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ML/AI for Wireless

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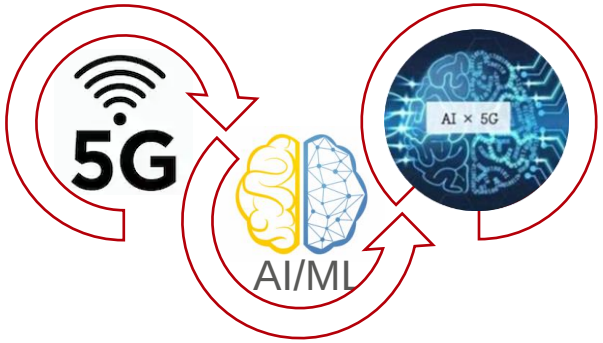
ML/AI for Wireless: Motivation



- ML/AI, deep learning, has proven to be a powerful mechanism in many image-processing and speech recognition related tasks and in developing data-driven signal processing algorithms.
- Artificial neural networks (ANN) or neural networks (NN) in short are generally designed to approximate other functions by selecting the parameter θ to minimize the approximation error.
  - Fully connected neural network (FCN) can approximate any continuous function arbitrarily well by utilizing a large but finite number of parameters [1].
  - Convolutional neural network (CNN) and recurrent neural network (RNN) are good at approximating certain types of functions by extracting spatial and temporal features from the input while requiring fewer parameters [2].
- Numerous research works have demonstrated deep learning is very effective in dealing with PHY communication problems [3]. A natural question/task for us is to identify the use cases where the powerful function approximation capability can be utilized to achieve large improvements compared to conventional techniques.
- ML/AI related activities in the standards:
  - RAN3 study on further enhancements for data collection (RP-201304) has been approved and upper layer RAN use cases are agreed/approved in RAN3 #112-e.
  - In the effort to answer the above question, ITU launched “AI/ML 5G Challenge” last year to explore how to best apply ML/AI in communication networks. Various PHY layer use cases were part of the challenge competition, e.g., channel estimation, best MIMO beam selection.
  - ITU-T Y.3170 SERIES Y “Machine learning in future networks” has introduced PHY layer use cases.

[1] G. Cybenko, “Approximation by superpositions of a sigmoidal function,” *Math. Control, Signals Syst.*, vol. 2, no. 4, pp. 303–314, Dec. 1989. doi: 10.1007/BF02551274.
[2] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA: MIT Press, 2016
[3] T.J. O'Shea, J.Hoydis, “An introduction to deep learning for the physical layer,” CoRR, vol.abs/1702.00832, 2017.

ML/AI for Wireless Potentials

Candidate problem areas for ML/AI

- Complicated non-convex optimization problems that are lacking optimal analytical solutions.
- Computationally complicated problems that are too costly to solve in real-time due to latency constraints.
- Increased margin of error caused by a chain of multiple sub-optimal solutions.
- Finding optimal solutions in ever-changing real-world with many imperfections.

Potential Use Cases

- CSI compression, channel estimation, reconstruction and prediction
- Beam selection/tracking
- mmWave signal blockage detection and prediction
- Link adaptation (MCS selection)
- End-to-end PHY layer optimization or joint-optimization of multi-functions.
- Data-driven user localization

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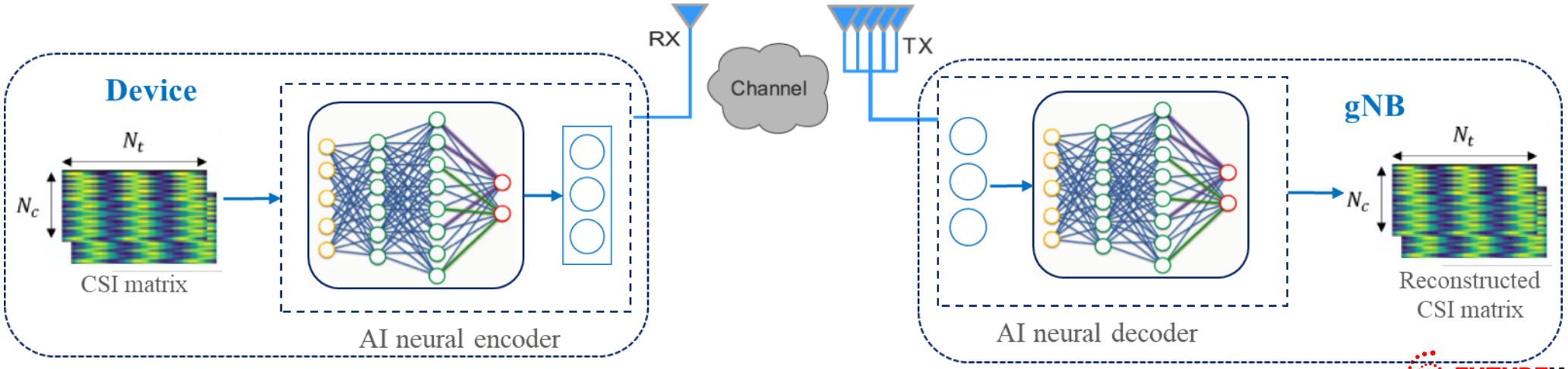
ML/AI for PHY: CSI feedback compression and reconstruction

