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Artificial intelligence and wireless communications

Key words: Wireless communications; Artificial intelligence; Machine learning

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Motivation

- Due to the development of advanced computing capabilities, progress in algorithms, and accessibility to big data, artificial intelligence (AI) is ushering in a new wave of technical revolution in human society.
- Wireless communication technologies are undergoing rapid development. Huge volumes of traffic with different quality-of-service (QoS) requirements are supposed to be handled by wireless communication networks.
- Despite all of the ML technologies that are combined with wireless communications, there are a range of opinions about whether they are being carried out properly.
- In this paper, we are trying to touch on some of the key points that are critical for making wireless AI useful in realistic systems. These key technical points correspond to the following fundamental open questions:
  1. How to handle and use the wireless data, especially the physical layer data?
  2. Are DNNs capable of replacing some traditional modules in wireless systems?
  3. Can data-driven ML help with the design of some parts of wireless systems?
  4. How can expert knowledge in communication theory help ML?
  5. Can ML help with the design of a post-Shannon structure of communication systems?

AI-based channel modeling

- **Traditional channel modeling**
  - Stochastic channel model: cannot fit realistically true channel
  - Deterministic channel model: impossible to generalize to other channels
- **AI-based pre-trained channel model[1,2]**
  - Method: multi-domain embedding + self-attention
  - Benefit
    - ✓ Extracting the multi-domain features of the channels
    - ✓ Strong generalization capability

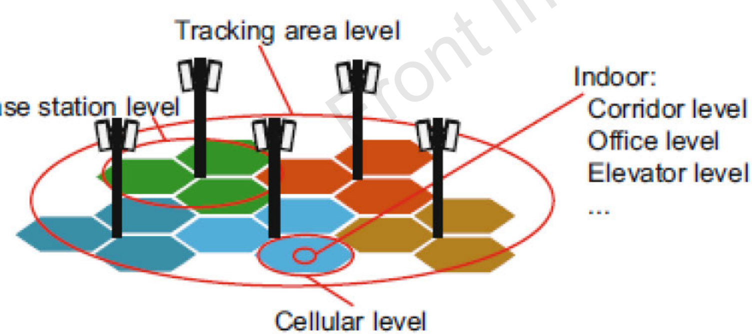


Fig. 1 Schematic of realistic channel models at different levels

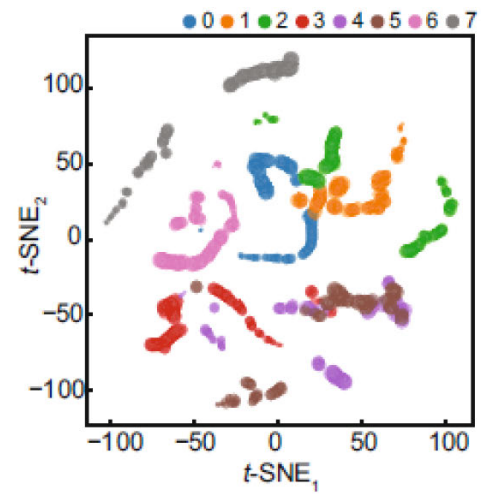
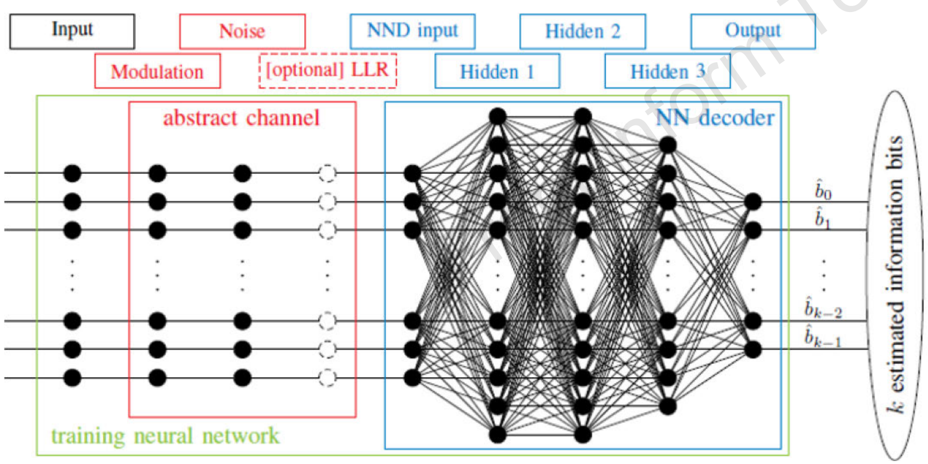


