Deep Learning for Future Wireless Communications

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ITP Lab Intelligent Transmission & Processing Laboratory
Imperial College London

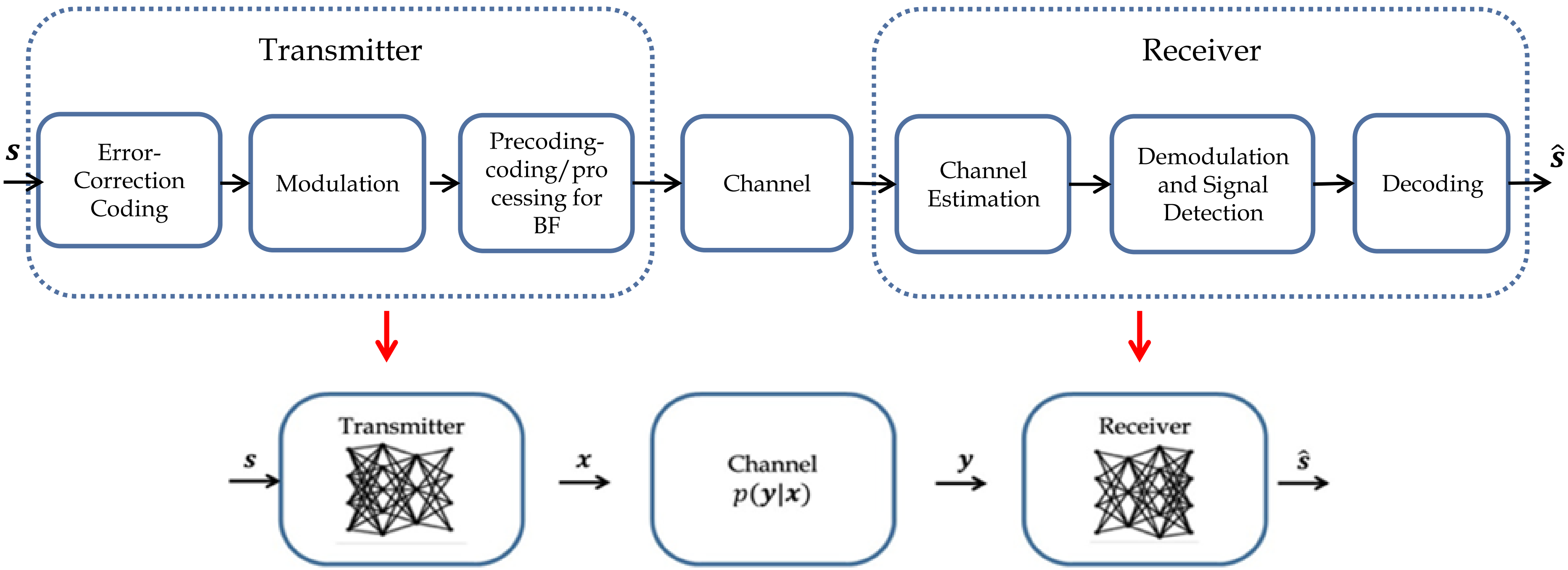
Outline

I. **Motivation**
II. Physical Layer Processing
III. Resource Allocation
IV. DL-enabled Semantic Communications
V. Communications and Federated Learning
VI. Conclusion Remarks

Motivation

- **Challenges in current communication systems**
  - Mathematical models versus practical imperfection
  - Block structures versus global optimality
  - Complexity and performance of optimization
  - Sequential decision in resource allocation
- **Why deep learning?**
  - No need for models for data-driven method
  - End-to-end loss optimization for global optimality
  - Reducing complexity and improve performance of physical layer processing and resource allocation

Block Structure or End-to-End?



- Z.-J. Qin, H. Ye, G. Y. Li, and B.-H. Juang, "Deep learning in physical layer communications," *IEEE Wireless Commun.*, vol. 26, no. 2, pp. 93-98, April 2019.
- H.-T. He, S. Jin, C.-K. Wen, F.-F. Gao, G. Y. Li, and Z.-B. Xu, "Model-driven deep learning for physical layer communications," *IEEE Wireless Commun*, vol. 26, no. 5, pp. 77- 83, Oct. 2019.
- W. Tong and G. Y. Li "Nine critical issues in AI and wireless communications to ensure successful 6G," *IEEE Wireless Commun.*, vol. 29, no. 4, pp. 140 – 145, Aug. 2022.

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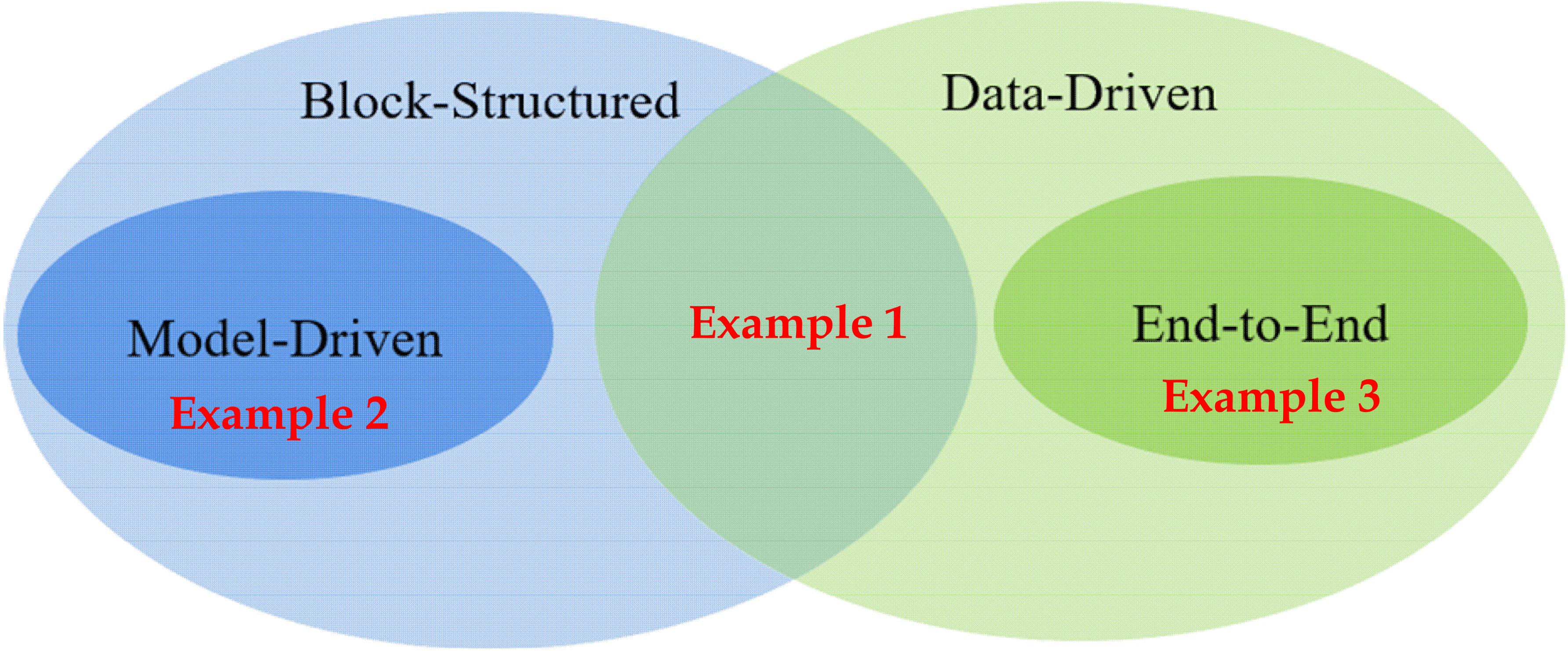
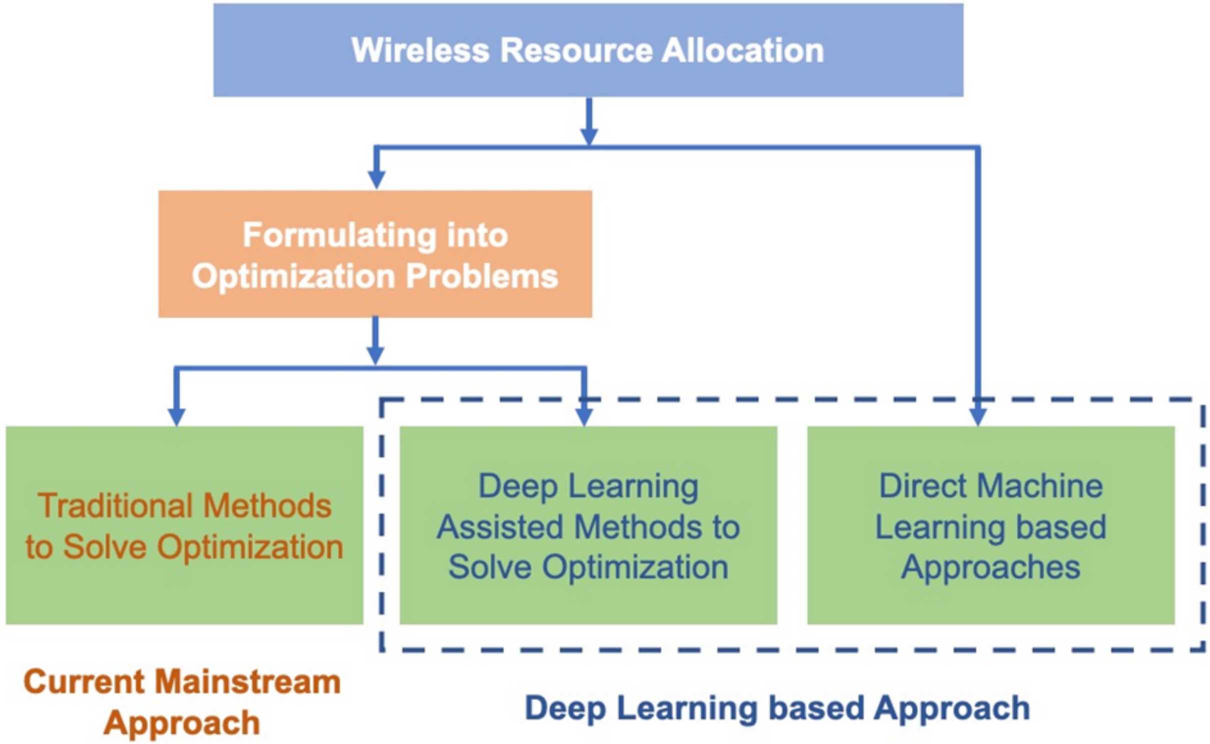
DL in Physical Layer Communications



