Deep Learning in Physical Layer Communications

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Outline

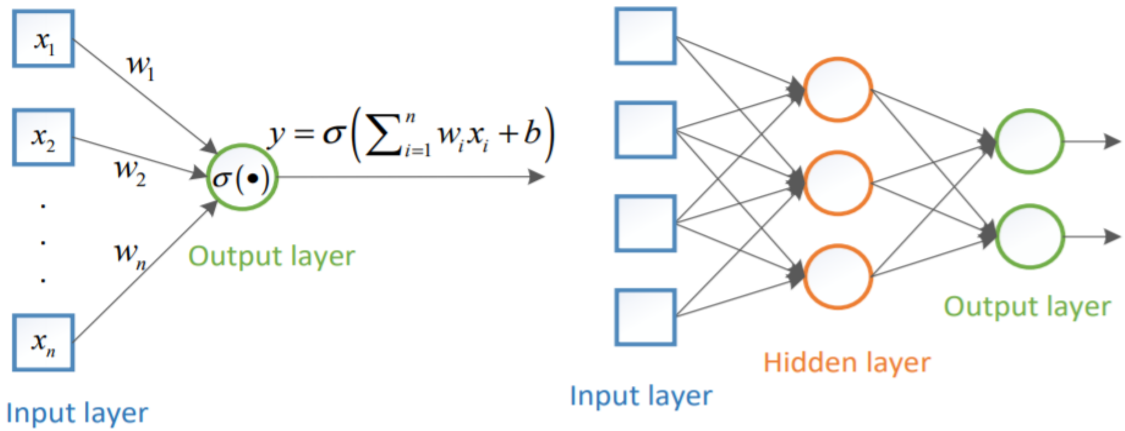
- Motivation
- Wireless Systems with Block Structure
- End-to-End Wireless Systems

Motivation

- **Challenges in current communication systems**
  - Mathematical channel models versus practical channel imperfection
  - Block structures versus global optimality
  - Effective signal processing algorithms versus low costs
- **Why deep learning?**
  - Data-driven method, no need for channel models
  - End-to-end loss optimization for global optimality
  - Concurrent architectures, suitable in fast-developing parallelized processing architectures

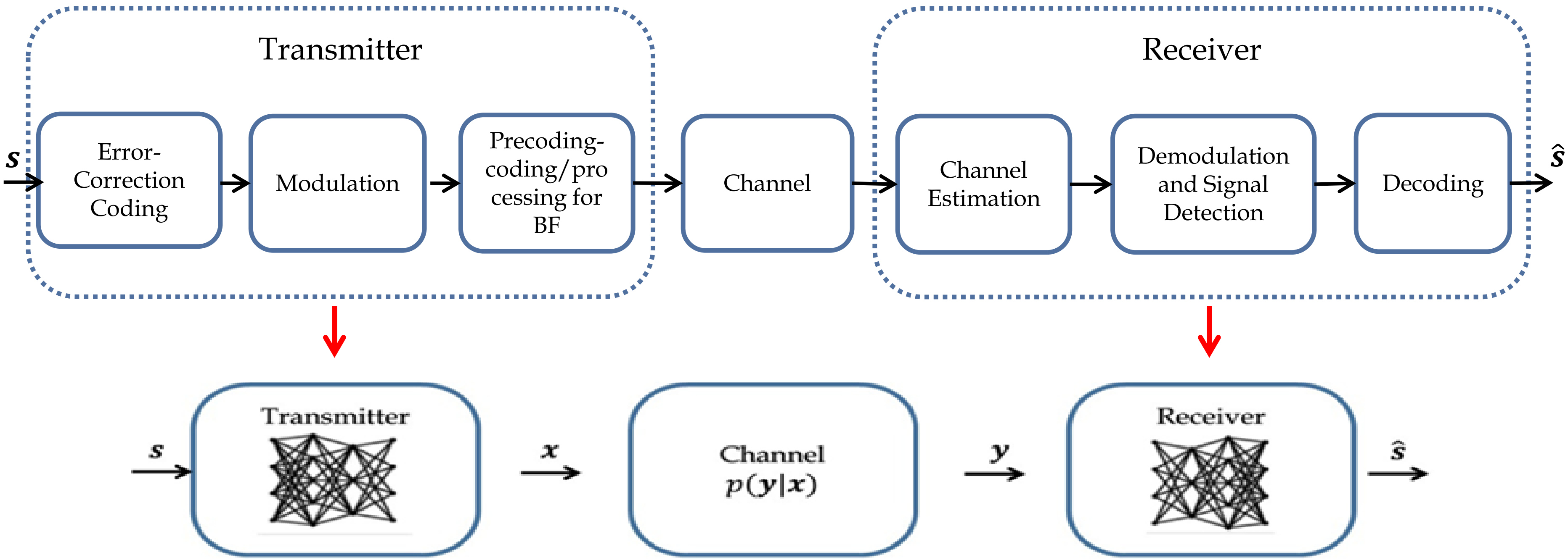
Z.-J. Qin, H. Ye, G. Y. Li, and B.-H. Juang, "Deep learning in physical layer communications," submitted to *IEEE Commun. Mag.*, July 2018.