- ML/AI based CSI feedback compression and reconstruction
  - Problem: In FDD, as the number of antenna increases, the feedback quantities increase dramatically
  - ML/AI approach
    - Device side: using NN encoder to encode the original CSI matrix and output an Mx1 encoded vector, where $M << N_c$ x N_t
    - gNB side: NN decoder decode the received input Mx1 then predict the original full CSI matrix.
    - Potential benefits:
      - Improve CSI reconstruction accuracy using low complexity NN encoder
      - May apply lossless compression after encoding to further reduce the overhead

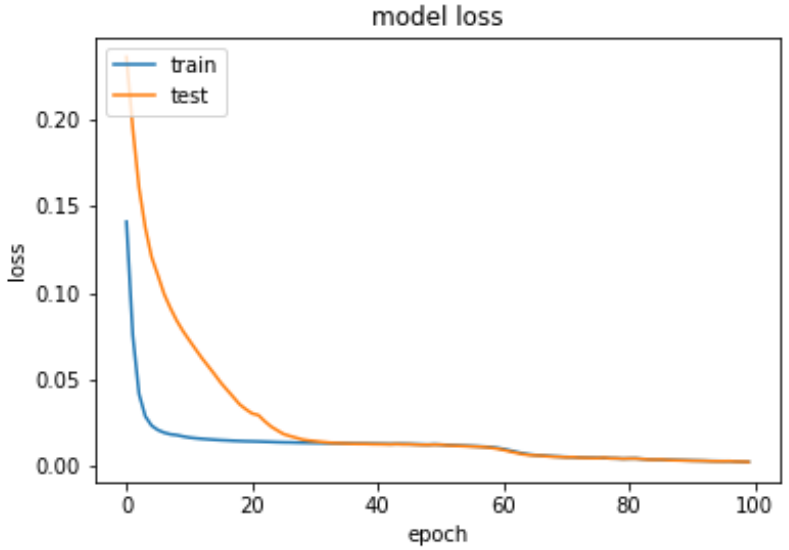


ML/AI for PHY: CSI feedback compression and reconstruction

- Preliminary results for ML/AI-based CSI compression
  - Antennas at gNB: 4 x 8
  - Antennas at UE: 1
  - Subcarriers: 2048
  - Evaluation metrics: NMSE, cosine similarity

Compression Rate	NMSE	Cosine Similarity
64X	0.006287	0.937651
128X	0.011067	0.898369

ML model training and validation loss (compression rate =64x)