Example 1: H. Ye, G. Y. Li, and B.-H. F. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 1, pp. 114 – 117, Feb. 2018.
Example 2: H.-T. He, C.-K. Wen, S. Jin, and G. Y. Li, "Model-driven deep learning for MIMO detection," *IEEE Trans. Signal Process.*, vol. 68, pp. 1702-1715, March 2020.
Example 3: H. Ye, L. Liang, G. Y. Li, and B.-H. F. Juang, "Deep learning-based end-to-end wireless communication systems with GAN as unknown channels," *IEEE Trans. Wireless Commun.*, vol. 19, no. 5, pp. 3133-3143, May 2020.

DL for Wireless Resource Allocation



- L. Liang, H. Ye, G.-D. Yu, and G. Y. Li, "Deep learning based wireless resource allocation with application in vehicular networks," *Proc. IEEE*, vol. 108, no. 2, pp. 341-356, Feb. 2020.
- H. Ye, G. Y. Li, B.-H. F. Juang, "Deep reinforcement learning based resource allocation for V2V communications," *IEEE Trans. Veh. Tech.*, vol. 68, no. 4, pp. 3163-3173, April 2019.

Information Content of English and Semantic Encoding

Encoding English Words Letter-by-Letter

- In English, on average there are 4.5 letters per word
- 5.5 characters per word if including space
- 5 bits to encode each letter (26 letters)
- 27.5 bits/word (5X5.5=27.5) **Need a codebook of 26 letters**

Encoding English Words Word-by-Word

- 171,476 English words (from Google)
- 18 bits/word ($2^{17} < 171{,}476 < 2^{18}$) **Need a codebook of 171,476 words**

Encoding English Semantically

- For example, only 1 bit if answering a YES or NO question
- …. More Efficient! **Need an extremely huge codebook**

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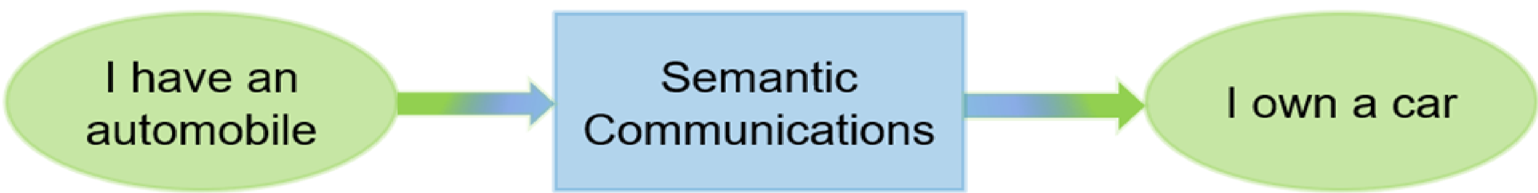
From Symbol to Semantic Transmission

- **Three Levels of Communications: Shannon and Weaver**
  - **Transmission of symbols (Shannon Paradigm)**
    following Shannon limit & well-developed near limit
  - **Semantic exchange of source information**
    semantic communications (transmission of intelligence)
  - **Effects of semantic information exchange**

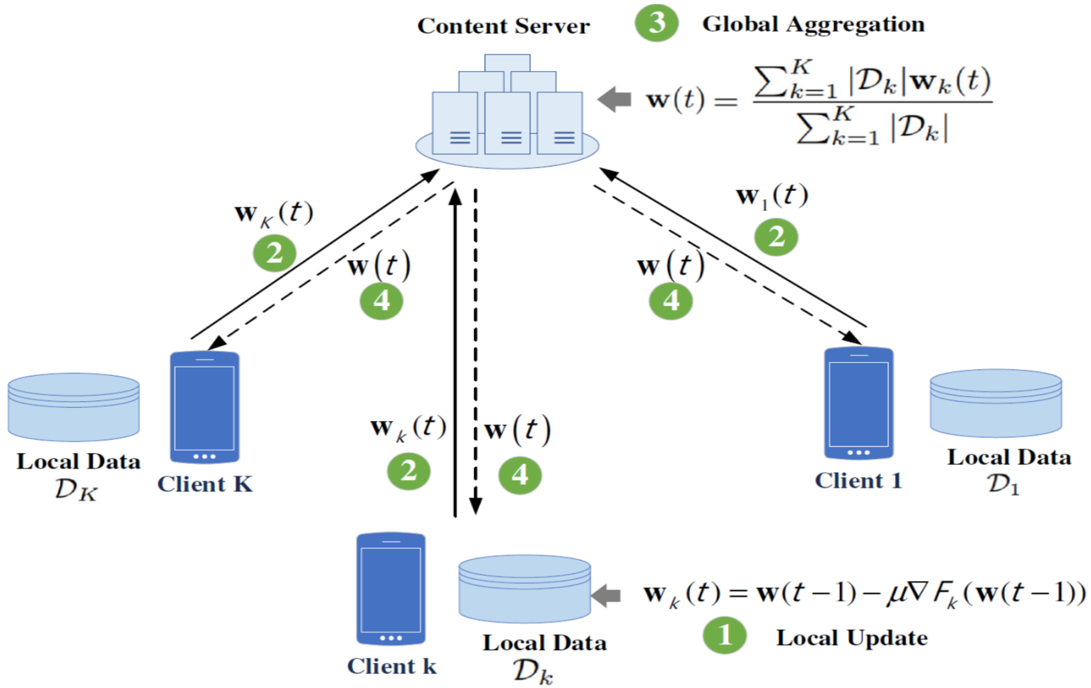
- **Semantic Communications: <u>Significantly improved efficiency</u>!**



- C. E. Shannon and W. Weaver, *The Mathematical Theory of Communication*. The University of Illinois Press, 1949.
- H. Xie, Z. Qin, G. Y. Li, and B.-H. Juang, "Deep learning enabled semantic communication systems," *IEEE Trans. Signal Process.* vol. 69, pp. 2663-2675, 2021, Apr. 2021.

Communications for AI: Federated Learning

- FL enabled by and applied in communications
- What are critical applications?



➢ Z.-J. Qin, G. Y. Li, and H. Ye "Federated learning and wireless communications," *IEEE Wireless Commun.*, vol. 28, no. 5, pp. 134 – 140, Oct. 2021.

