The School of Electronic Engineering and Computer Science

Native Intelligent Communication

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The Applications of Semantic-aware Channel Capacity

Semantic-aware channel capacity

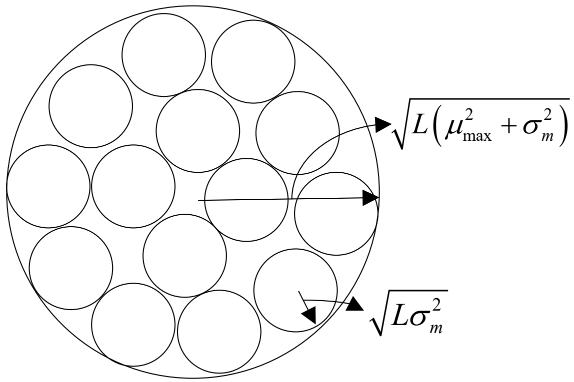
- **Semantic noise model**

$$\mathbf{x} = \mathbf{z} + \mathbf{n}_{\text{model}}$$

  - $\mathbf{x} \in R^{L\times 1}$ is the output of one layer
  - $\mathbf{z} \in R^{L\times 1}$ is the semantic information selected from the latent semantic codeword
  - $\mathbf{n}_{\text{model}} \sim N\left(0, \sigma_m^2\right)$ is the model noise

Semantic-aware channel capacity

- **Semantic capacity**
  - Employ the sphere packing to compute the minimum length of L



$$L=\frac{2\log N}{\left(1+\frac{\mu_{\max}^2}{\sigma_m^2}\right)}$$

  - N is the number of semantic codewords
  - $\mu_{\max}$ is the maximum value in the semantic codewords

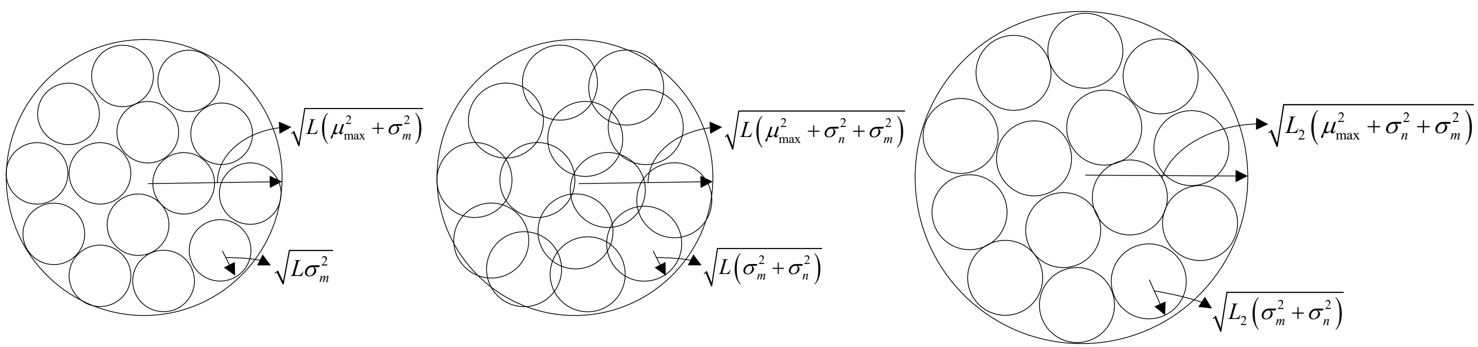
Semantic-aware channel capacity

- **Transmit over the AWGN channels**

$$\mathbf{y} = \mathbf{z} + \mathbf{n}_{\text{model}} + \mathbf{n}_{\text{channel}}$$

  - $\mathbf{n}_{\text{channel}} \sim N\left(0, \sigma_n^2\right)$ is the channel noise

- **Semantic-aware channel capacity**
  - Enlarge the *L* to avoid the overlap between semantic codewords



(a) (b) (c)