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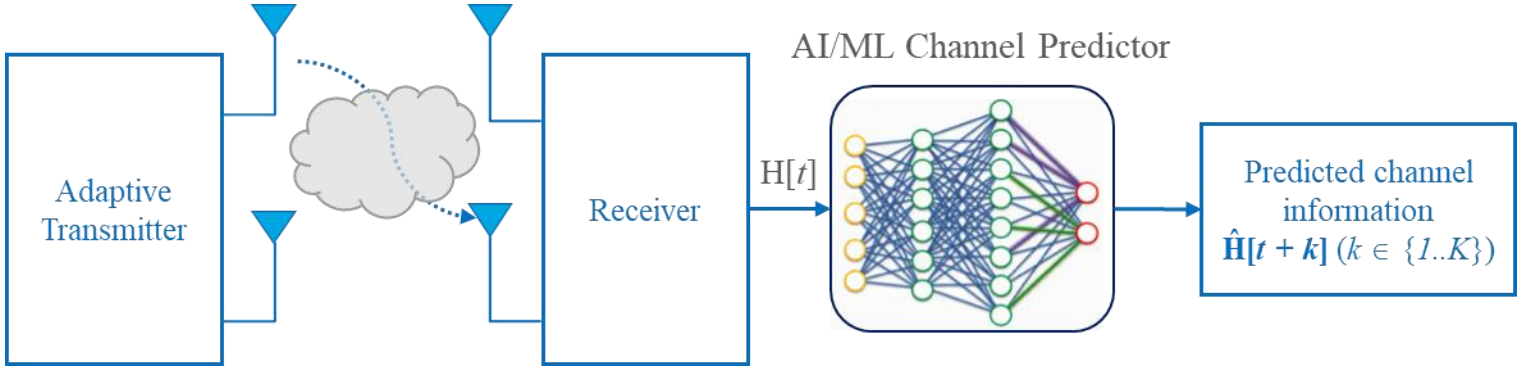
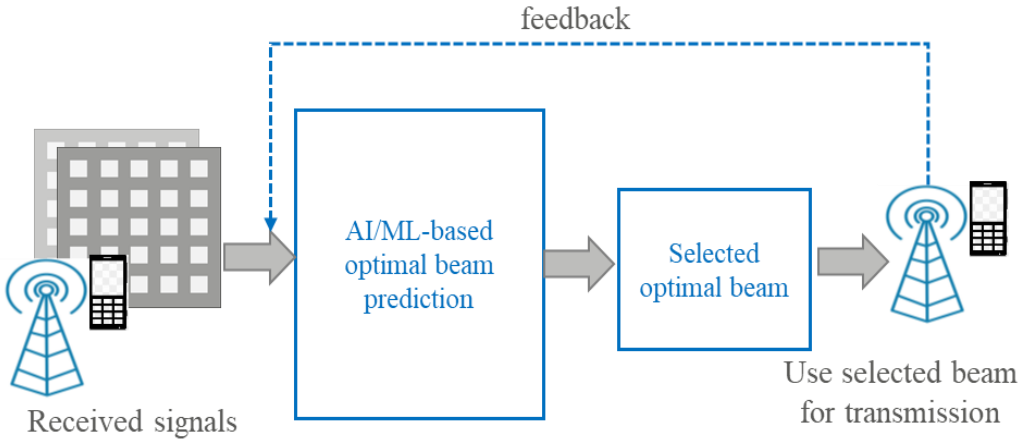
ML/AI for PHY: Channel Prediction

- ML/AI based Channel Prediction
  - Problem: In rapid channel variation scenarios, e.g., high mobility, accurate channel estimation is especially important but more challenging
  - ML/AI approach
    - Predict subsequent channels by exploiting the strong temporal correlation in channel history
    - Potential benefits:
      - Reduce RS overhead with improved accuracy
      - Adaptive to changing environment in mobility scenario



