cup \{j\}$
  - **end if**
- **end for**
- **Output:** $\hat{\boldsymbol{R}}_{t+1}$ (predicted ROI for next time step)

7. Results and Analysis

- **Dataset:** All the samples in the dataset are being created using Markov Chain method.

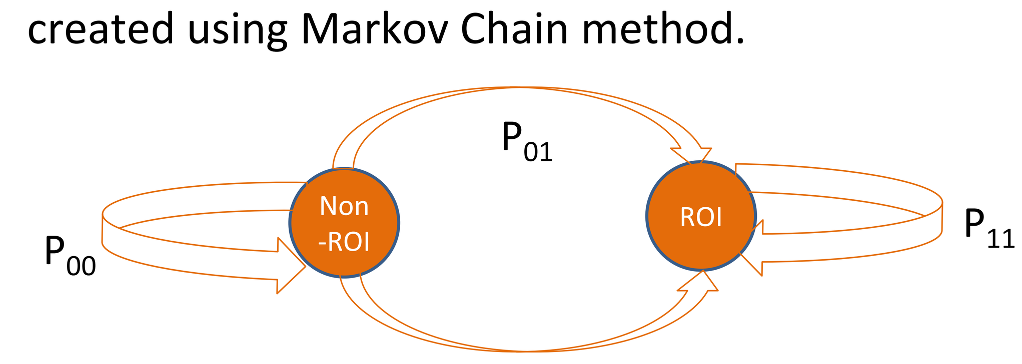


Figure: Markov Chain with defined transition probabilities.

- **Reconstruction algorithm:** *l1-minimization.*
- **Performance Metric:** Time-averaged normalized Mean Square Error (TNMSE).
- **Important Simulation Parameters:**

Upper Threshold	Lower Threshold	Reward	Episode Length	Large Signal Coefficients	Small Signal Coefficients
0.8	0.1	[0,2]	200	5	0.01