Semantic-aware channel capacity

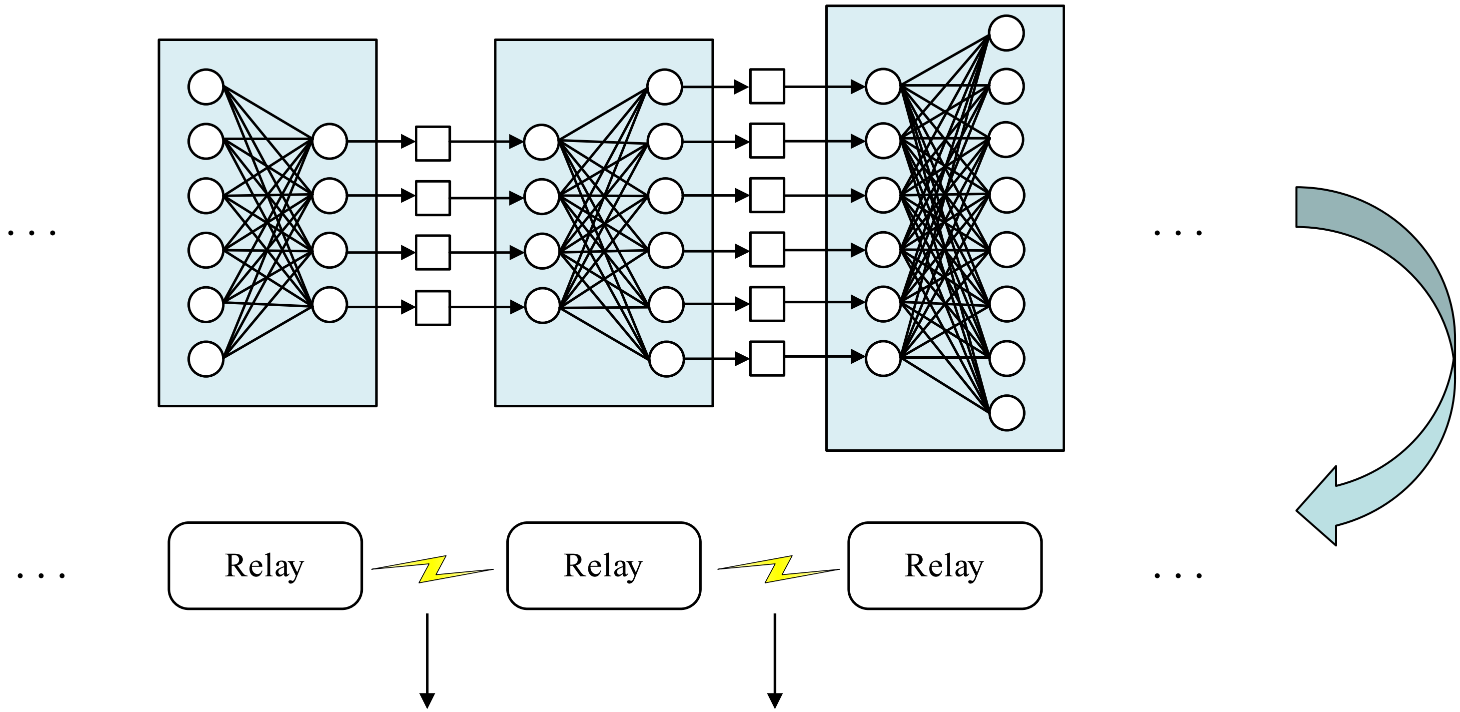
- **Semantic-aware channel capacity**

$$L_2 = L \frac{\log\left(1+\frac{\mu_{\max}^2}{\sigma_m^2}\right)}{\log\left(1+\frac{\mu_{\max}^2}{\sigma_m^2+\sigma_n^2}\right)}$$

- **Remarks**
  - Indicate how much semantic information can be transmitted reliably
  - When channel noise disappears, it has the lower bound, *L*.
  - Affect by several factors, N, $\mu_{\max}$, σ_m^2, and σ_n^2.

Guide the design of neural network

- **The neural network**



View it as communication

$$\mathbf{x}^{(l)} = \mathbf{z}^{(l)} + \mathbf{n}^{(l)}_{\text{model}} \qquad \mathbf{x}^{(l+1)} = \mathbf{z}^{(l+1)} + \mathbf{n}^{(l+1)}_{\text{model}}$$

Guide the design of neural network

- **Target**
  - Transmit the semantic information over multiple layers
- **Insights**
  - Compute the *L* to decide the width of each layer
  - Measure the model noise to decide the depth of neural network
- **Difficulty**
  - How to measure the *N*, $\mu_{\max}$, and σ_m^2

Resource Allocation

- **Target**
  - Perform the resource allocation based on the semantic-aware channel capacity
- **Insights**
  - The number of semantic codewords
  - The model noise
  - The channel noise