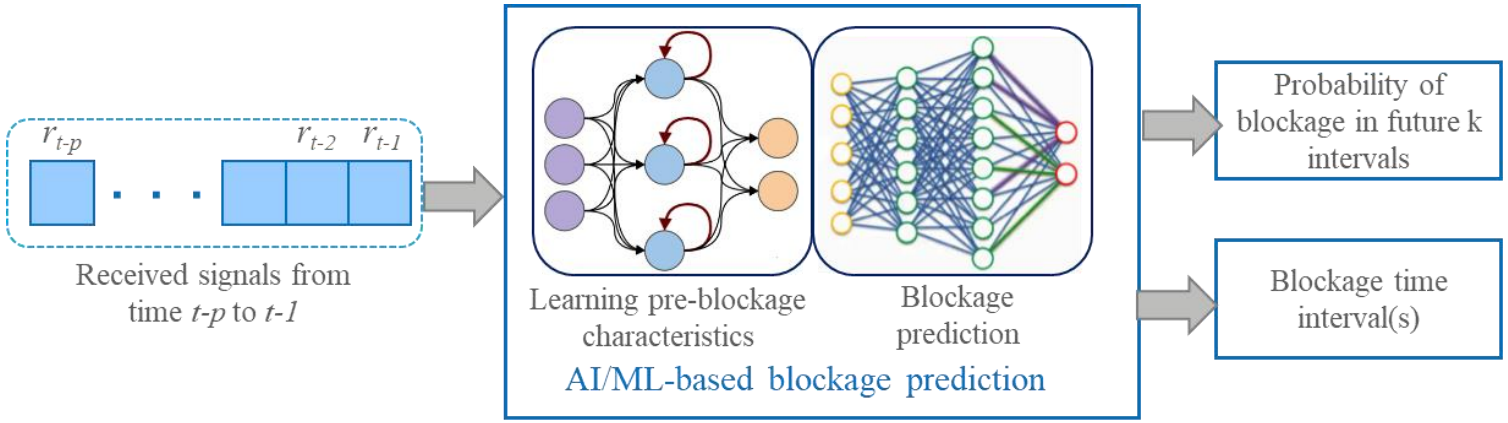
ML/AI for PHY: Beam Selection

- ML/AI based Beam Selection
  - Problem:
    - When the number of antennas is large, it is not possible to obtain complete channel state information to determine the optimal beamforming due to high signaling overhead.
    - Using a limited set of beamforming vectors is a practical alternative. The transceiver can switch beams among a predefined beam sets (gNB performs exhaustive search to find the optimal beam vector).
  - ML/AI approach
    - Using the received signals at Rx, adaptively find the beamforming vector that maximize the channel capacity.
    - Potential benefits:
      - Reduce the time/search overhead
      - Improve accuracy / spectral efficiency
      - Adaptive to changing environment



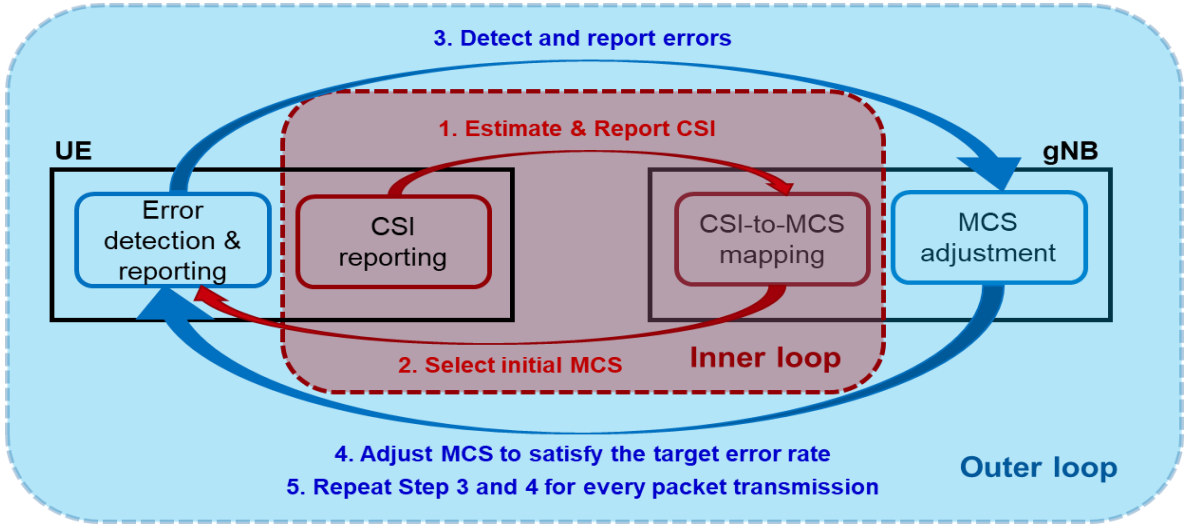
ML/AI for PHY: mmWave blockage prediction

- ML/AI based mmWave blockage prediction
  - Problem:
    - mmWave bands provide many benefits like increased performance and higher BW. However, mmWave radio signals are sensitive to blockage. Sudden blockage in the LOS link leads to abrupt disconnection.
  - ML/AI approach
    - Predict the upcoming blockage in advance using learned pre-blockage characteristics from measurements prior to the blockage.
    - Predict the timing when the blockage will occur.
    - Potential benefits
      - Allow proactive HO to another gNB
      - Reduce overhead associated with disconnection then re-establishment



ML/AI for PHY: Link Adaptation (MCS Selection)

- Problem: channel fading causes variations in the SNR
  - Large-scale and small-scale variations
  - Due to time frequency channel dynamics and interference
- 5G Solution: link adaptation
  - Rate control (AMC) + Transmit power control (uplink)
  - Goal is to enable reliable transmission at a data rate that maximizes the throughput
  - In this proposal, we focus on AMC (MCS Selection).
- 5G Approaches:
  - Inner Loop Link Adaptation (ILLA)
  - Outer Loop Link Adaptation (OLLA)