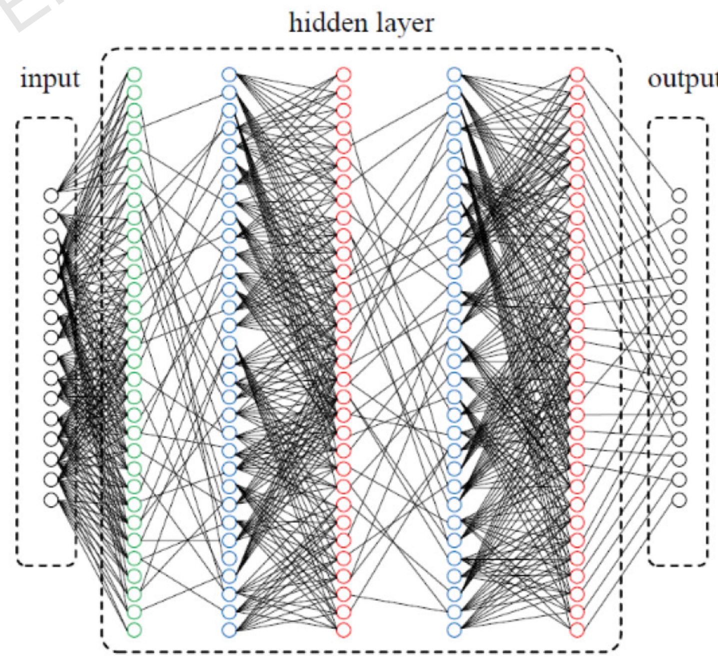
Fig. 2 Channel charting of low-dimensional representations of channel fingerprints using t-SNE

AI-based channel decoding

- MLP based decoder[3]
- Tanner graph based NN decoder[4]
- RNN decoder for sequential codes[5]
- **Challenges**: high training complexity; low efficiency; limit performance improvement