The different L

- **Difficulty**
  - Introduce the new characteristics

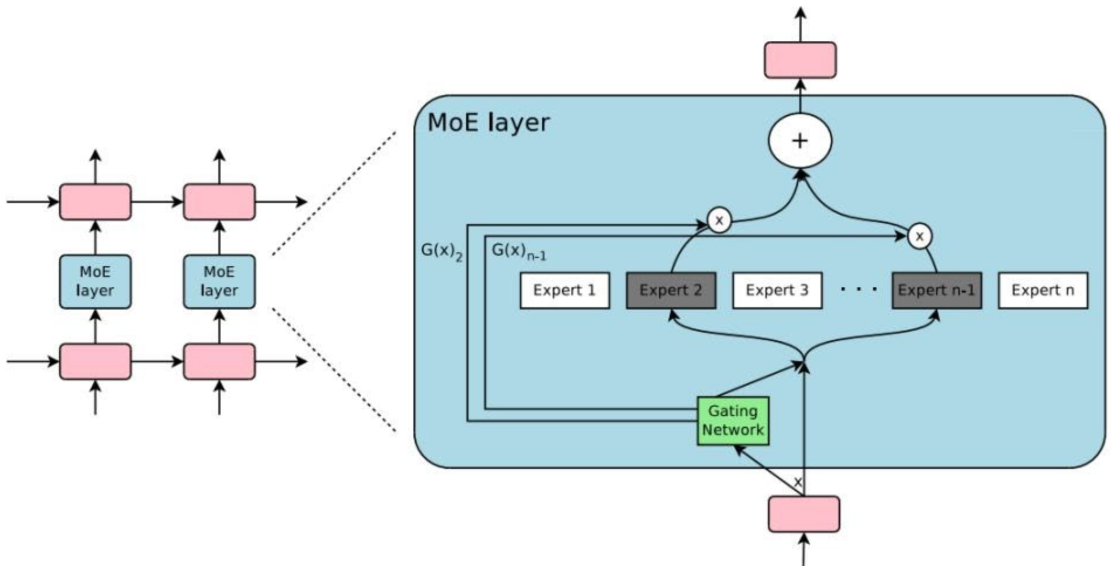
The Basic Model in Communications

The Basic Model

- **The pre-trained model**
  - BERT, GPT-3, Switch-Transformer for text tasks
  - MAE, Resnet for image tasks
  - The multimodal pre-trained model?
  - The communication pre-trained model?
- **Communication tasks**
  - Channel estimation
  - Channel feedback
  - Symbol detection
  - Modulation and demodulation
  - Precoding
  - …

The Pathways

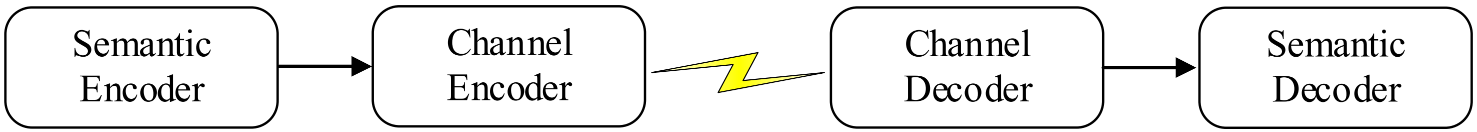
- **Benefits**
  - Employ one or more expert networks to perform tasks
  - Each expert is independent
  - Easy to deploy on the devices



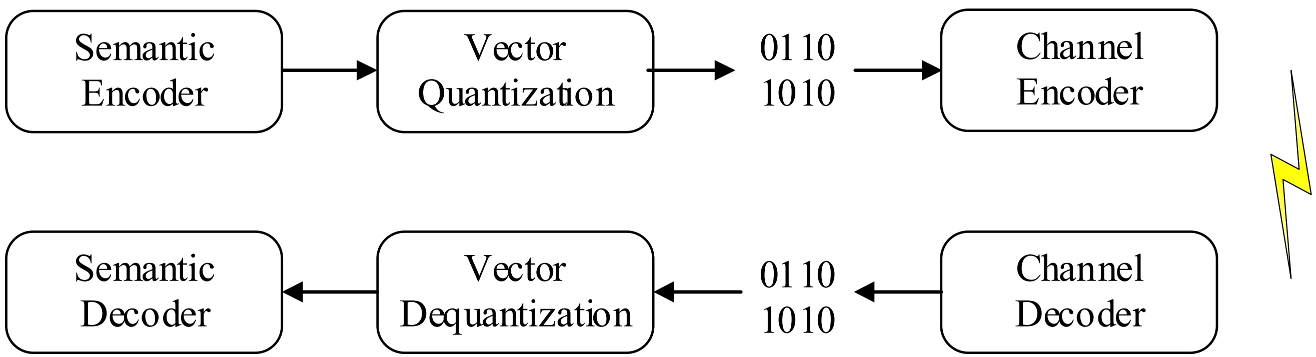
Hybrid Semantic-Conventional Communication