DNN



- **Neurons: nonlinear function of a weighted sum of the outputs of neurons in preceding layers**
- **Minimize a loss function by adjusting the weight on training set**
- **Deep Neural Networks: with more than one layer**

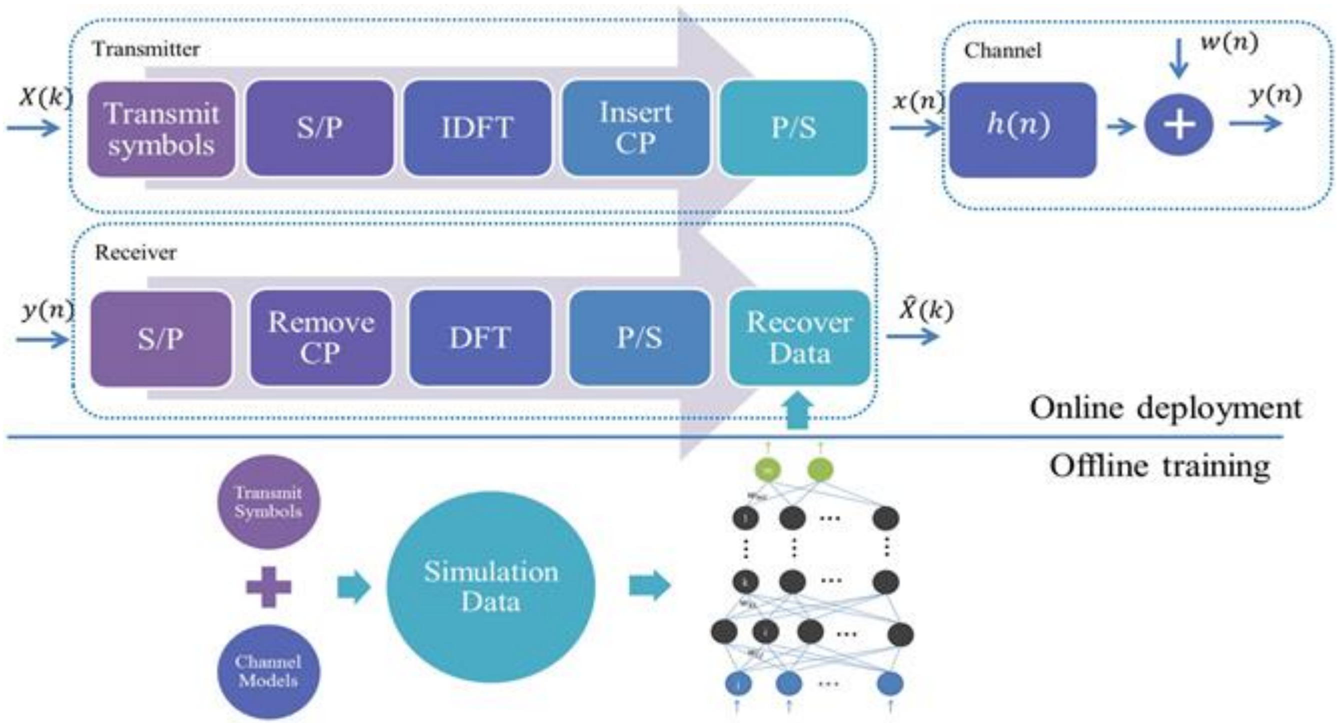
Block Structure or End-to-End?



Wireless Systems with Block Structure

- **Joint channel estimation and detection**
- **MIMO detection using deep learning**

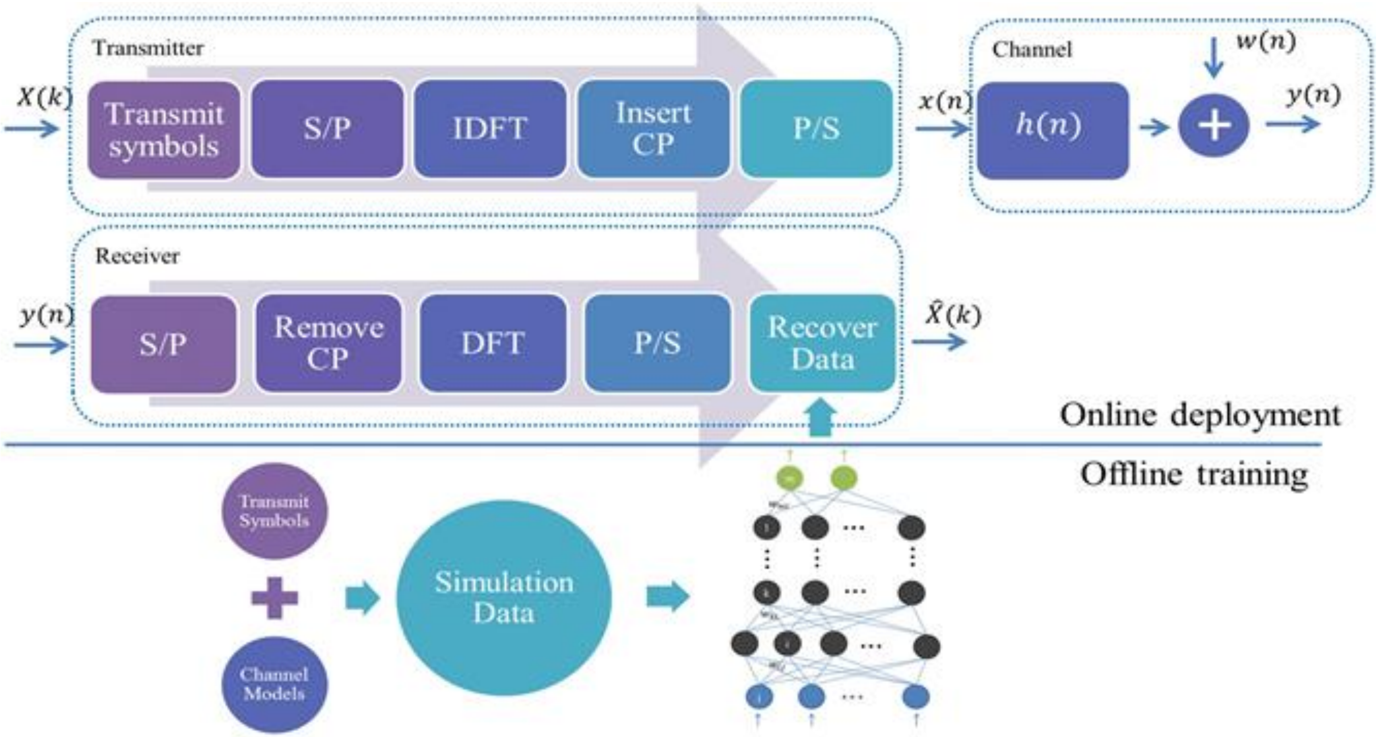
Joint Channel Estimation and Signal Detection