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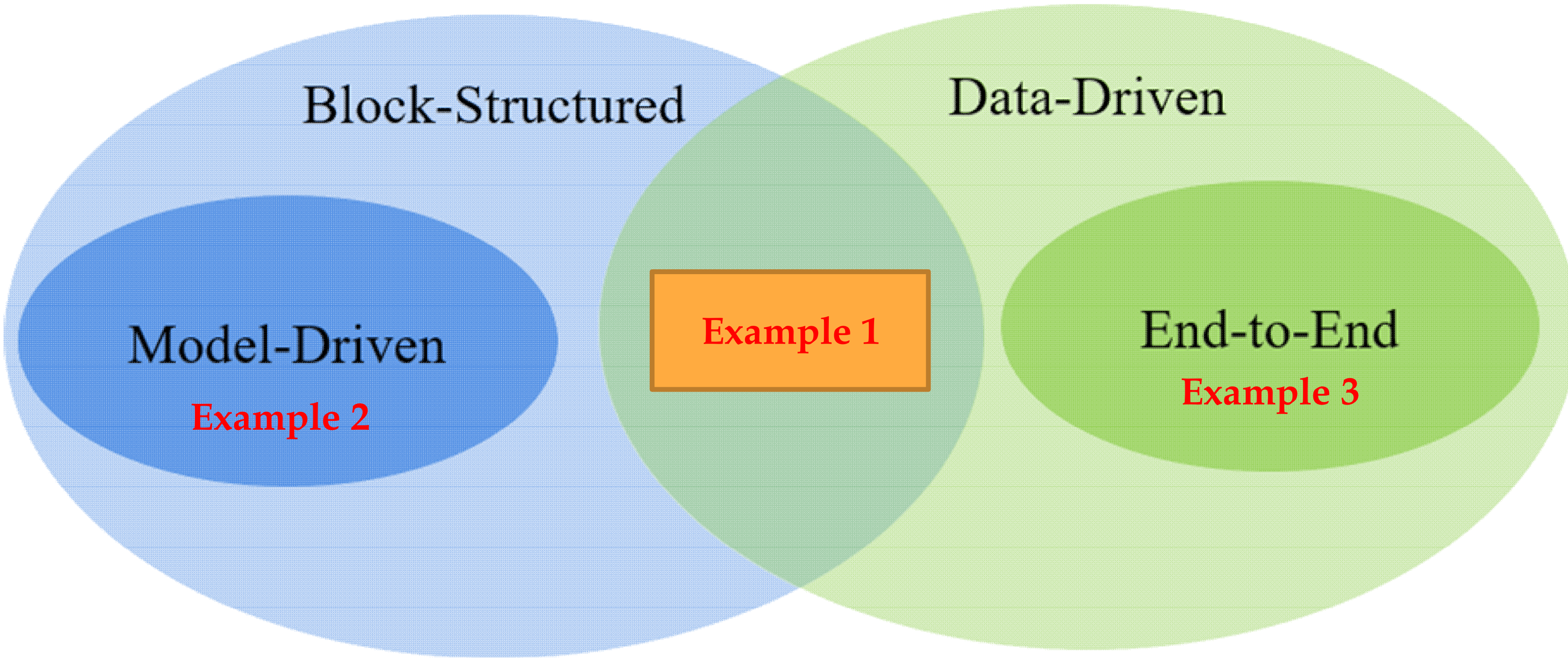
DL in for Conventional Communications



Channel Estimation (CE) and Signal Detection (SD)

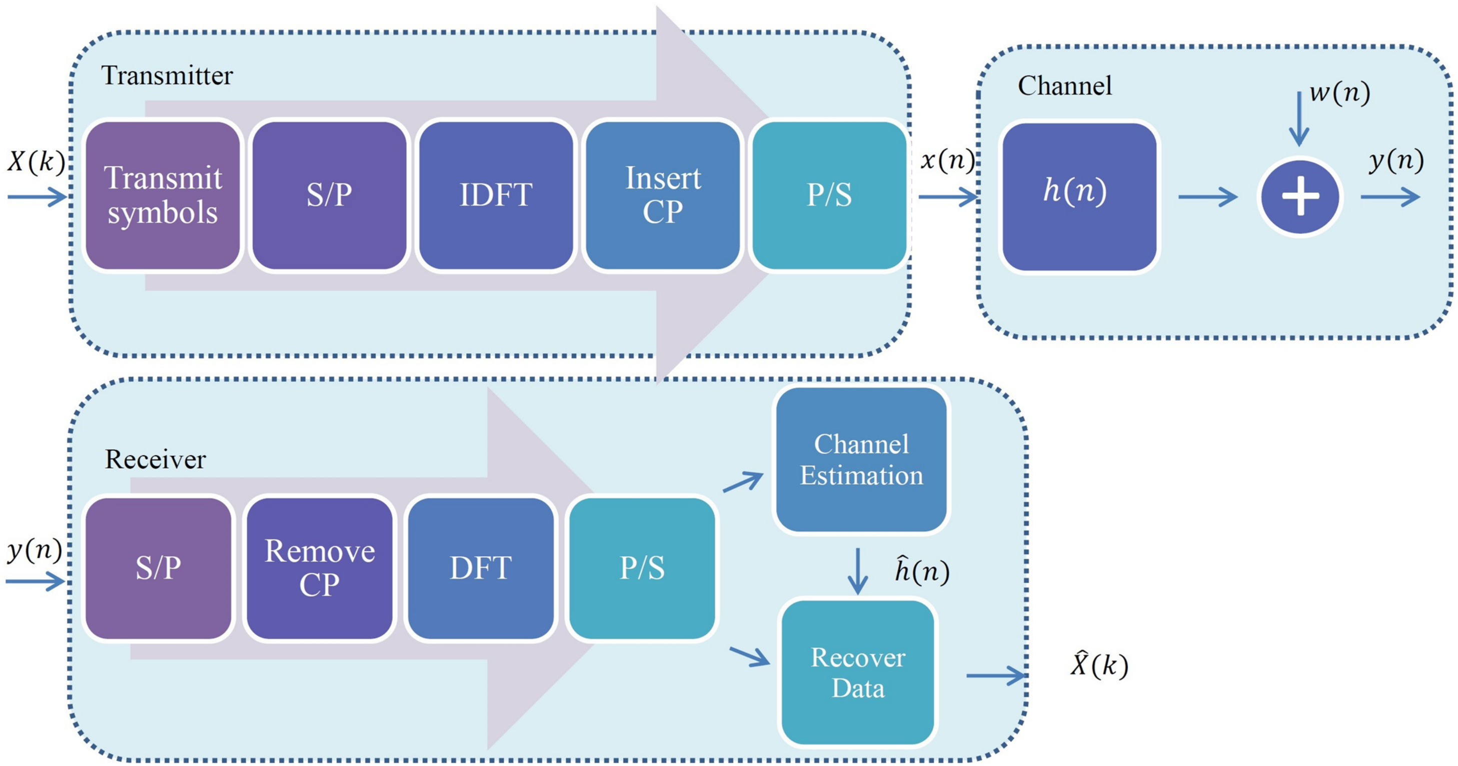
- **Related works:**
  - MMSE for channel estimation [1]
  - Neural networks and DL in equalization [2] and decoding [3]
- **Challenges:**
  - Nonlinear distortion and interference
- **Innovations:**
  - DL for joint channel estimation and symbol detection
  - DL-based method: robust and insensitive to nonlinear distortion and interference

[1] Y. G. Li, L. J. Cimini, and N. R. Sollenberger, "Robust channel estimation for OFDM systems with rapid dispersive fading channels," *IEEE Trans. Commun.*, vol. 46, no. 7, pp. 902-915, Jul. 1998.

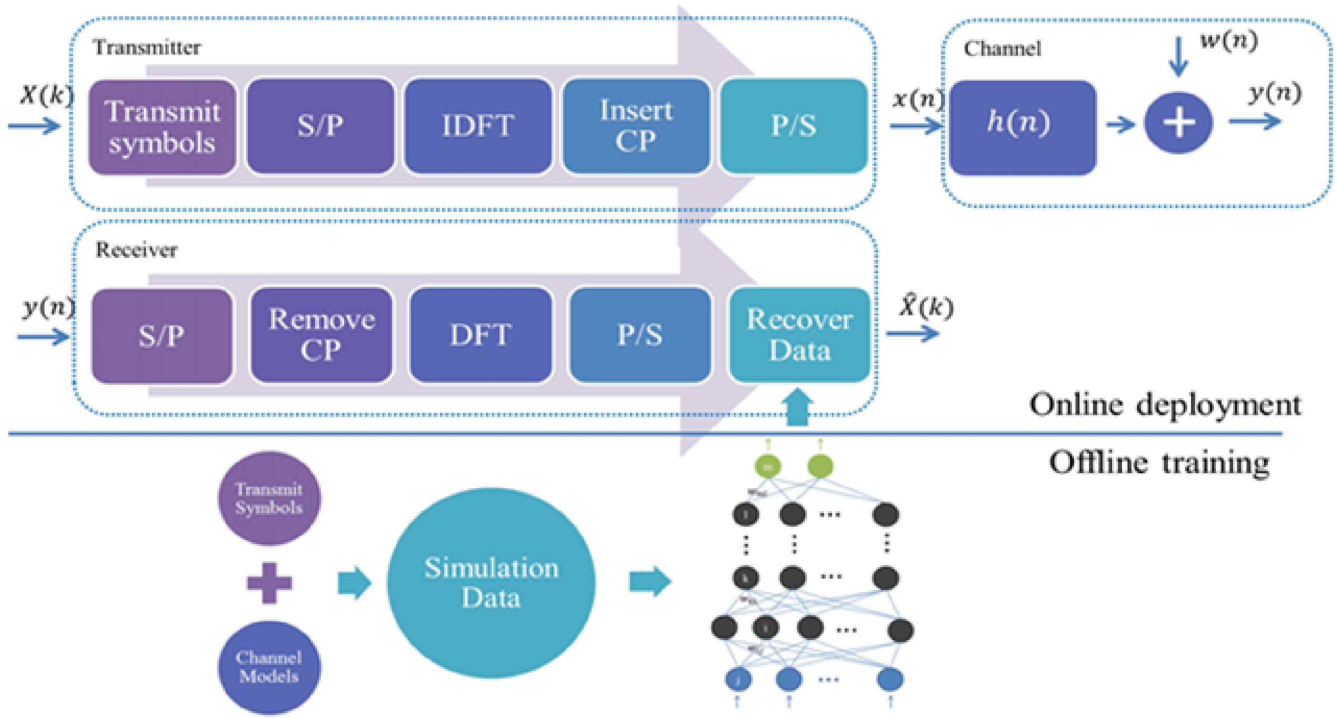
[2] S. Chen, G. Gibson, C. Cown, and P. Grant, "Adaptive equalization of finite nonlinear channels using multilayer perceptrons," *Signal Process.*, vol. 20, no. 2, pp. 107–119, Jun. 1990.