System Model

- **Two types of System**
  - End-to-end Semantic communication



  - Hybrid semantic-conventional communication

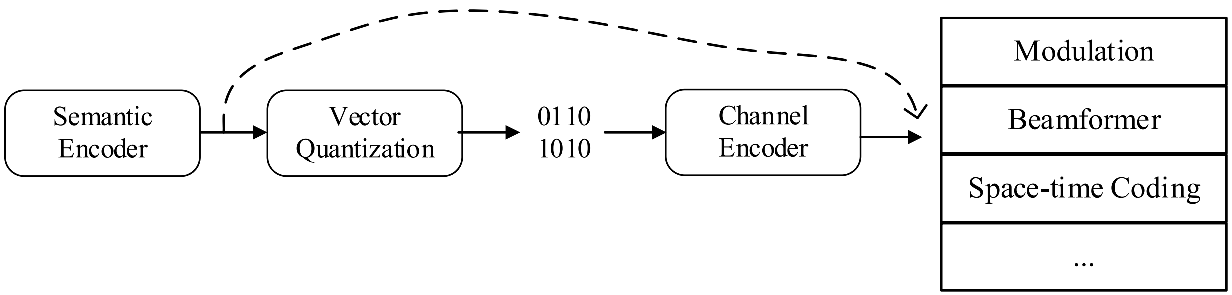


Key Problems in the Hybrid Systems

- **Vector Quantization Design**
  - Find the optimal vector quantization to preserve more the semantic information

- **Semantic-aware design**
  - Constellation design
  - Beamformer design
  - Space-time coding for MIMO
  - …

To prevent the important information from distortion



Thanks!

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Regular Meeting for Project Native Intelligent Communication Systems

04 July 2022

Huynh Van Nguyen
ITP Lab, Department of EEE, Imperial College London, United Kingdom

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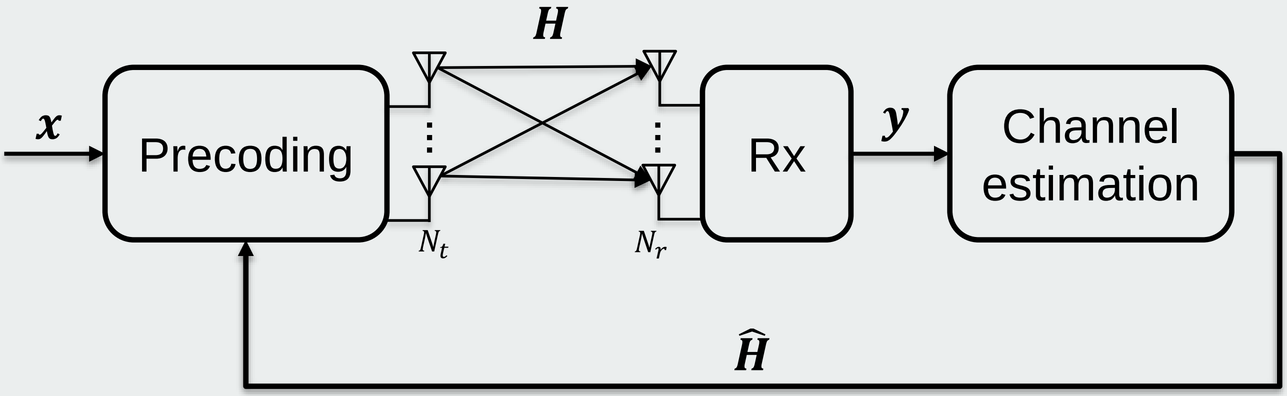
MIMO Communication Systems