- ➢Pilot OFDM block + data OFDM block
- ➢Channel varying frame-to-frame, constant over pilot and data blocks

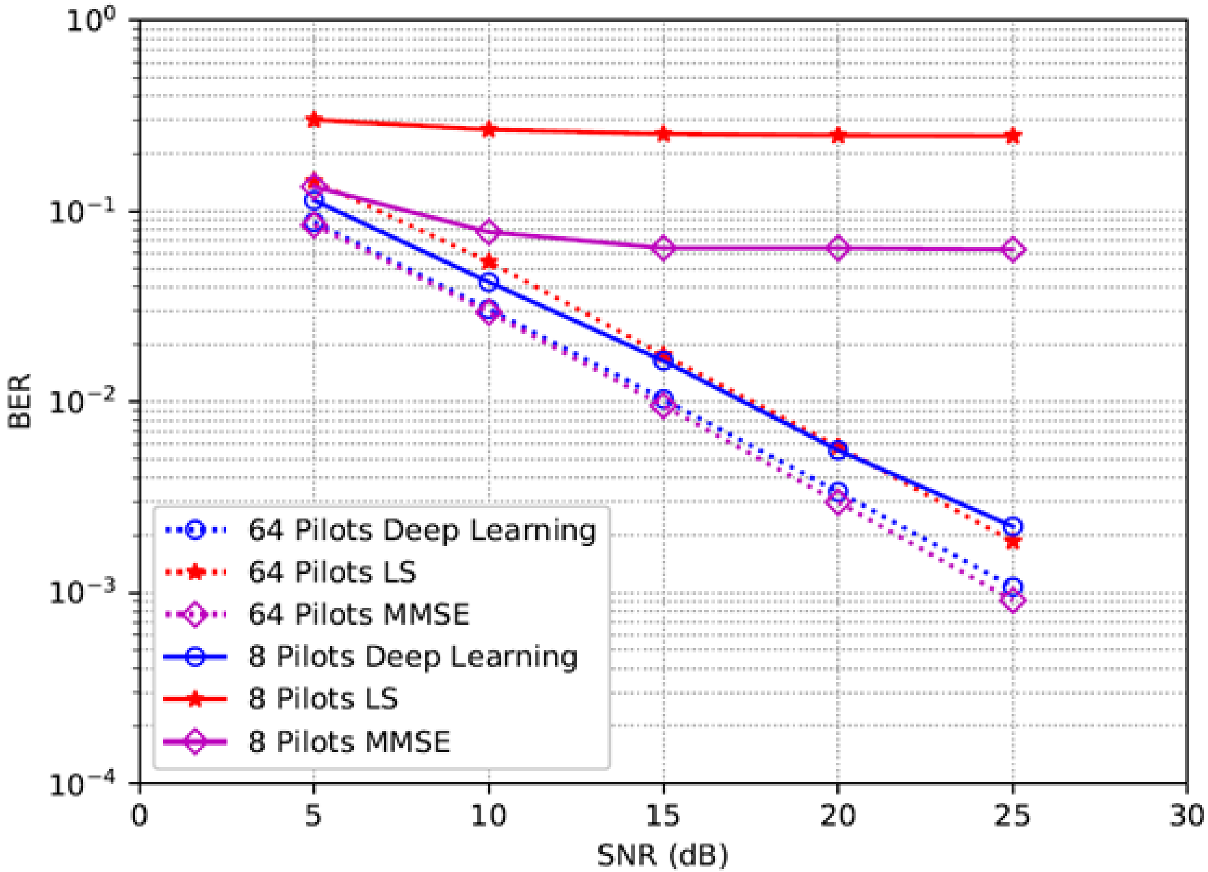
H. Ye, G. Y. Li, and B.-H. F. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE WCL*, vol. 7, no. 1, pp. 114 – 117, Feb. 2018.

DNN Model Training



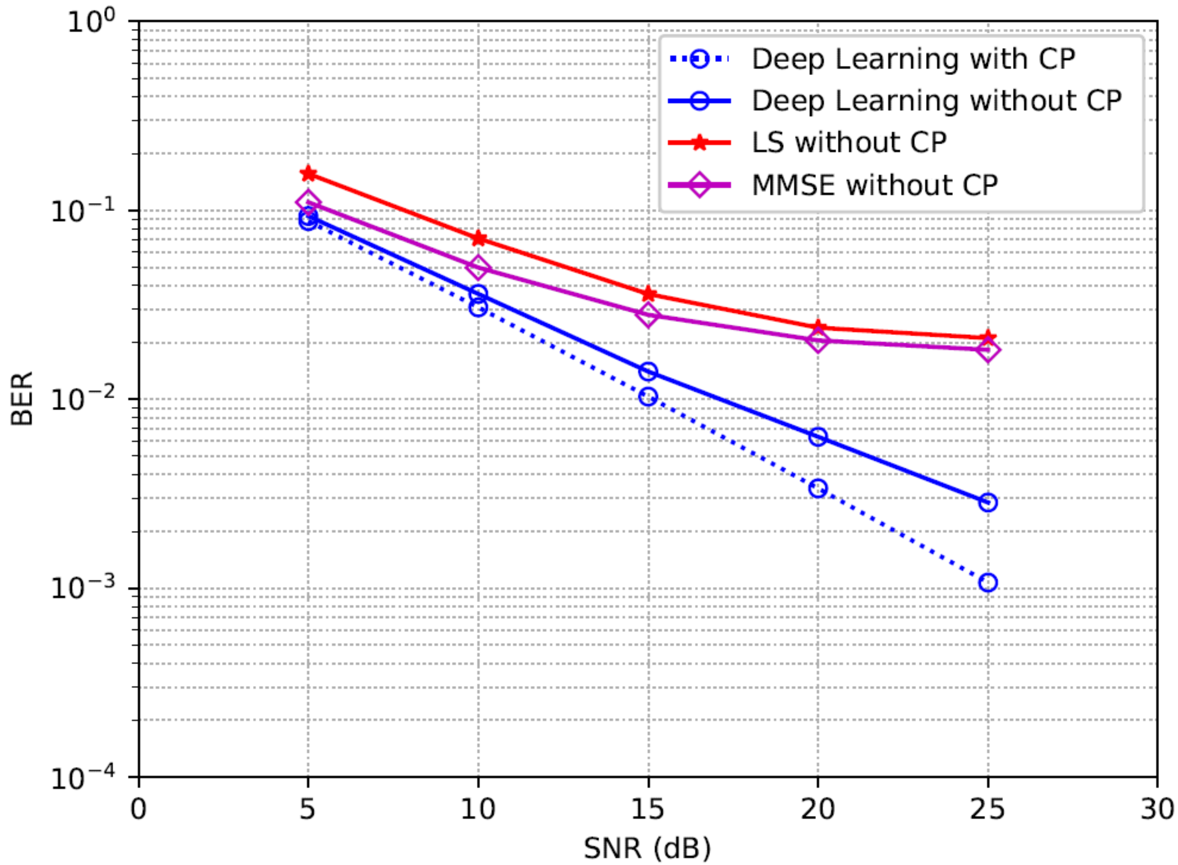
- ➢Training to predict the transmit data
- ➢Training with received OFDM samples generated under diverse channel conditions
- ➢Optimizing parameters to minimize distance of model output and transmit data