[3] E. Nachmani, Y. Beery, and D. Burshtein, "Learning to decode linear codes using deep learning," *54'th Annual Allerton Conf. On Commun., Control and Computing*, Mouticello, IL, Sept. 2016.

Traditional CE and SD



DL-based CE and SD



- ➢ Input: received pilot OFDM block + received data OFDM block
- ➢ Output: recovered data

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

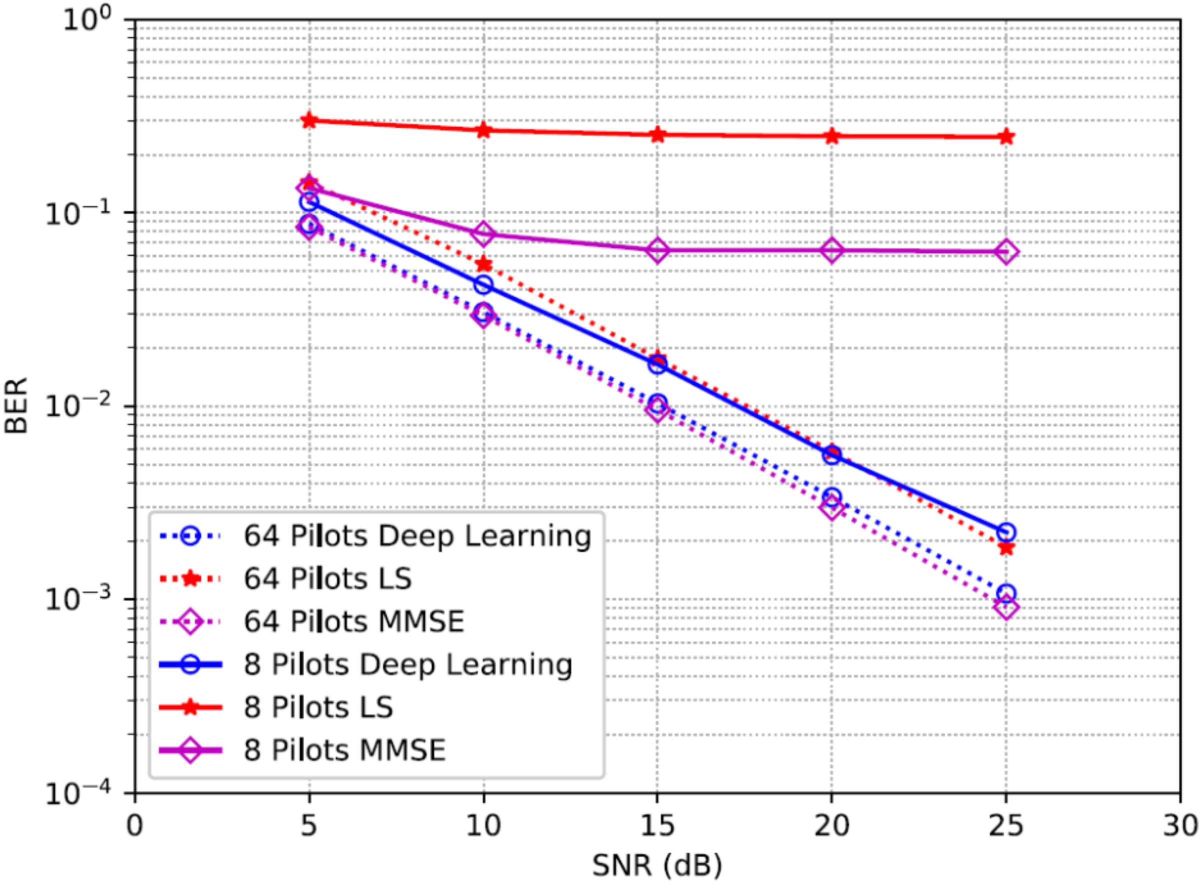
DL-based CE and SD: Impact of Pilot Number

64 pilots:

- Better than LS
- Comparable to LMMSE

8 pilots:

- Better than LMMSE



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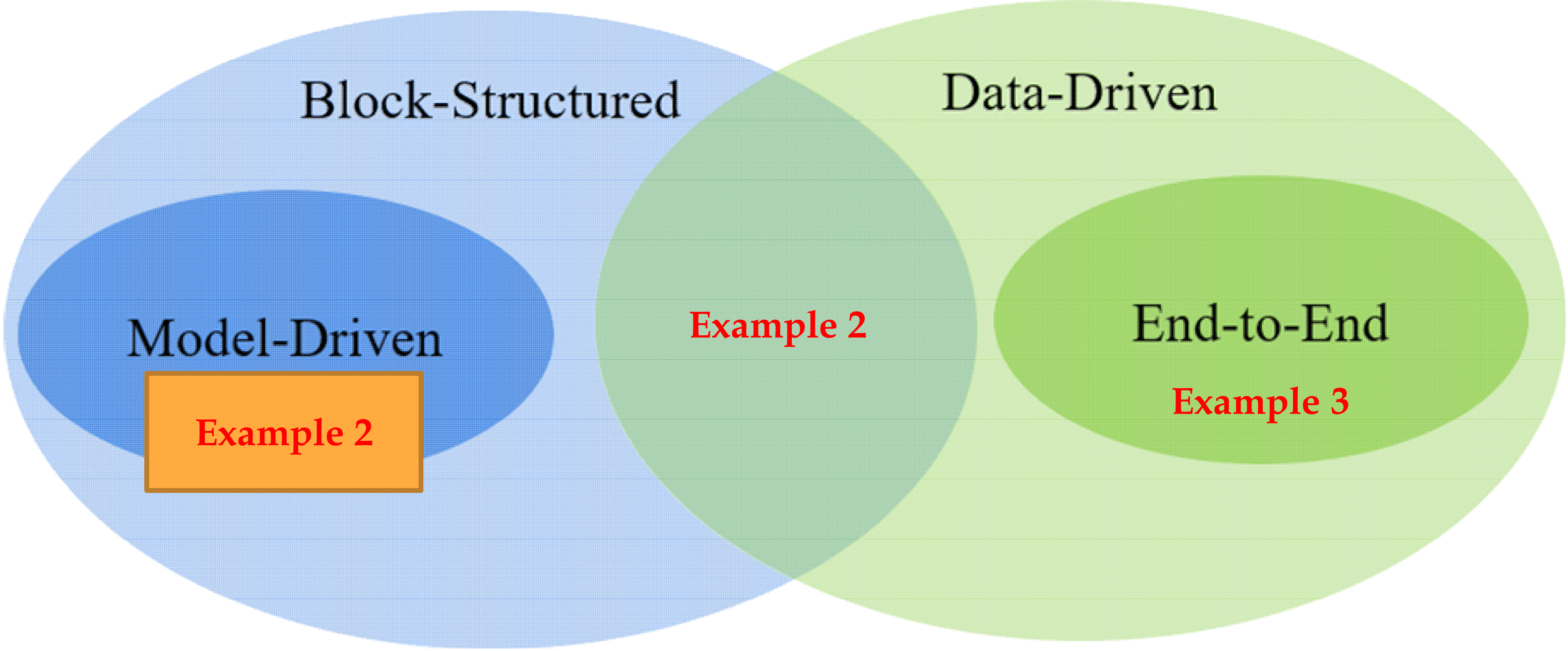
DL in for Conventional Communications



Model-Driven DL for MIMO Detection

- **MIMO System**:

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

- **Goal**: estimating $\mathbf{x}$ from received signal $\mathbf{y}$ and channel matrix $\mathbf{H}$
- **Conventional Detectors:**
  - Optimal detector: ML detector, high complexity
  - Linear detectors: ZF, LMMSE, low complexity but poor performance
  - Iterative detectors: AMP-based detector, EP-based detector, excellent performance, moderate complexity, performance degradation with ill-conditioned channel matrix
- **Motivation**: deep learning to perform iterative detection

H.-T. He, C.-K. Wen, S. Jin, and G. Y. Li, "Model-driven deep learning for MIMO detection," *IEEE Trans. Signal Process.*, vol. 68, pp. 1702-1715, March 2020.

OAMP for MIMO Detection
(Orthogonal Approximate Message Passing)

- **OAMP algorithm for MIMO detection**:

$$\hat{\mathbf{x}} = \int \mathbf{x}\mathcal{P}(\mathbf{x}|\mathbf{y}, \mathbf{H})d\mathbf{x}$$

Algorithm 1: OAMP algorithm for MIMO detection

Input: Received signal $\mathbf{y}$, channel matrix $\mathbf{H}$, noise level σ^2.

Output: Recovered signal $\mathbf{x}_t$.