CSI Feedback

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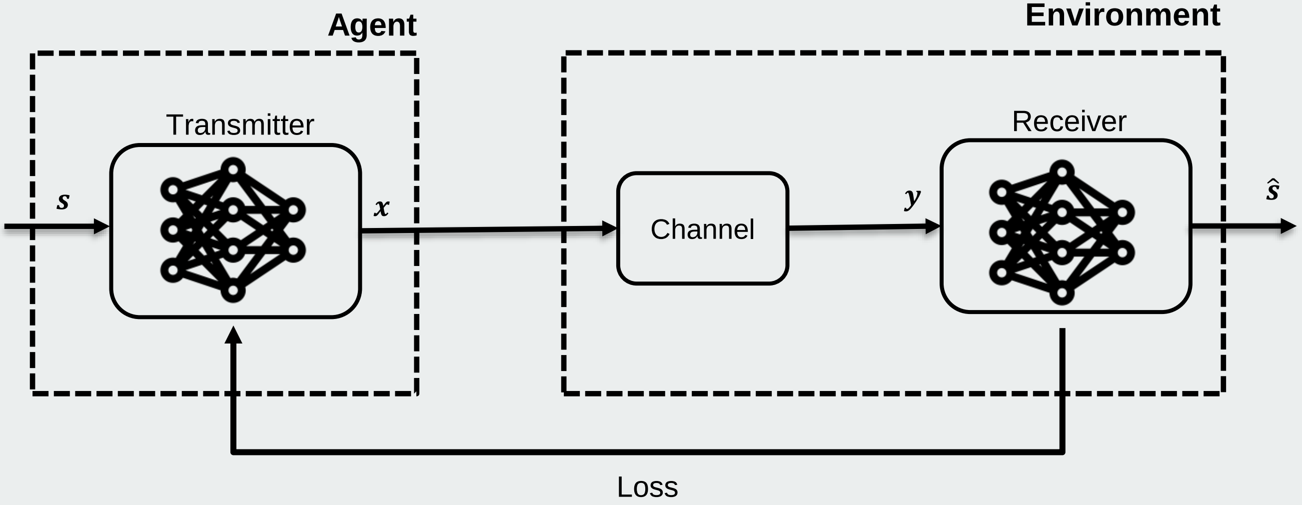
E2E with Reinforcement learning

- **State**: s
- **Action**: x
- **Reward**: loss from receiver
- Use Deep Deterministic Policy Gradient (DDPG) algorithm



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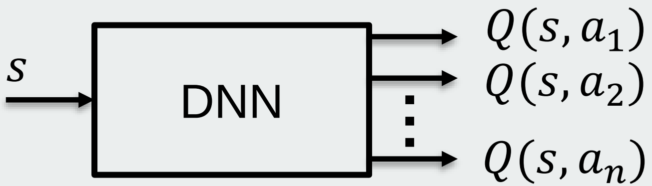
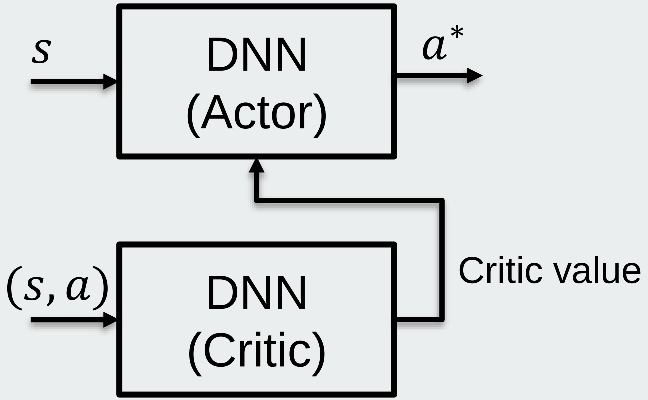
E2E with Reinforcement learning

Traditional deep reinforcement learning



Cannot handle continuous action space

DDPG



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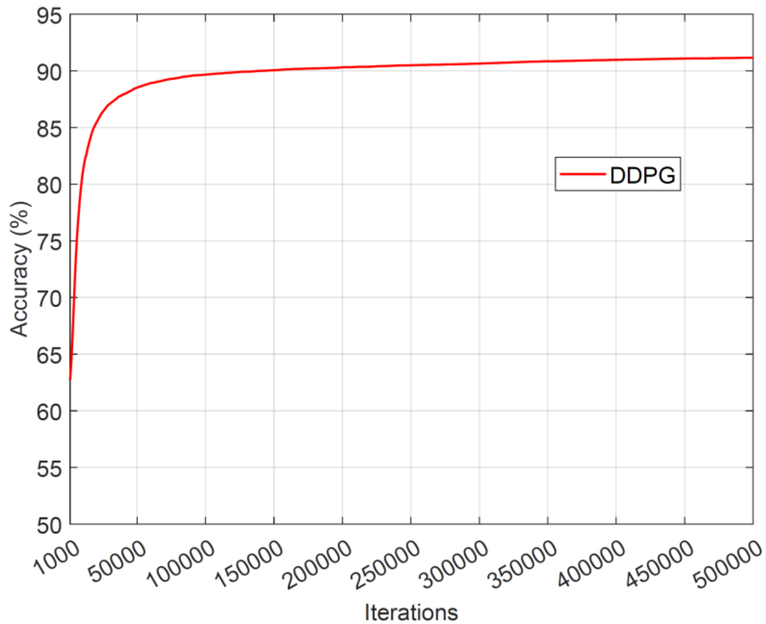
E2E with Reinforcement learning