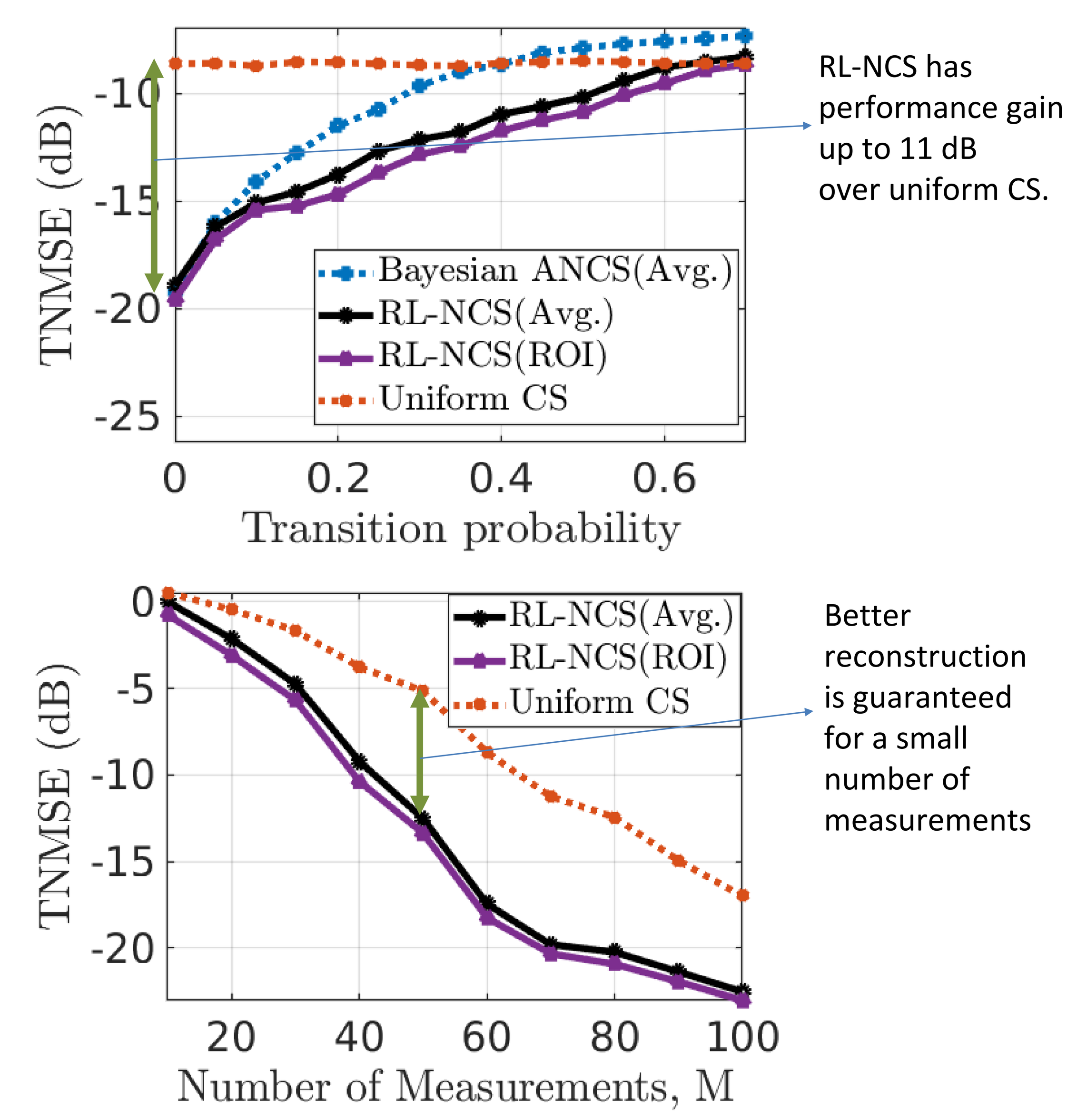


Figure: Performance evaluation (for sparse signal in the canonical basis) of RL-NCS in comparison with uniform and Bayesian method.