Impact of Pilot Number



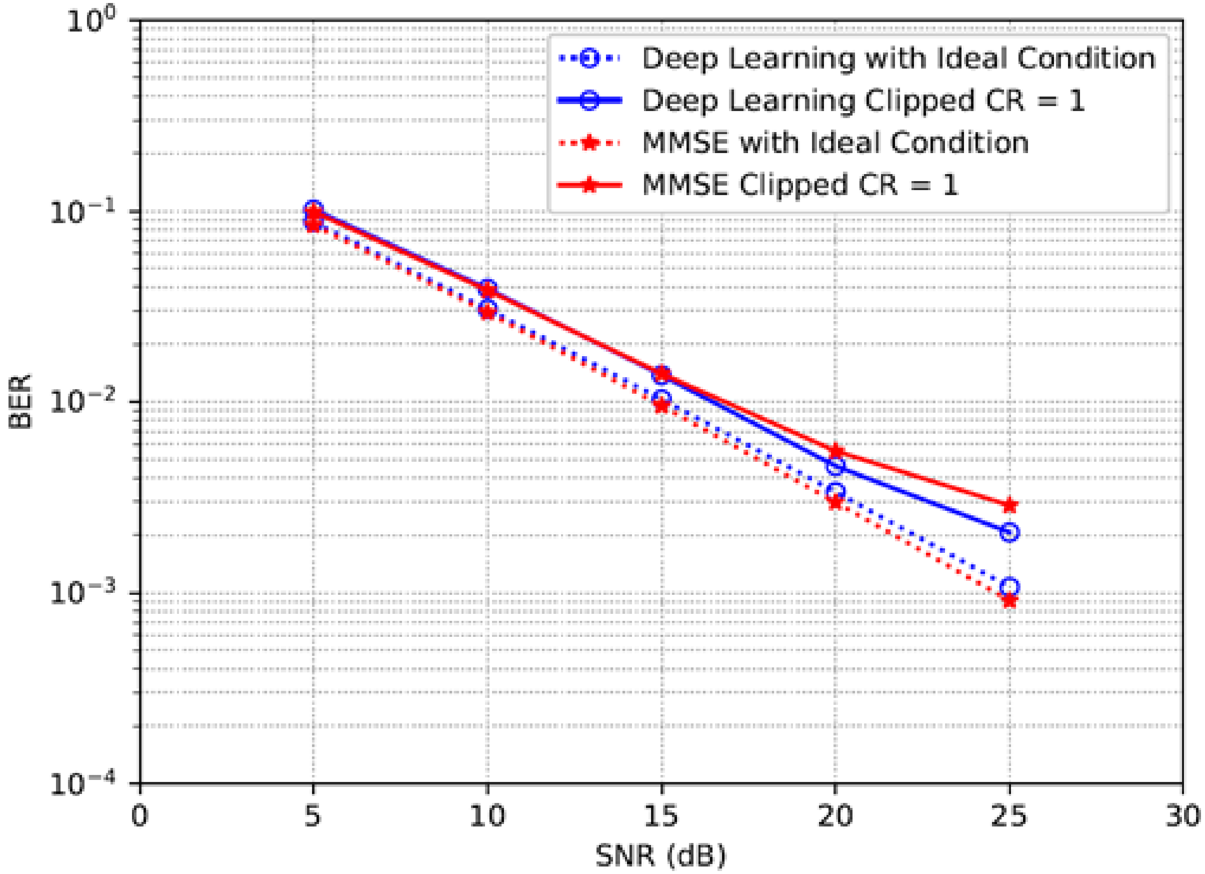
- Better than LS; comparable to MMSE
- Better than MMSE with 8 pilots

Impact of Cycle Prefix



- Conventional methods: error floor when SNR over 15 dB
- Deep learning method: robust to CP removal

Impact of Clipping Noise



- Clipping and filtering: reducing PAPR but introducing nonlinear noise
- Better than MMSE when SNR over 15 dB
- More robust to the nonlinear clipping noise

Machine Learning for Communication Blocks

- **Joint channel estimation and detection**
- **MIMO detection using deep learning**

Deep Learning for MIMO

- MIMO Detection:

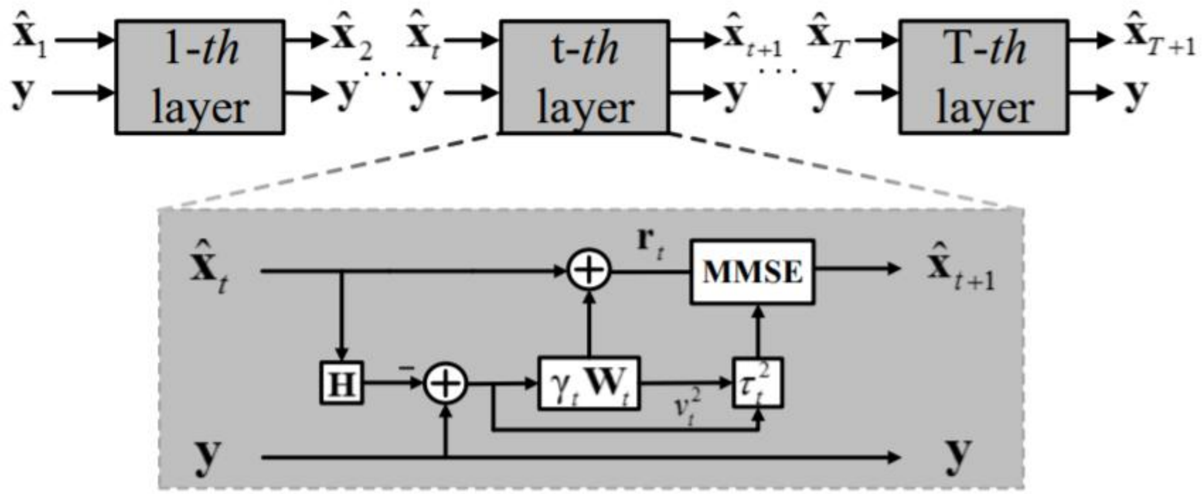
$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$$

- Goal: estimate **x** from received signal **y** and channel matrix **H**
- Conventional Detectors:
  - Optimal detector: ML detector, optimal detector, high complexity
  - Linear detectors: ZF,LMMSE, low complexity, poor performance
  - Iterative detectors: AMP-based detection, EP-based detector, excellent performance, moderate complexity, performance degradation with ill-conditioned channel matrix
- Motivation: deep learning improve performance of iterative detectors

H.-T. He, C.-K. Wen, S. Jin, and G. Y. Li "A model-driven deep learning approach for MIMO systems," submitted to *IEEE GlobalSIP'18* , Anaheim, CA, Dec. 2018.

OAMP-Net

Architecture



Math Iteration:

$$\mathbf{r}_t = \hat{\mathbf{x}}_t + \gamma_t \mathbf{W}_t(\mathbf{y} - \mathbf{H}\hat{\mathbf{x}}_t),$$

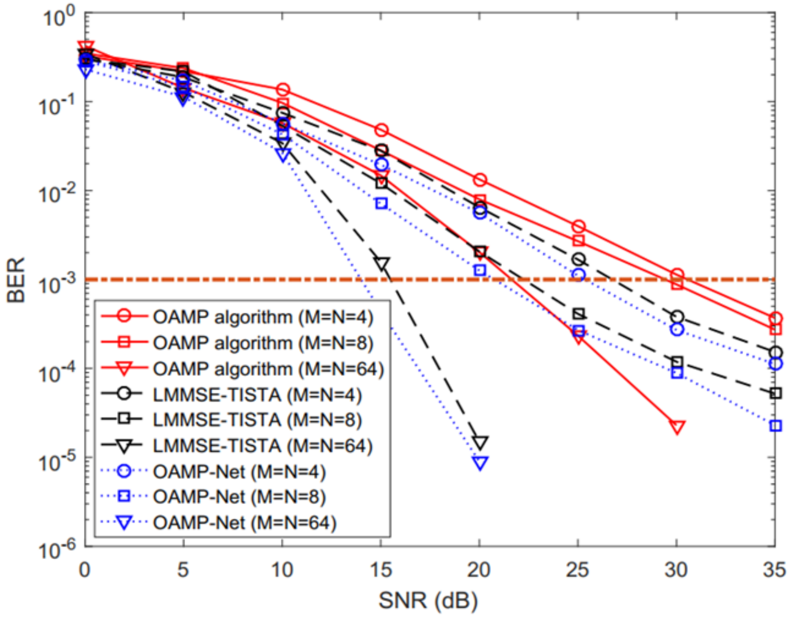
$$\hat{\mathbf{x}}_{t+1} = \mathbb{E}\left\{\mathbf{x} \middle| \mathbf{r}_t, \tau_t\right\},$$

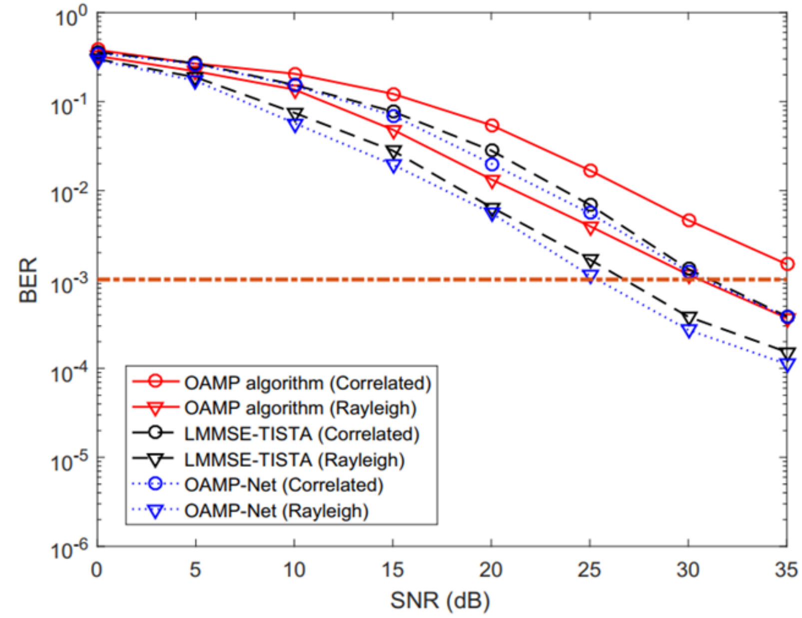
$$v_t^2 = \frac{\|\mathbf{y} - \mathbf{H}\hat{\mathbf{x}}_t\|_2^2 - M\sigma^2}{\mathrm{tr}(\mathbf{H}^T\mathbf{H})},$$