$N_t = N_r = 2$
SNR = 20 dB



Accuracy $\approx 91\%$
BER ≈ 0.09

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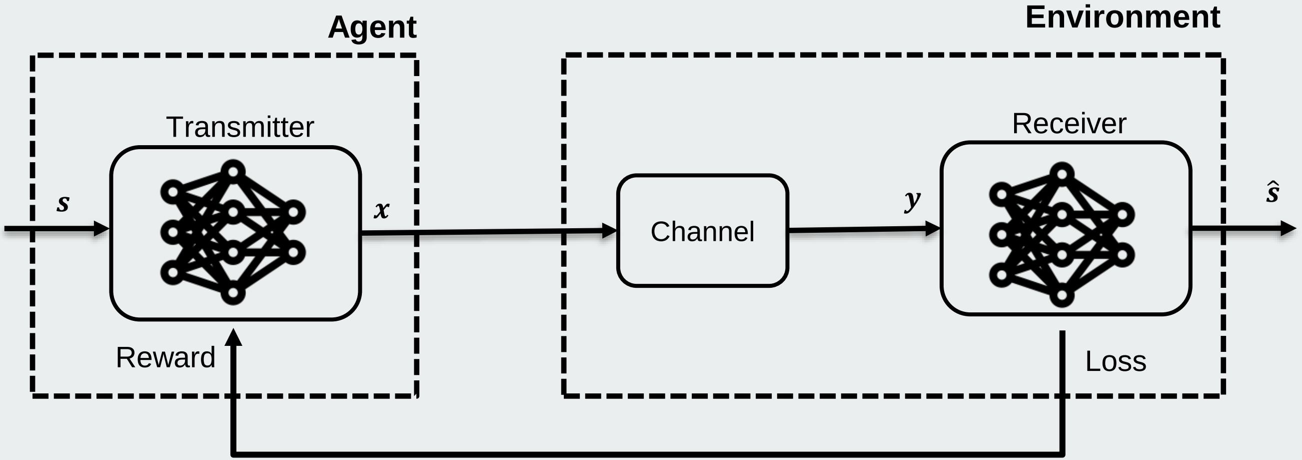
E2E with Reinforcement learning

- **State**: s (random bit sequence)
- **Action**: x
- **Next state**: a new random bit sequence

➡ Action x does not have any impact on the next system state



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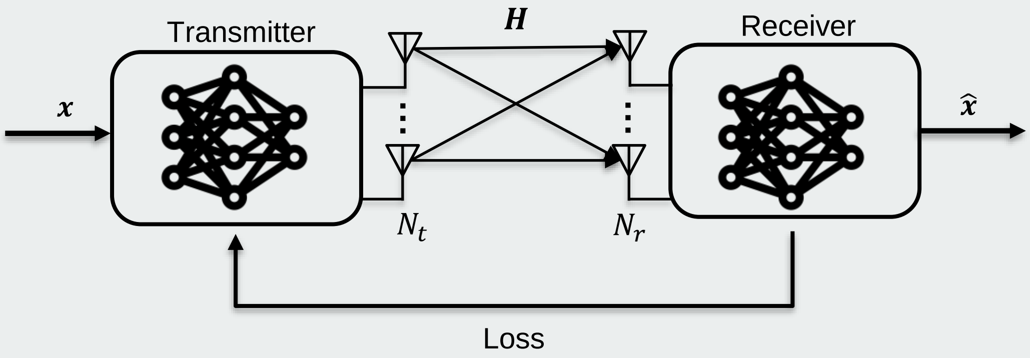
E2E MIMO with Loss Feedback

- Loss value from DNN of receiver is used to update DNN of transmitter



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Results

BER

SNR	N_t=N_r=2
0	0.189136819
2	0.136107842
4	0.096050134
6	0.061630068
8	0.034085964
10	0.019189639
12	0.009617051
14	0.004677095
16	0.002291753
18	0.001358665
20	0.000862222

Plans

- Further improve the accuracy of E2E with loss feedback.
- Compare proposed solution with baseline approaches