Issues of ILLA and OLLA

- Performance depends heavily on the accuracy of CSI;
- The CQI feedback is often out of date and cannot capture the interference in the actual downlink transmission
- Link adaptation in 5G with large numbers of antennas and channels is more challenging due to the high CSI dimension
- The initial OLLA offset parameter, if not selected carefully, could lead to a slow convergence;
- Slow convergence of the OLLA has a negative impact on the performance;

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ML/AI for PHY: Link Adaptation (MCS Selection)

- How can ML/AI help MCS selection?
  - By using historical channel condition data and corresponding KPIs, ML/AI can help to find the optimized MCS and rank.
- Applying ML/AI to the problem
  - ML/AI can be used to enhance performance of ILLA and/or OLLA
  - Example: ML/AI can be used to adapt the step size of OLLA
  - As an ultimate form, ML/AI can be used to replace ILLA and/or OLLA.
    - In this case, ML/AI can learn a policy to select the most appropriate MCS index for a certain environment state
- Potential benefits:
  - Higher link throughput
  - Faster convergence time
  - Higher spectral efficiency
  - Lower block error rate

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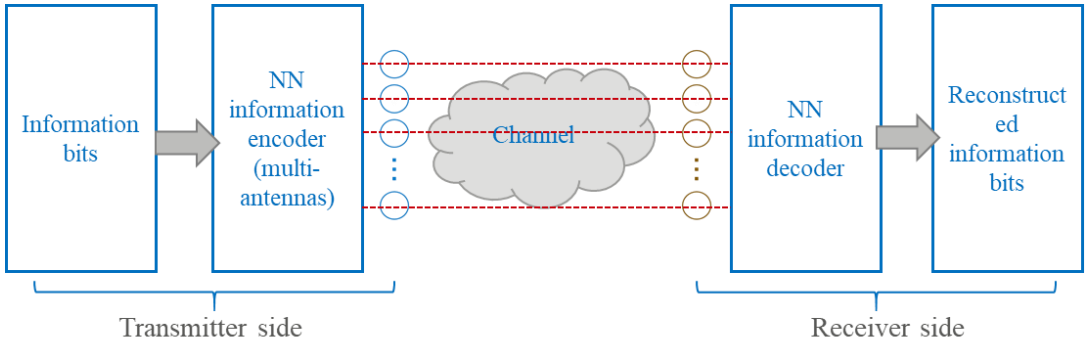
ML/AI for PHY: Joint optimization of multi-functions at PHY

- Multi-function optimization at PHY using deep learning
  - Problem:
    - Conventional block-by-block design communication model increases complexity of PHY layer optimization.
    - When applying ML/AI approach to individual blocks, prediction errors may propagate, and the amount of data required to train multiple ML/AI models may be massive.
  - Multi-function optimization using ML/AI
    - Tx side: feeding information bits (e.g., k-bit codeword) into a NN information encoder.
    - Rx side: feeding the received characteristic representation of the information bits into a NN information decoder to estimate the original message(s).
    - Potential benefits
      - Joint optimization of multiple functional blocks in PHY
      - Alleviate the data demand for training multiple ML/AI models, one for each block.



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ML/AI for Wireless: Proposal

- Propose to have an **R18 SI** to:
  - Focus on study ML/AI based PHY/link layer enhancement
  - Consider the following ML/AI based PHY enhancement use cases
    - CSI feedback compression and reconstruction, channel prediction
    - Beam selection/tracking enhancement
    - mmWave signal blockage prediction
    - Link Adaption (MCS Selection)
    - Multi-functional-block PHY optimization
  - For each PHY enhancement use case:
    - Study the potential gains using ML/AI based approach in comparison with existing method
    - Investigate deployment scenario, feasibility, trade-offs, and justification for ML/AI based approach
    - Study standardization impacts (leveraging the framework introduced in the R17 SI FS_NR_ENDC_data_collect), including:
      - New input and output requirements related to the use case
      - Information to be exchanged across interfaces and interoperability
      - Requirements on hardware, software, UE capability etc.
  - Use case prioritization based on preliminary performance evaluation and standards impact
  - Study methodology of performance and robustness evaluation for ML/AI-based approach for PHY layer enhancement
  - Consider establishing common test datasets to facilitate performance evaluation and benchmark study

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