Initialize: $\tau_t \leftarrow 1$, $\mathbf{x}_t \leftarrow \mathbf{0}$

$$\mathbf{r}_t = \hat{\mathbf{x}}_t + \mathbf{W}_t(\mathbf{y} - \mathbf{H}\hat{\mathbf{x}}_t), \quad (8)$$

$$\hat{\mathbf{x}}_{t+1} = \mathbb{E}\left\{\mathbf{x}|\mathbf{r}_t, \tau_t\right\}, \quad (9)$$

$$v_t^2 = \frac{\|\mathbf{y} - \mathbf{H}\hat{\mathbf{x}}_t\|_2^2 - M\sigma^2}{\mathrm{tr}(\mathbf{H}^T\mathbf{H})} \quad (10)$$

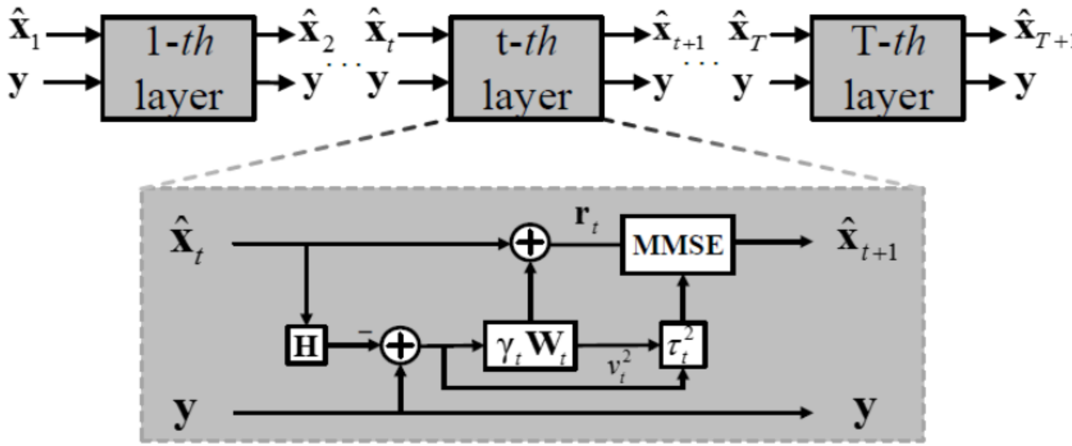
$$\tau_t^2 = \frac{1}{N}\mathrm{tr}(\mathbf{B}_t\mathbf{B}_t^T)v_t^2 + \frac{1}{N}\mathrm{tr}(\mathbf{W}_t\mathbf{W}_t^T)\sigma^2. \quad (11)$$

- **Obtained a Network by Unfolding OAMP Algorithm**

J. Ma and L. Ping, "Orthogonal OAMP," IEEE Access, vol. 5, no. 14, pp. 2020 – 2033, Jan. 2017

Modified OAMP-Net for MIMO Detection

- **Architecture:**



- **Iterative Algorithm:**

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

$$\mathbf{W}_t = \frac{2N}{\mathrm{tr}(\hat{\mathbf{W}}_t\mathbf{H})}\hat{\mathbf{W}}_t \quad \hat{\mathbf{W}}_t = v_t^2\mathbf{H}^T(v_t^2\mathbf{H}\mathbf{H}^T + \frac{\sigma^2}{2}\mathbf{I})^{-1}$$

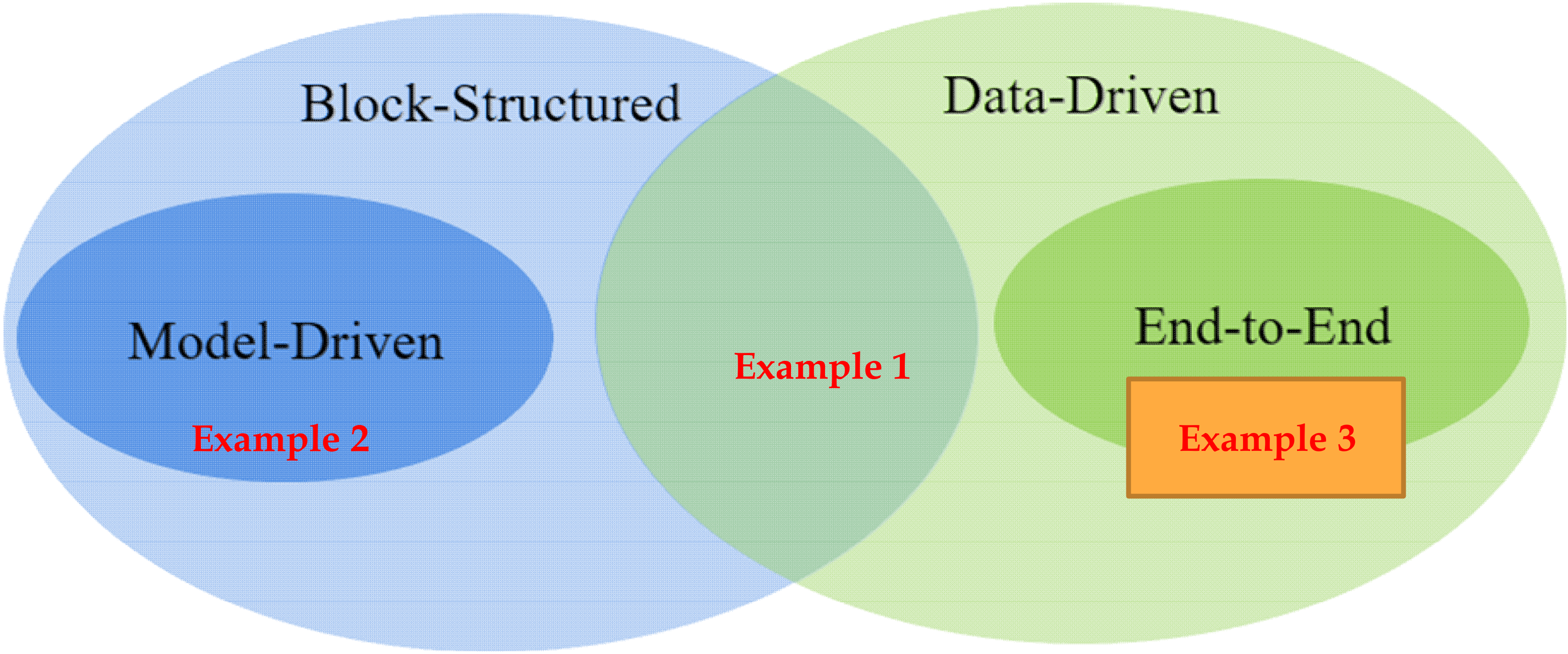
$$\mathbf{r}_t = \hat{\mathbf{x}}_t + \gamma_t\mathbf{W}_t(\mathbf{y} - \mathbf{H}\hat{\mathbf{x}}_t)$$

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

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

- **Tainable Parameters:** **Only two parameters (γ_t, θ_t) for each iteration!**

DL in for Conventional Communications



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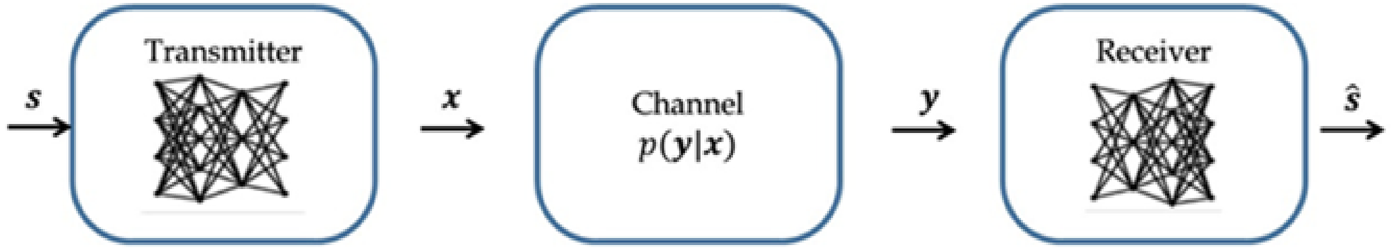
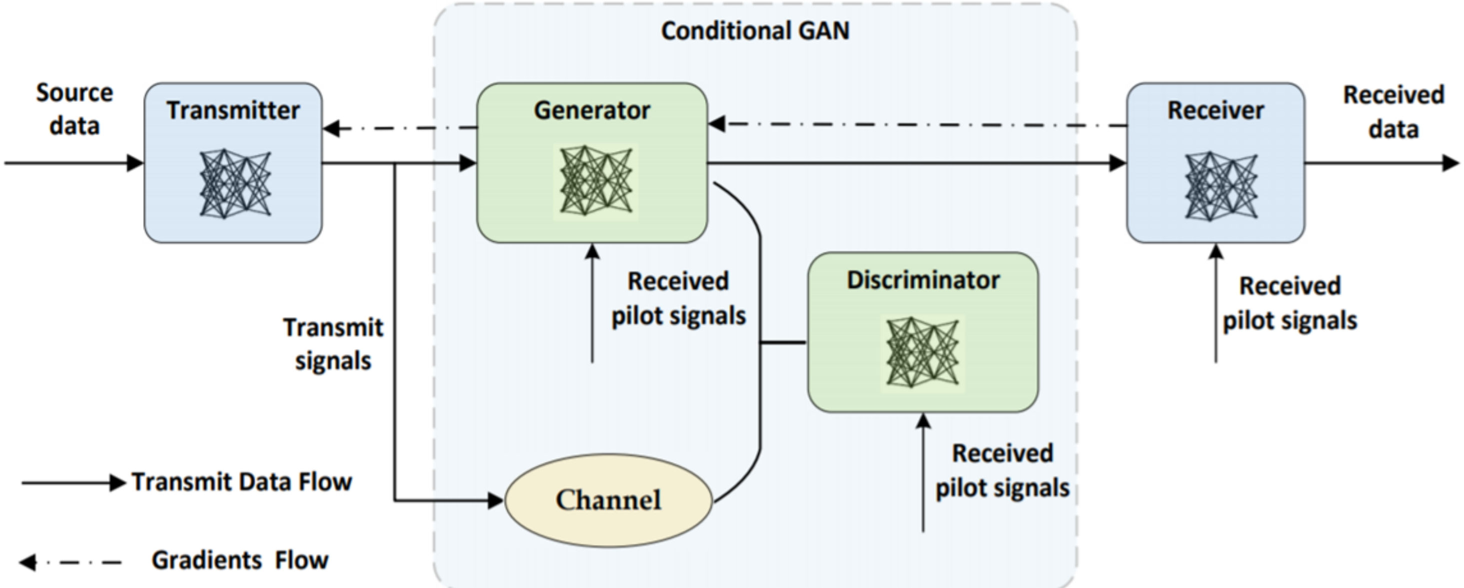
Why End-to-End Learning?