Q&A

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Multi-agent resource allocation in multi-cell wireless communication systems

Joint pilot power control and precoding design

Kaidi Xu

Outline

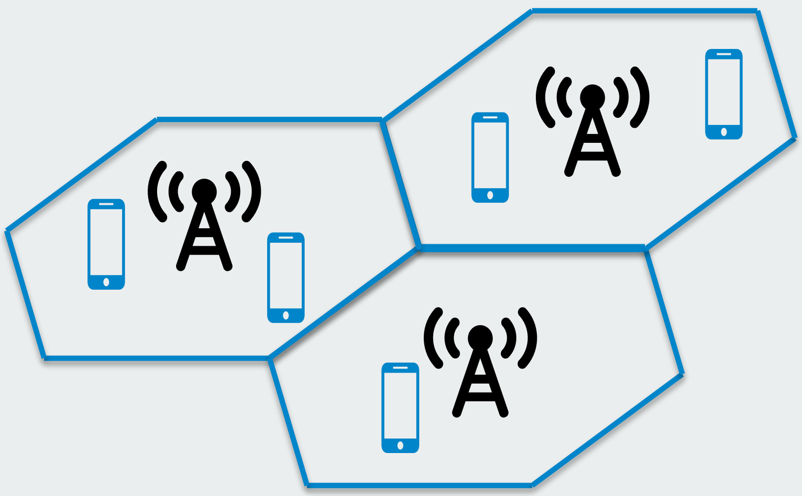
- Joint pilot power control and precoding in multi-cell TDD MISO systems
- Connection to the Learn-to-communicate MARL
- Next steps

Pilot power control (motivation)

- Pilot contamination can cause severe performance degradation
- Suppress the pilot contamination
- A chance for agent to learn the wireless environment
- Perform learn-to-communicate scheme without additional cost

V. Saxena, G. Fodor, and E. Karipidis, "Mitigating Pilot Contamination by Pilot Reuse and Power Control Schemes for Massive MIMO Systems," in Proc. IEEE VTC Spring, May 2015.

Multi-cell MISO TDD system



- Multi-cell multi-user TDD MISO system
- Uplink and downlink channel reciprocity
- Uplink pilot transmission and downlink data transmission
- Orthogonal pilot sequences are available within a cell
- Joint pilot power control and precoding design

Signal model

- At the beginning of time slot t, user m in cell j sends the orthogonal pilot sequence $\boldsymbol{\phi}_{p(m_j)}^{t}$ with pilot transmit power $P_{m_j,p}$.

- The received signal at BS k after filtered by $\boldsymbol{\phi}_{p(m_k)}^{t}$

$$\mathbf{Y}_k^t \phi_{p(m_k)} = \mathbf{h}_{m_k,k}^t \sqrt{P_{m_k,p}} + \sum_{m'_{k'} \neq m_k,\, p(m'_{k'}) = p(m_k)} \mathbf{h}_{m'_{k'},k}^t \sqrt{P_{m'_{k'},p}} + \mathbf{N}_k \phi_{p(m_k)}$$

- BS k estimates its channel $\widehat{\boldsymbol{h}}_{m_k}^{t}$ to user m_k based on $\mathbf{Y}_k^t \phi_{p(m_k)}$