Tanner graph based NN decoder



RNN decoder

AI-based signal detection

- LSTM-based multi-use neural receiver
- Outperforms Rake receiver

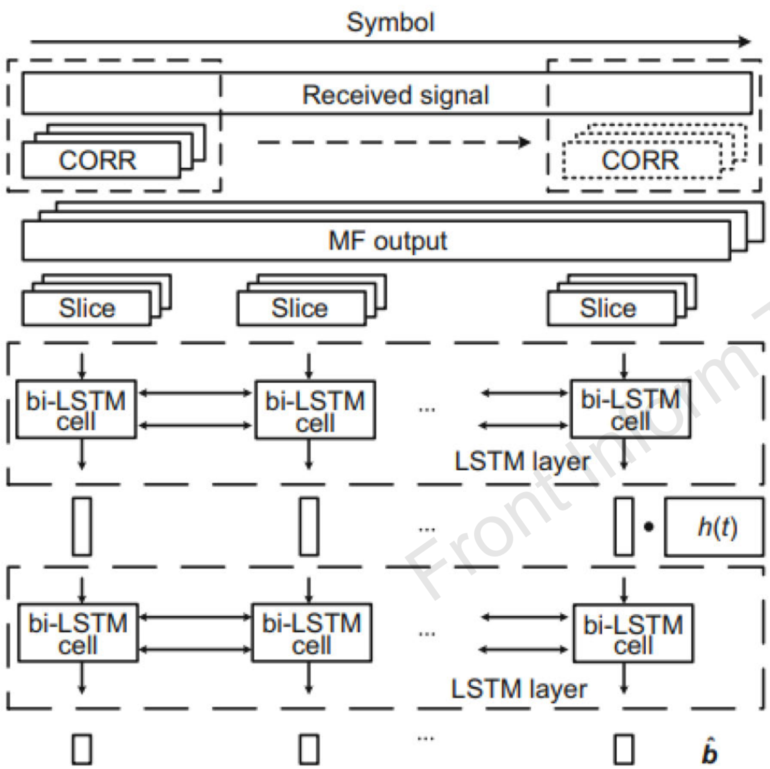


Fig. 3 Structure of the proposed multi-user neural receiver

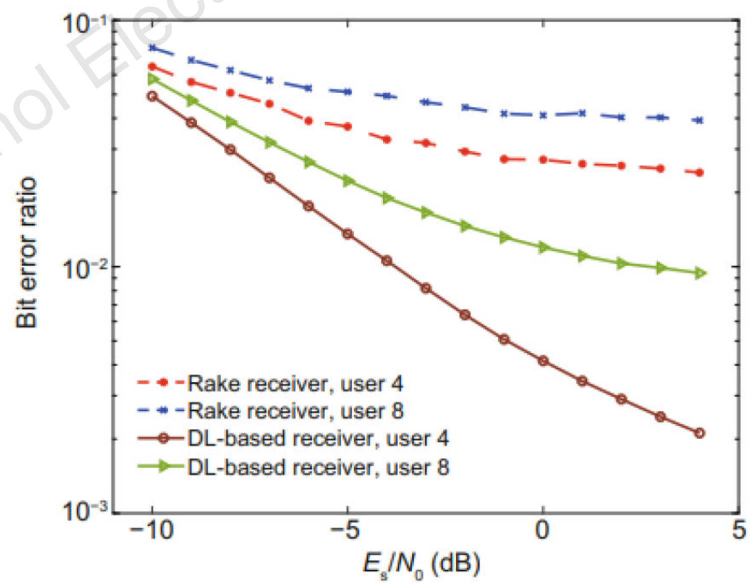


Fig. 4 Performance comparison with the rake receiver

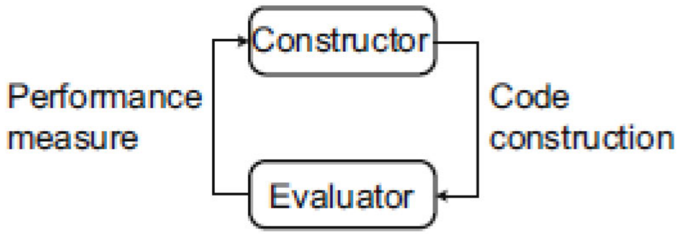
AI-based channel coding design

◻ Coding theory based design

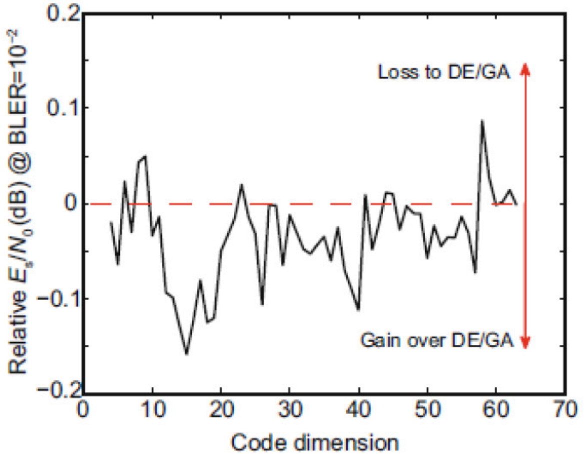
- Hamming distance (maximum distance separable (MDS) codes), free distance (conventional codes), and decoding threshold (low-density parity check (LDPC) codes)
- In some cases, theory is lacking, e.g., Polar codes with SCL decoders

◻ AI-based coding design[6]

- Constructor-evaluator framework (similar to reinforcement learning)
  - ✓ Constructor: construct codes, adjust the construction policy based on performance fed back by the evaluator
  - ✓ Evaluator: measure the performance of codes output by the constructor