$$\tau_t^2 = \frac{1}{2N}\mathrm{tr}(\mathbf{C}_t\mathbf{C}_t^T)v_t^2 + \frac{\theta_t^2\sigma^2}{4N}\mathrm{tr}(\mathbf{W}_t\mathbf{W}_t^T).$$

Trainable Variables (only two!): (γ_t, θ_t)

Similation Results

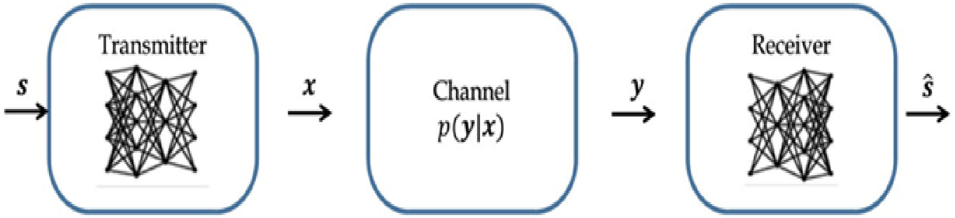




- OAMP-Net outperform the OAMP algorithm and LMMSE-TISTA network
- OAMP-Net obtain more performance gain under correlated channels
- Number of trainable variables is 2 *times of iteration number* and independent of the number of antennas *N* and *M*

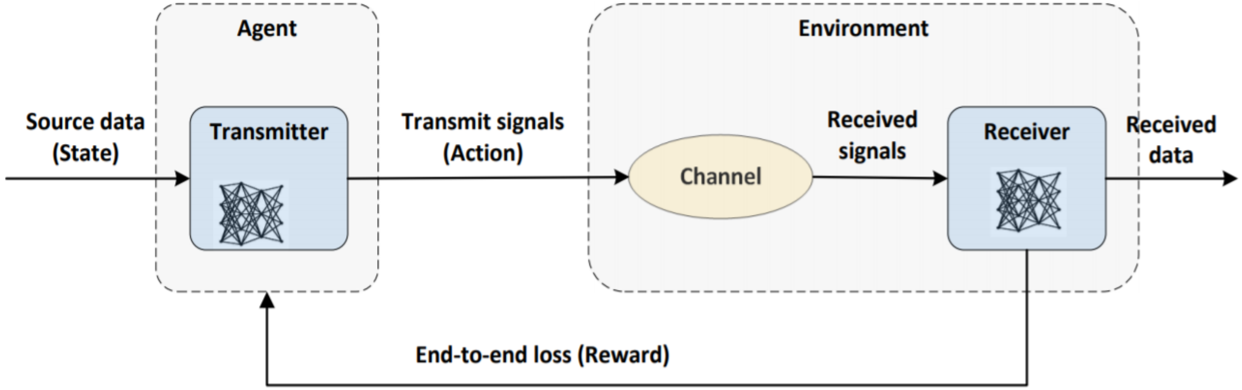
End-to-End Learning based Communications

- Background
  - Transmitter learns to encode the transmitted data into x
  - Receiver leans to recover the transmitted data based on y
- Challenges:
  - Channel transfer function is unknown
  - Channel is time-varying
- Approaches:
  - Reinforcement Learning
  - Conditional GAN



H. Ye, G. Y. Li, B.-H. Juang, and K. Sivanesan, "Channel agnostic end-to-end learning based communication systems with conditional GAN," submitted to *IEEE Global Commun. Conf.*, Abu Dhabi, UAE, Dec. 2018.

E2E based on Reinforcement Learning



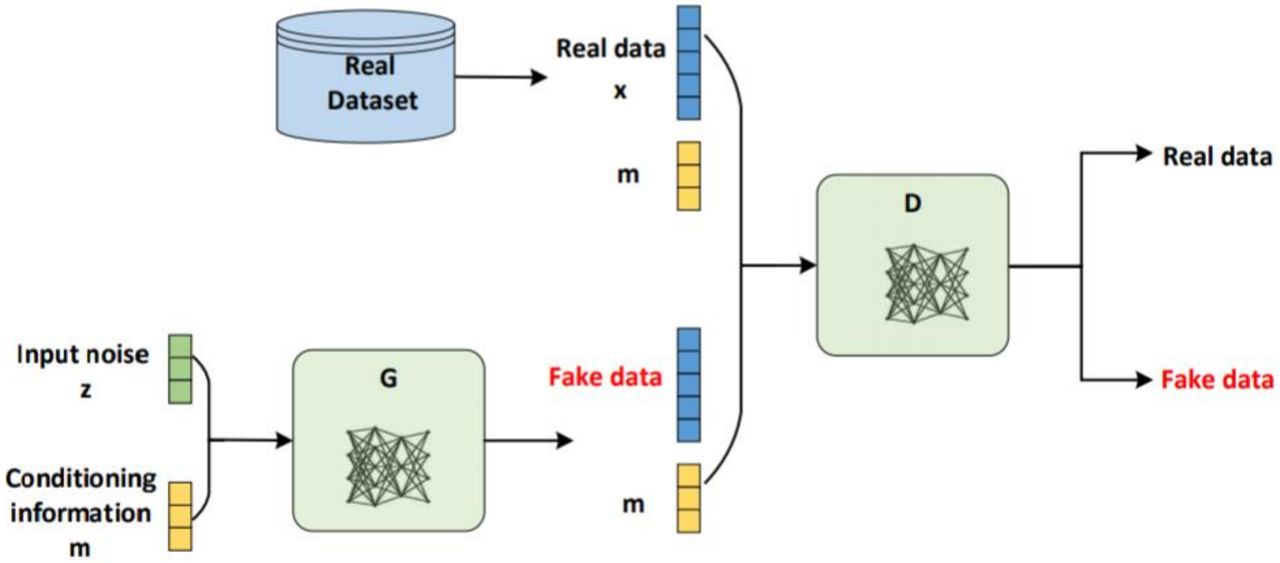
❑ **Reinforcement Learning Formation:**

- Agent: transmitter
- Environment: channel and receiver
- States: source data
- Actions: transmit signals