- BS transmits data with precoding vector $\boldsymbol{w}_{m_k}$ to user m_k

Sum throughput maximization problem

$$\max \quad \sum_{m,k} R_{m,k}$$

$$s.t. \quad \sum_{m'} \| \mathbf{w}_{m',k'} \|^2 \le P_{k',t}, \forall k'$$

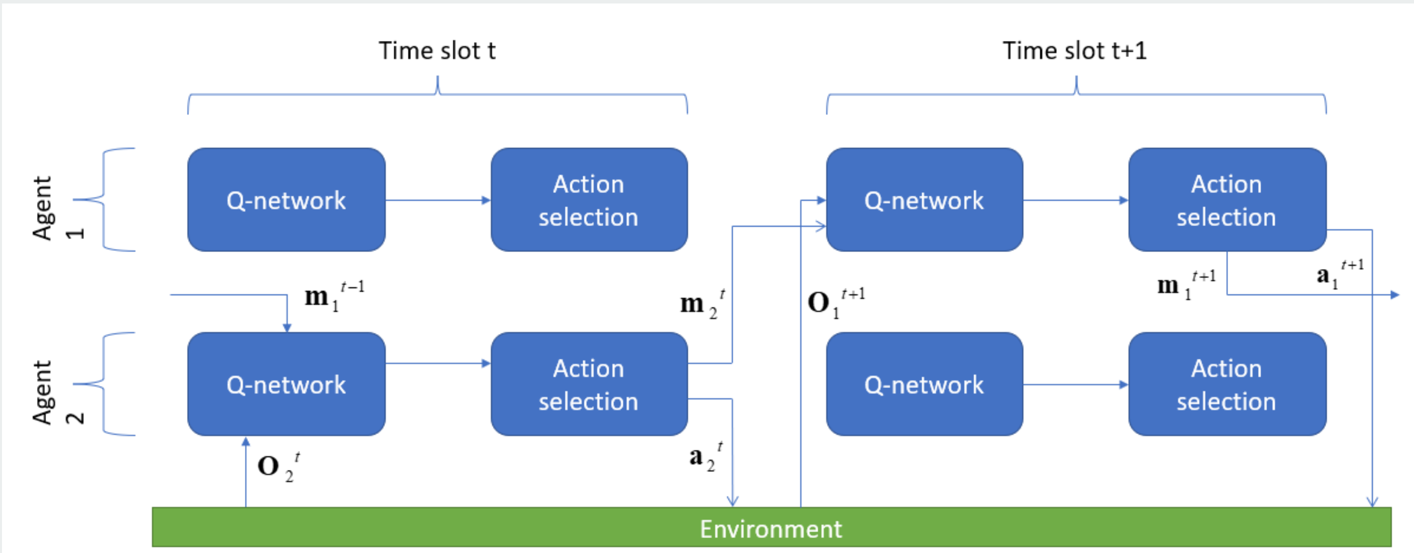
$$P_{m'_{k'},p} \le P_p, \forall m', k'$$

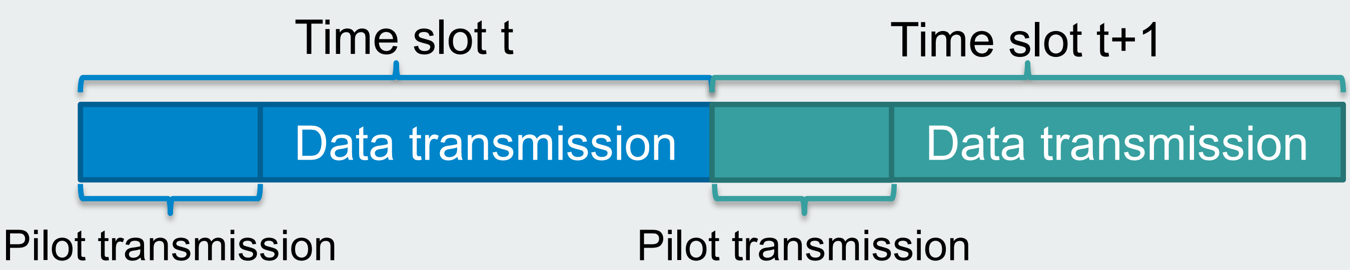
$$R^t_{m_k} = \log(1 + \gamma^t_{m_k}(\mathbf{W}^t))$$

$$\gamma^t_{m_k}(\mathbf{W}^t) = \frac{|(\mathbf{h}^t_{m_k,k})^H \mathbf{w}_{m_k}|^2}{\sum_{m' \neq m} |(\mathbf{h}^t_{m_k,k})^H \mathbf{w}_{m'_k}|^2 + \sum_{j \neq k, m' \neq m} |(\mathbf{h}^t_{m_k,j})^H \mathbf{w}_{m'_j}|^2 + \sigma^2}$$

- The accurate CSI is not available
- Pilot power affects the accuracy of channel estimation and thus the system performance
- Agents need to make decision based on the environment feedback after pilot transmission

Connection between learn-to-communicate and pilot power control





J. Foerster, Y. M. Assael, N. de Freitas, and S. Whiteson, “Learning to communicate with deep multi-agent reinforcement learning,” in Proc. Neural Information Processing Systems, 2016, pp. 2137–2145.

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Pilot power control via learn-to-communicate MARL

- The pilot transmit power is seen as communication message between agents, i.e., $\boldsymbol{m}_i^t$ in the figure.

- The precoding vectors and pilot transmit power are determined by the deep Q networks.

- At each time slot t, the agent decides the precoding vectors in the current time slot t and the pilot transmit power in the next time slot t+1.

Next steps

- Constructing the reinforcement learning environment
- Realize some baselines and the learn-to-communicate MARL
- Apply the coach-agent method to this system

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Thank you!