- **Architecture:**
  - Representing both transmitter and receiver by DNNs
  - Leaning to encode transmit symbols at transmitter
  - Learning to recover transmit symbols at receiver

- **Merits:**
  - Achieving global optimum
  - Universal solution to different channels
  - Beating current state-of-arts

E2E based on Conditional GAN



- Using CNN to address curse of dimentionity
- Conditional GAN: modelling the channel output distribution
- Surrogate of real channel when training the transmitter
- Received pilots as a part of conditioning for unknown channel

H. Ye, L. Liang, G. Y. Li, and B.-H. F. Juang, "Deep learning based end-to-end wireless communication systems with GAN as unknown channel," *IEEE Trans. Wireless Commun.*, vol. 19, no. 5, pp. 3133-3143, May 2020.

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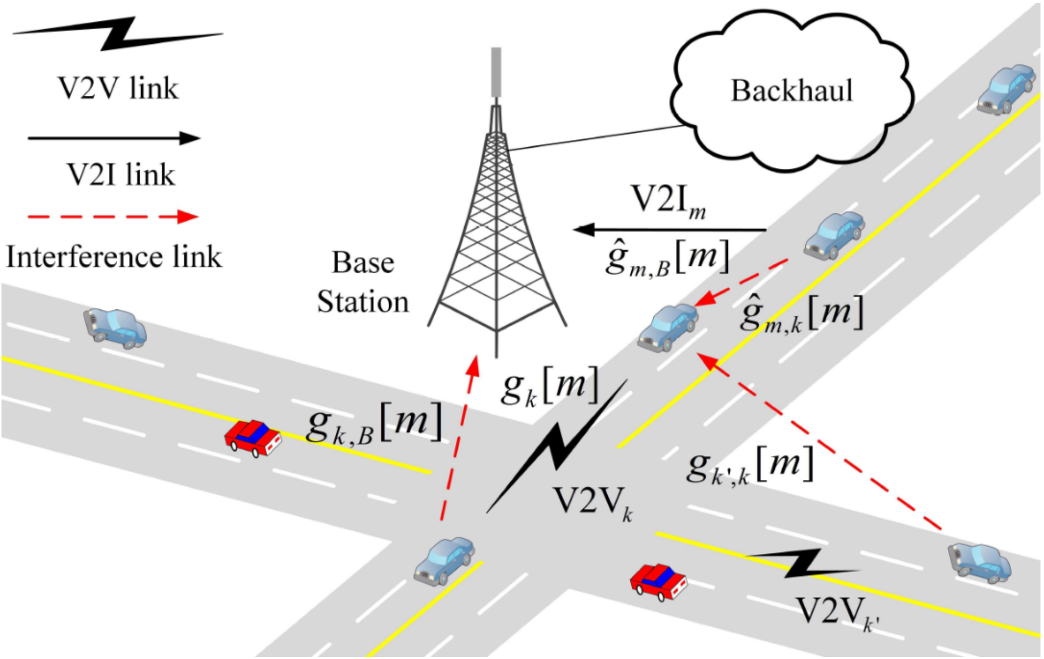
DRL for RA in V2X Communications

- **Requirements of V2V**
  - Stringent latency and reliability
  - Small payload
- **Requirements of V2I**
  - High data rate
  - Large payload
- **Resource Allocation**
  - Fixing V2I resource allocation
  - Selecting spectrum and power level for each V2V link
- **Objectives:** Satisfying Constraints of V2V and V2I

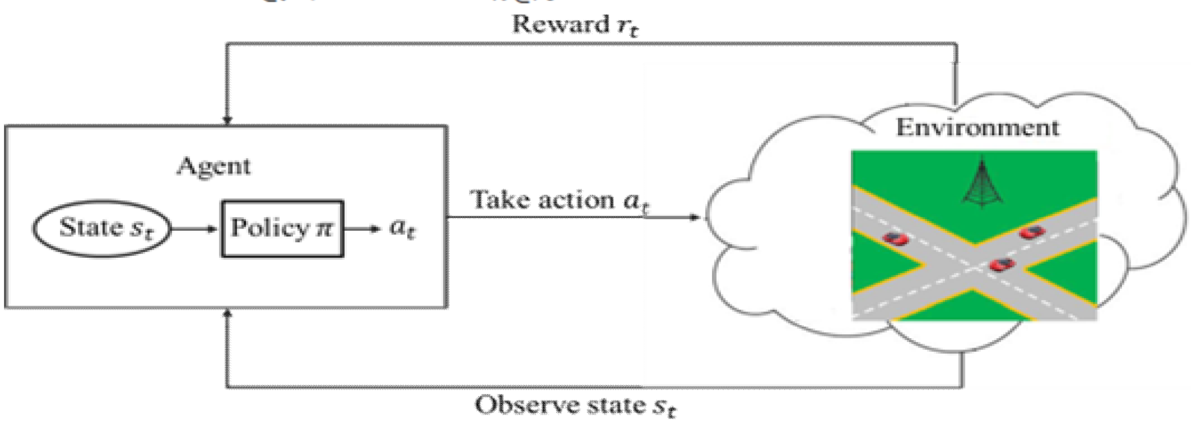


H. Ye, G. Y. Li, B.-H. F. Juang, "Deep reinforcement learning based resource allocation for V2V communications," *IEEE Trans. Veh. Tech.*, vol. 68, no. 4, pp. 3163-3173, April 2019.

DRL for RA for V2X

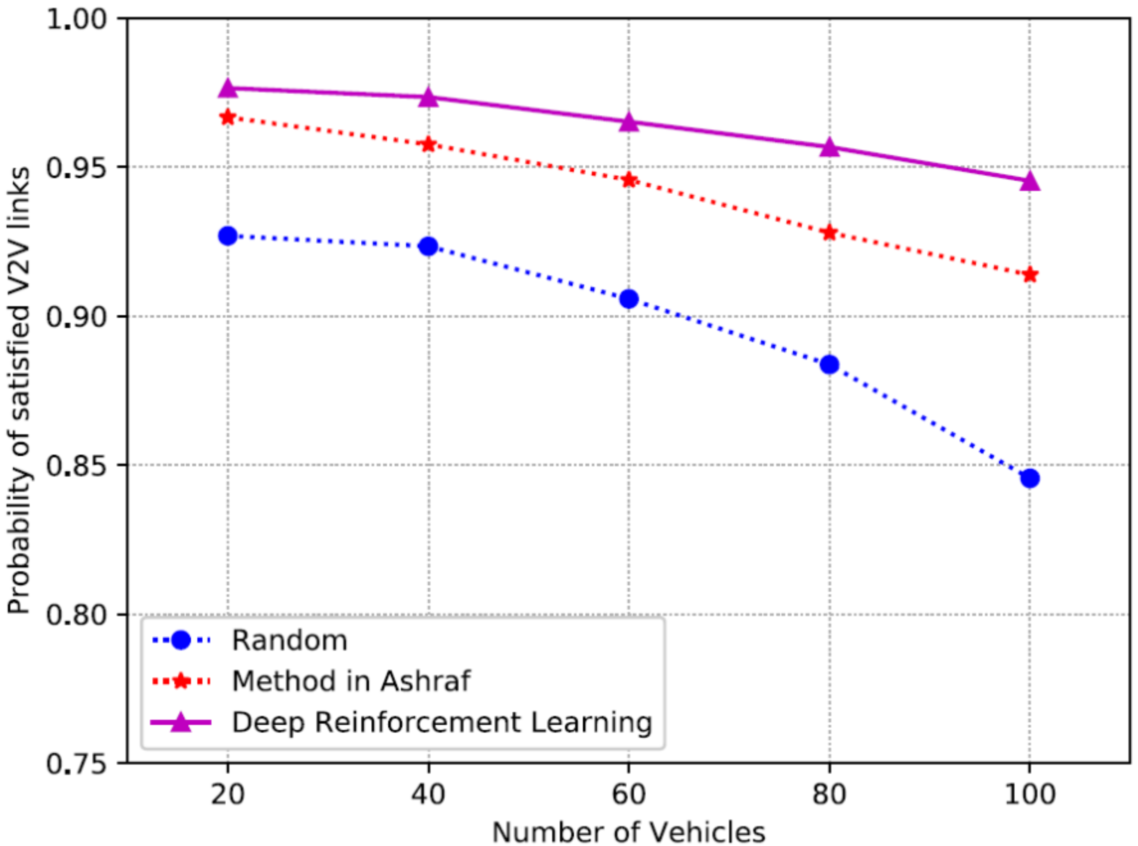
- **Agent:** Every V2V link
  - State s_t: V2V channel, interference, V2I channel, neighbors,…
  - Action a_t: sub-channel selection and transmission power level
- **Environment:**
  - Everything outside the V2V link: wireless channels + other V2V links.
  - Receiving action a_t , sending reward r_t to agents, transiting to new state s_{t+1}
- **Reward:** V2I capacity, V2V capacity, & latency constraint

$$r_t = \lambda_c \sum_{m \in \mathcal{M}} C_m^c + \lambda_d \sum_{k \in \mathcal{K}} C_k^d - \lambda_p (T_0 - U_t)$$