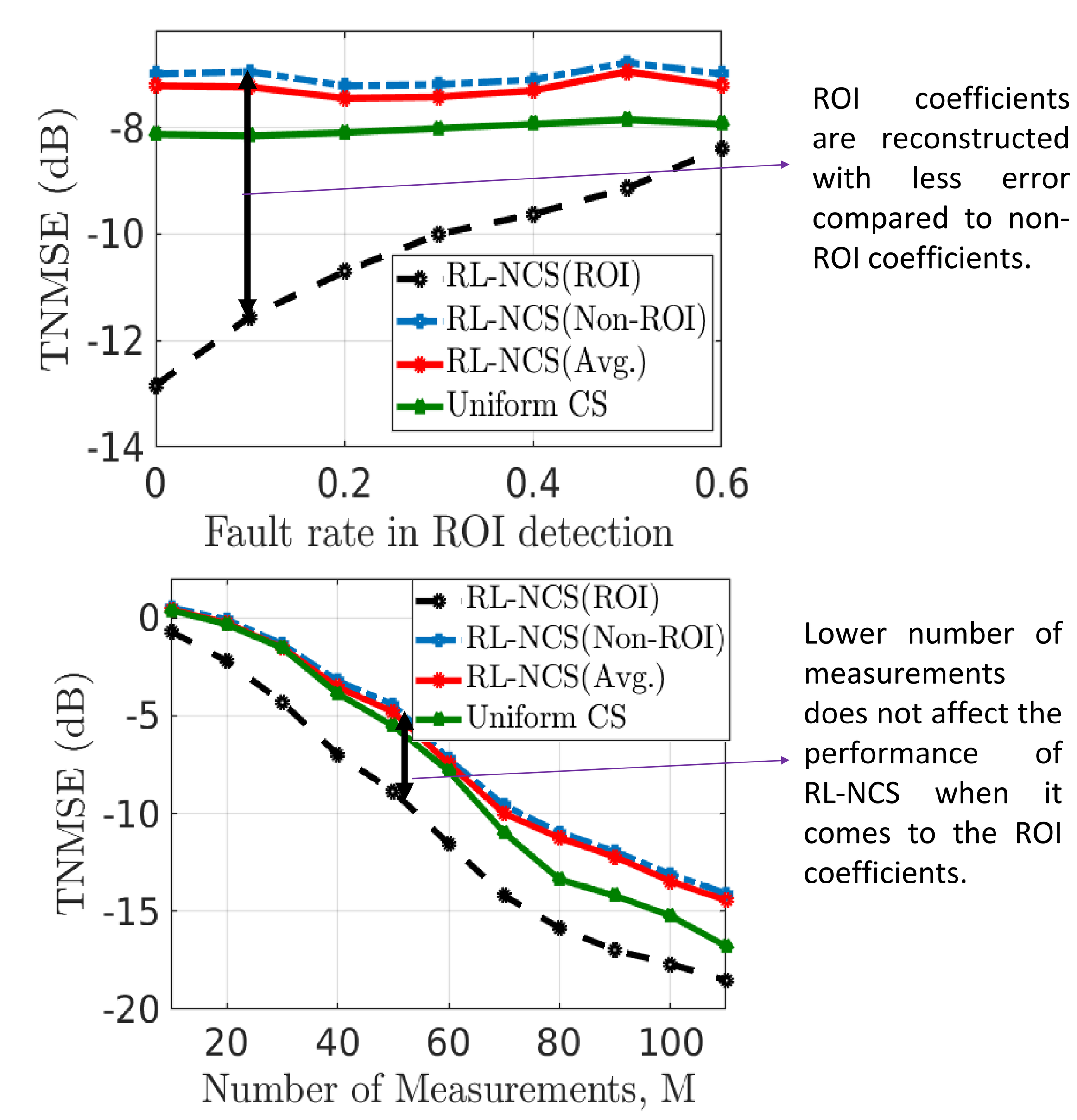
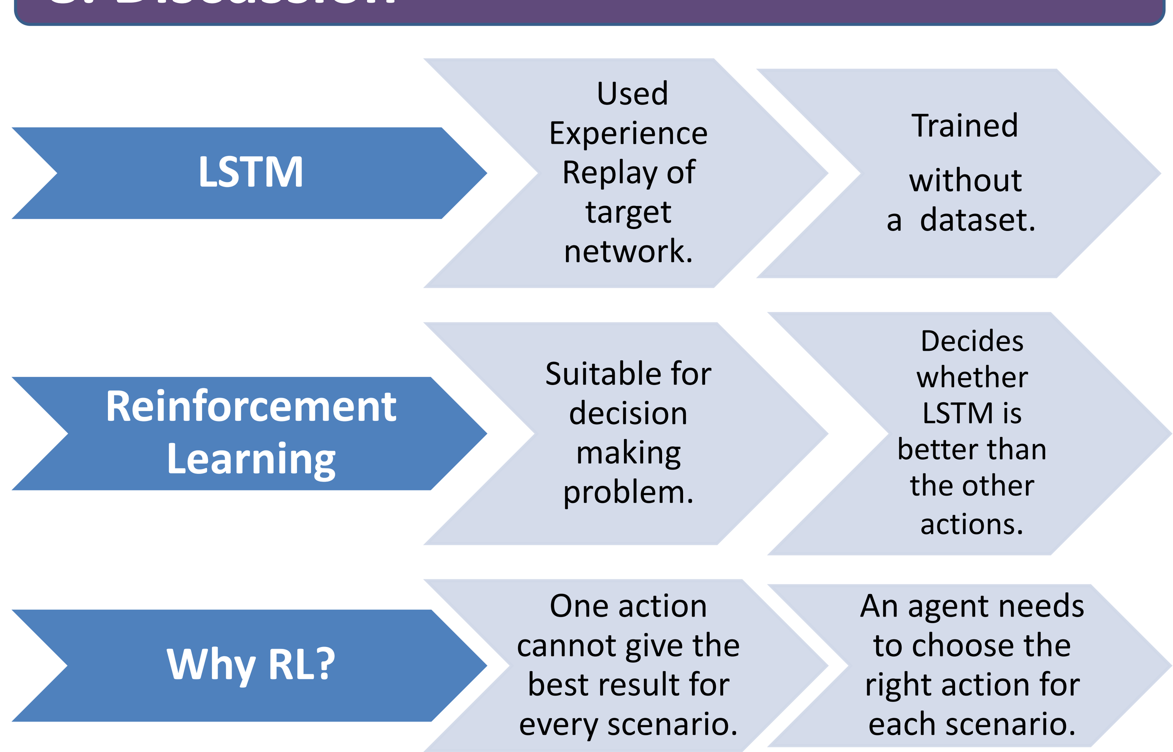


Figure: Performance evaluation (for sparse signal in DCT domain) at different fault rate and number of measurements.

8. Discussion



9. References

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[2] Zaeemzadeh A, Joneidi M, Rahnavard N. Adaptive non-uniform compressive sampling for time-varying signals.
[3] Mnih V, Kavukcuoglu K, Silver D, Graves A, Antonoglou I, Wierstra D, Riedmiller M. Playing atari with deep reinforcement learning.

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