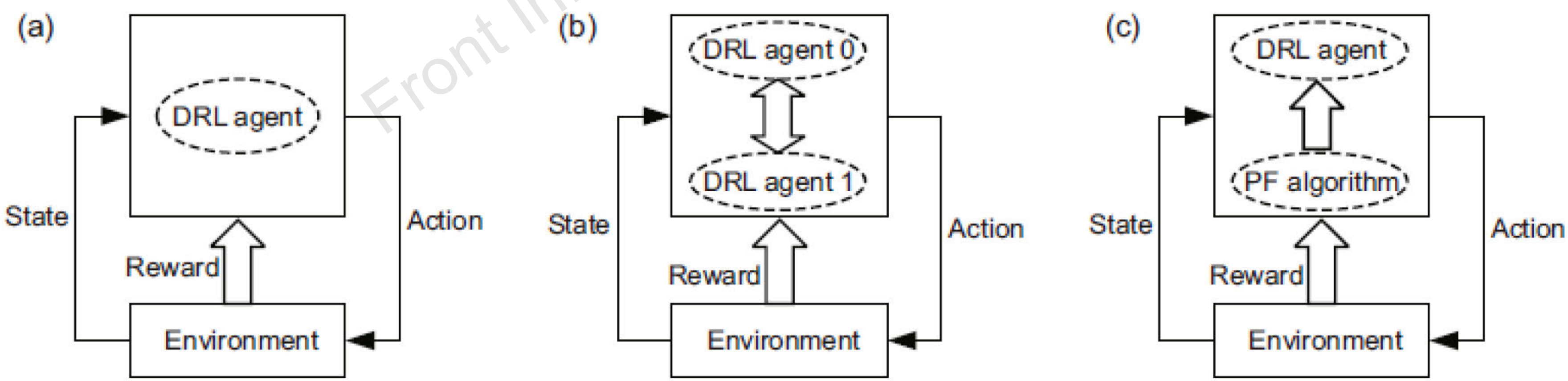
Constructor-evaluator framework



Performance of Polar codes constructed by AI

AI-based scheduling

- Decision-making tasks in wireless communication systems, e.g., scheduling, can be solved by deep reinforcement learning (DRL)[7][8]
- Learning methodologies
  - Direct learning: traditional DRL framework where agent learns from environment
  - Dual learning: two agents learns from each other
  - Expert learning: the agent learns from expert knowledge
- Observations
  - Direct learning is slow and easy to fall into local optima
  - For dual learning, the two agents can compete with each other to reduce the risk of local optima, but the convergence speed is still low

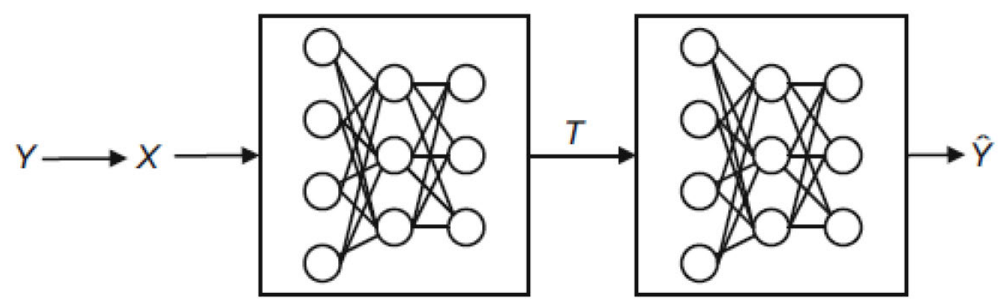


Direct learning Dual learning Expert learning

AI and information theory

- Despite the success of AI and deep learning in many particular tasks, such as image classification, speech understanding, and strategic game playing, there are still some drawbacks preventing the wide success of AI
  - Data hungry for good generalization
  - Low training efficiency
  - Non-interpretability (black box)
- Information bottleneck[9]
  - The network uses the latent variable *T* to represent the noisy input data *X*, retaining only the features most relevant to general concepts *Y*
  - Trade-off should be made between the compression level and the captured relevant information

$$\min\Big(\underbrace{I(X,T)}_{\text{Compression level}} - \beta\,\underbrace{I(Y,T)}_{\text{Captured relevant information}}\Big)$$



Information bottleneck in a deep neural network

Future of wireless AI

☐ AI-enabled wireless communications

- Wireless big data analytics can be applied to future wireless communication systems based on the AI technologies.
- AI technologies can be used to optimize many physical layer modules for wireless links.
- AI technologies play a critical role in refining the end-to-end chain for wireless communications.

☐ Wireless communications for AI

- Wireless communications can help handle AI applications in a distributed way with low latency and fulfill the requirements of critical privacy and security.
- Future wireless communication systems should be designed with the consideration that distributed computation and data storage with privacy protection are supported to enable distributed AI applications.
- The bandwidth allocation and scheduling among all the mobile devices should be carefully designed.

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