❑ **Advantage and Disadvantage:**

- Channel model is unnecessary
- Reinforcement learning for continuous action space is hard

E2E based on Conditional GAN



- ❑ **GAN:**

  - Generator: maps an input noise, **z**, to a sample
  - Discriminator: maximizes the ability to distinguish between the two categories

- ❑ **Conditional GAN:**

  - Both G and D are conditioned on some extra information, **m**

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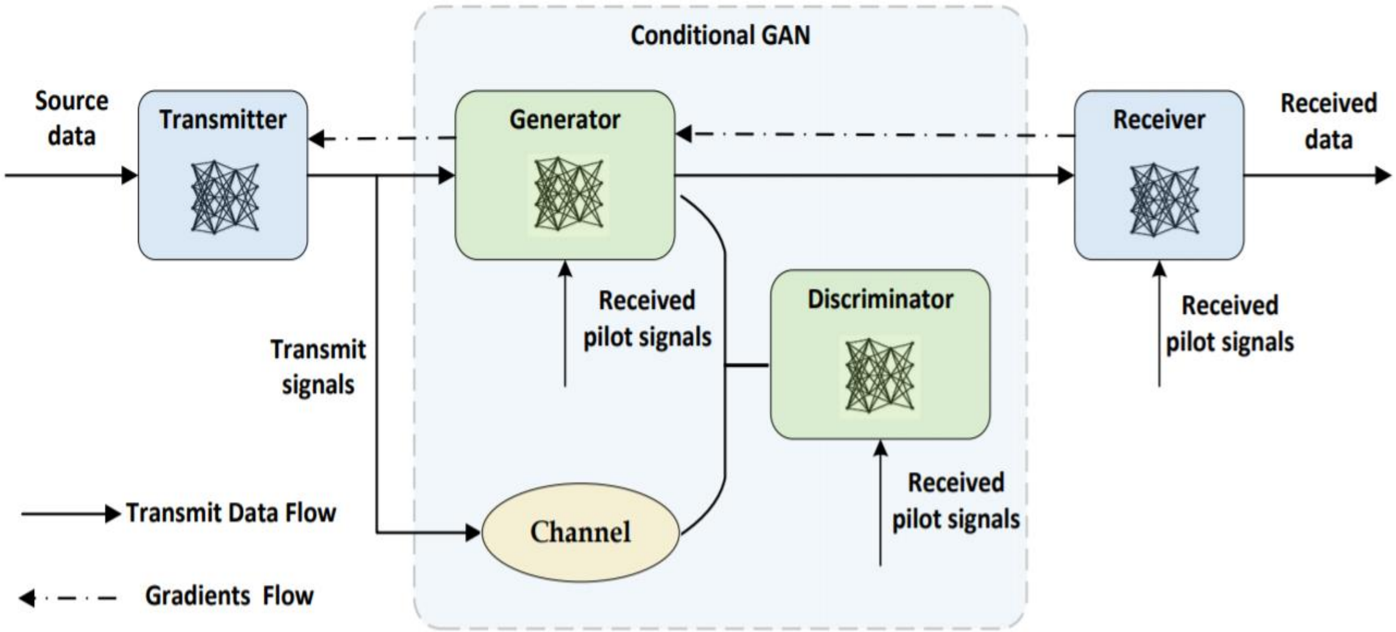
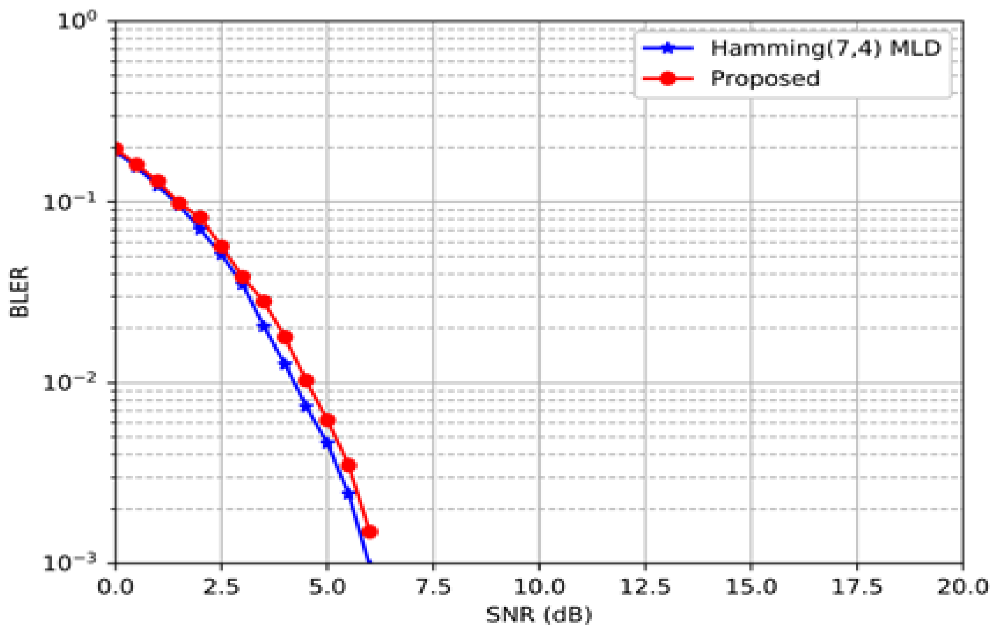
E2E based on Conditional GAN