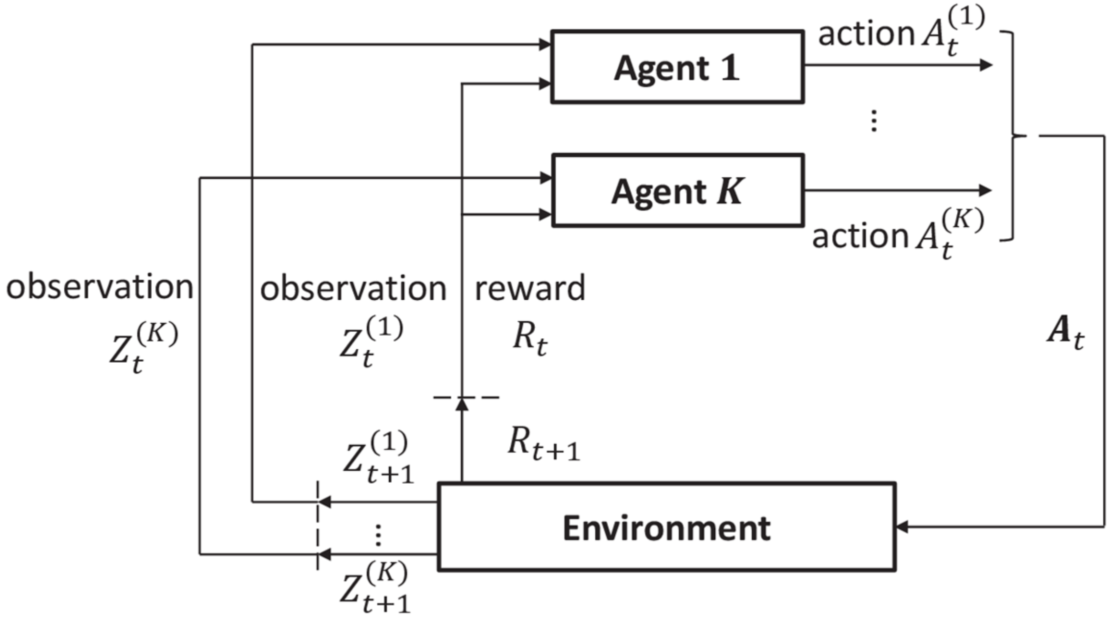


DRL for RA for V2X: Latency Constraints

- Better than existing one
- Much better than random



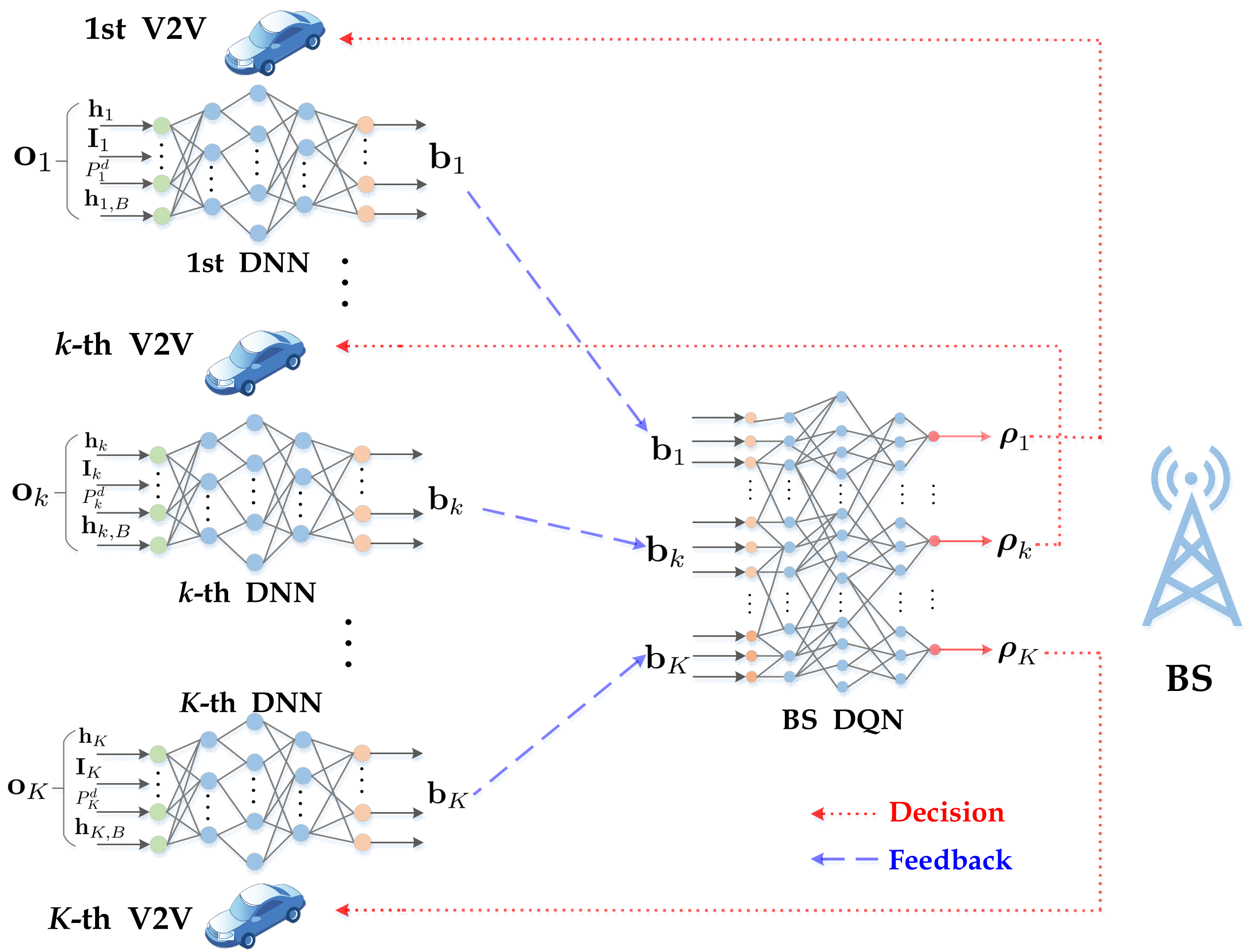
Multi-Agent Reinforcement Learning (MARL)



- Local observation $Z_t^{(k)} = O(S_t, k)$ of the underlying environment state S_t
- Joint actions of all agents: $\mathbf{A}_t = (A_t^{(1)}, A_t^{(2)}, \dots, A_t^{(K)})$, taken simultaneously
- Receives same/distinctive rewards: $R_{t+1}^{(k)}$

L. Liang, H. Ye, and G. Y. Li, "Spectrum sharing in vehicular networks based on multi-agent reinforcement learning," ***IEEE J. Sel. Areas Commun.*****, vol. 37, no. 10, pp.2282-2292, Oct. 2019.**

Learn to Feed Back and Allocate Resource



L. Wang, H. Ye, L. Liang, and G. Y. Li, "Learn to compress CSI and allocate resources in vehicular networks," *IEEE Trans. Commun*. vol. 68, no. 6, pp. 3640 – 3653, June 2020.