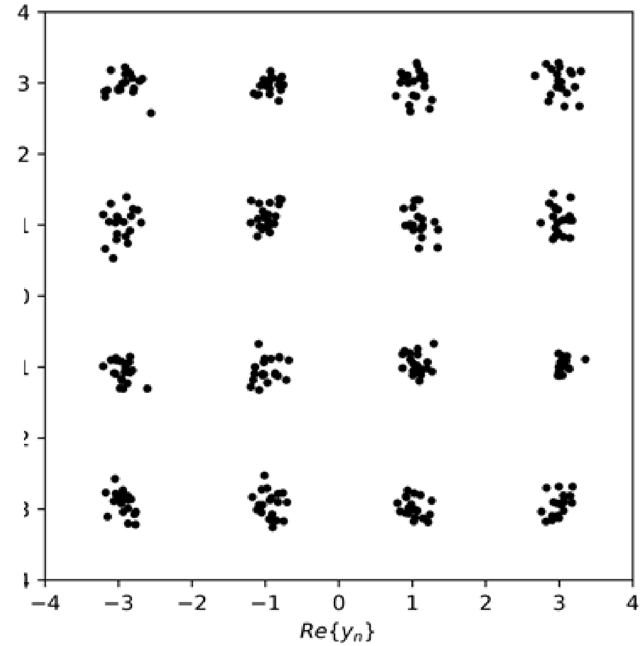


- Conditional GAN: model the channel output distribution
- Surrogate of the real channel when training the transmitter
- Received pilots as a part of conditioning for time-varying channel

Simulation Results: AWGN Channels

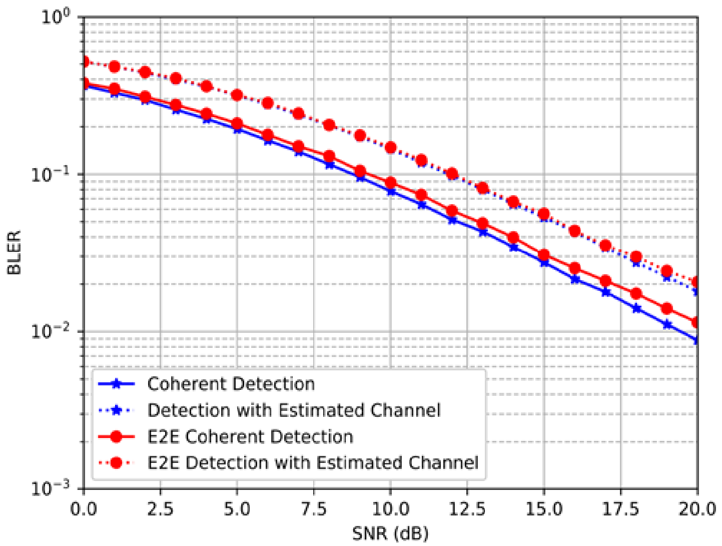
- Similar to AWGN with standard 16 QAM input
- Similar to hamming(7,4) with MLD

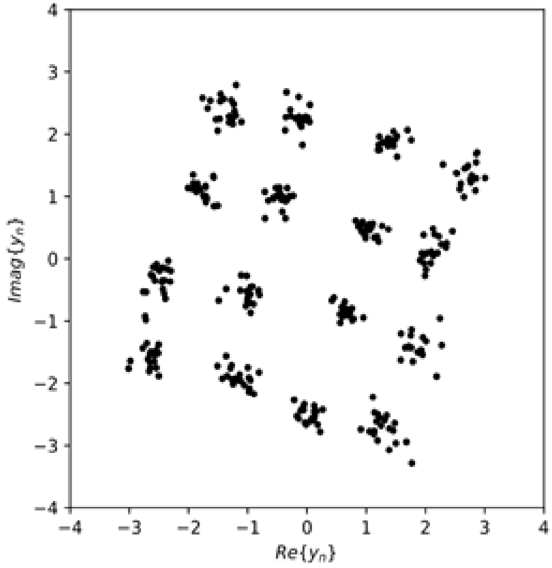


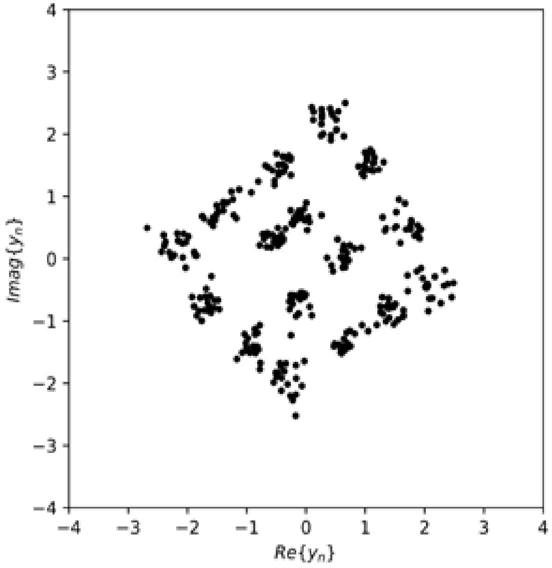


Simulation Results: Rayleigh Fading Channels

- ➢ **Learn to generate samples with different instantaneous h**
- ➢ **Similar E2E result in coherent detection and joint detection and channel estimation**







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Conclusions and Future Topics

- **Conclusions:**
  - Learning for improving blocks in communication systems
  - Learning for novel end-to-end communicaiton archietecture

- **Future Directions:**
  - Deep learning based physical layer security
  - Tradeoff between system performance and training efficiency
  - Communication metric learning
  - Open access real-world data sets

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Thank you!