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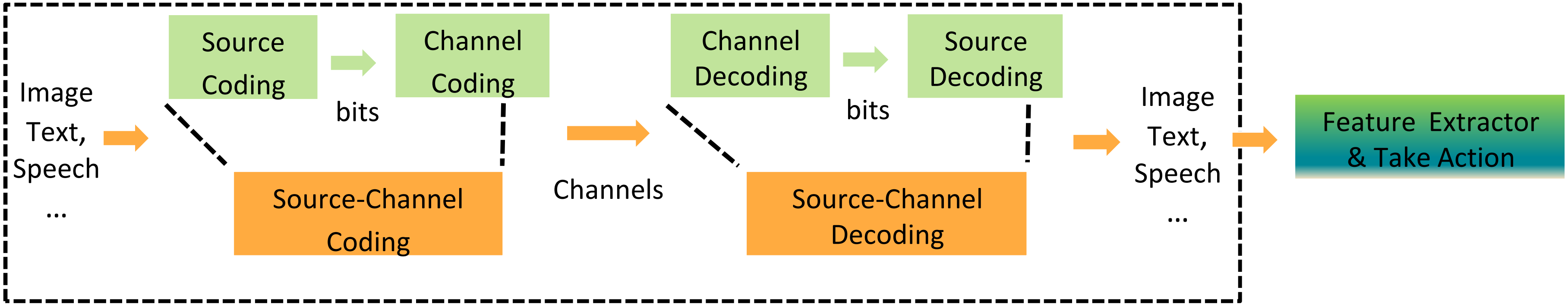
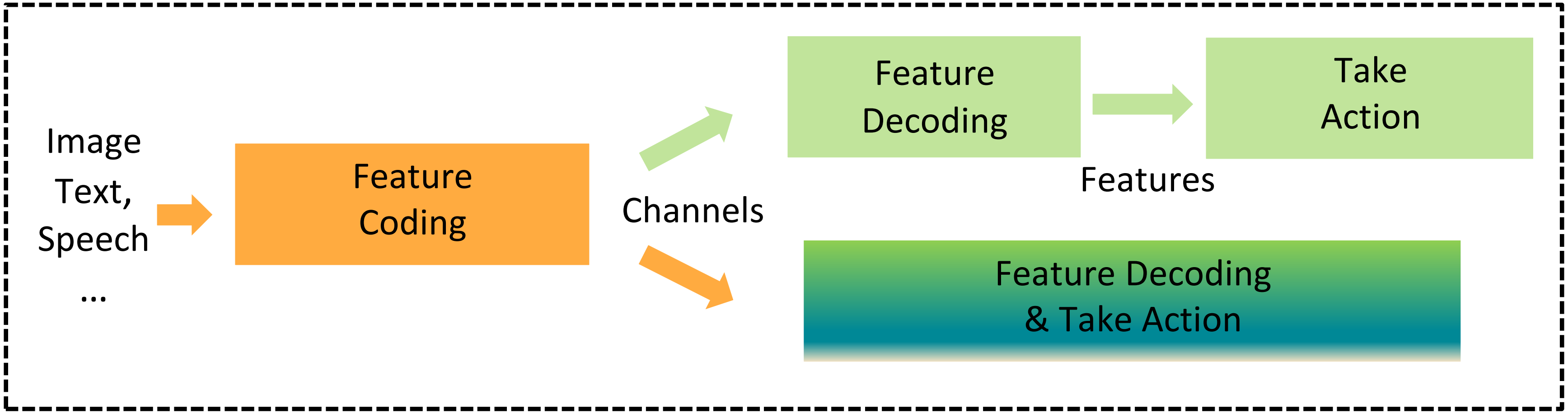
Conventional Communications

- Only considering the **accurate data recovery**
- Removing Information redundancy in **entropy-domain**
- Transmitting all information, including **useless and irrelevant,** to the receiver



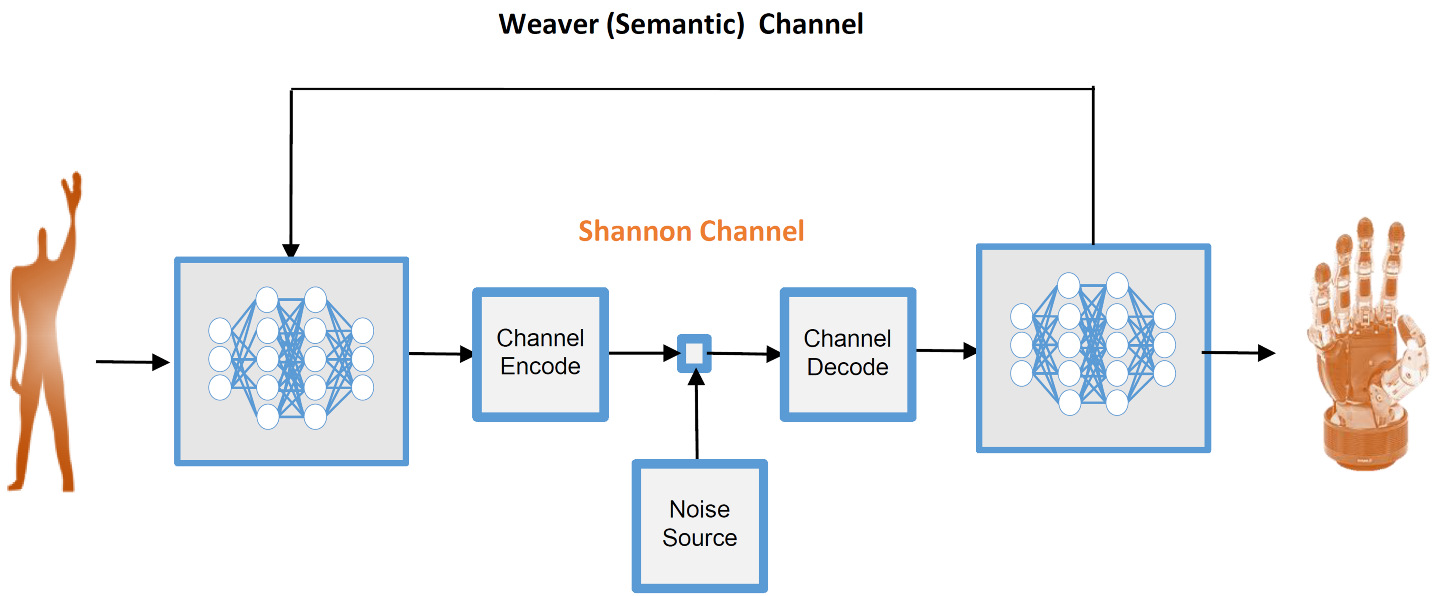
Semantic Communications

- Considering **Feature** networks and **action** networks
- Removing Information redundancy in **semantic domain**
- Transmitting only **useful and relevant** information to the receiver



Z.-J. Qin, X.-M. Tao, J.-H. Lu, and G. Y. Li, "Semantic communications: Principles and challenges," https://arxiv.org/abs/2201.01389.

Semantic Communications



W. Tong and G. Y. Li "Nine critical issues in AI and wireless communications to ensure successful 6G," *IEEE Wireless Commun.*, vol. 29, no. 4, pp. 140 – 145, August 2022.

Semantic Transceiver

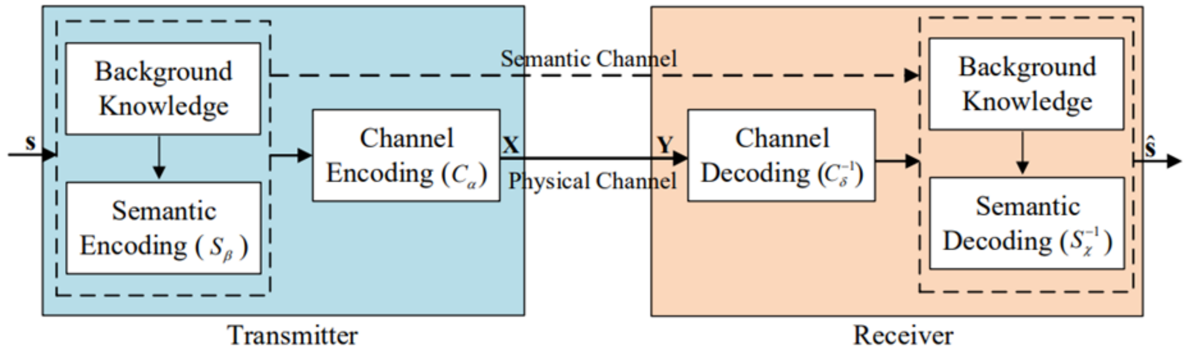
- **Transceiver**
  - Transmitter

    $$\mathbf{X} = C_{\boldsymbol{\alpha}}\left(S_{\boldsymbol{\beta}}\left(\mathbf{s}\right)\right),$$

  - Receiver

    $$\mathbf{Y} = \mathbf{HX} + \mathbf{N},$$

    $$\hat{\mathbf{s}} = S_{\boldsymbol{\chi}}^{-1}\left(C_{\boldsymbol{\delta}}^{-1}\left(\mathbf{Y}\right)\right)$$



- **Channels**
  - Physical channel noise is caused by the physical channel impairment
    - AWGN, fading channels…
  - Semantic channel noise refers to misunderstanding
    - Caused by interpretation error and disturbance in estimated information.

H. Xie, Z. Qin, G. Y. Li, and B.-H. Juang, "Deep learning enabled semantic communication systems," *IEEE Trans. Signal Process.* vol. 69, pp. 2663-2675, 2021, Apr. 2021.

Loss Function

- Loss function used to train the transceiver

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{CE}}(\mathbf{s}, \hat{\mathbf{s}}; \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\chi}, \boldsymbol{\delta}) - \lambda \mathcal{L}_{\text{MI}}(\mathbf{x}, \mathbf{y}; T, \boldsymbol{\alpha}, \boldsymbol{\beta})$$

- **Cross-Entropy**: Through reducing the loss value of channel encoder, the network can learn the syntax, phrase, the meaning of words

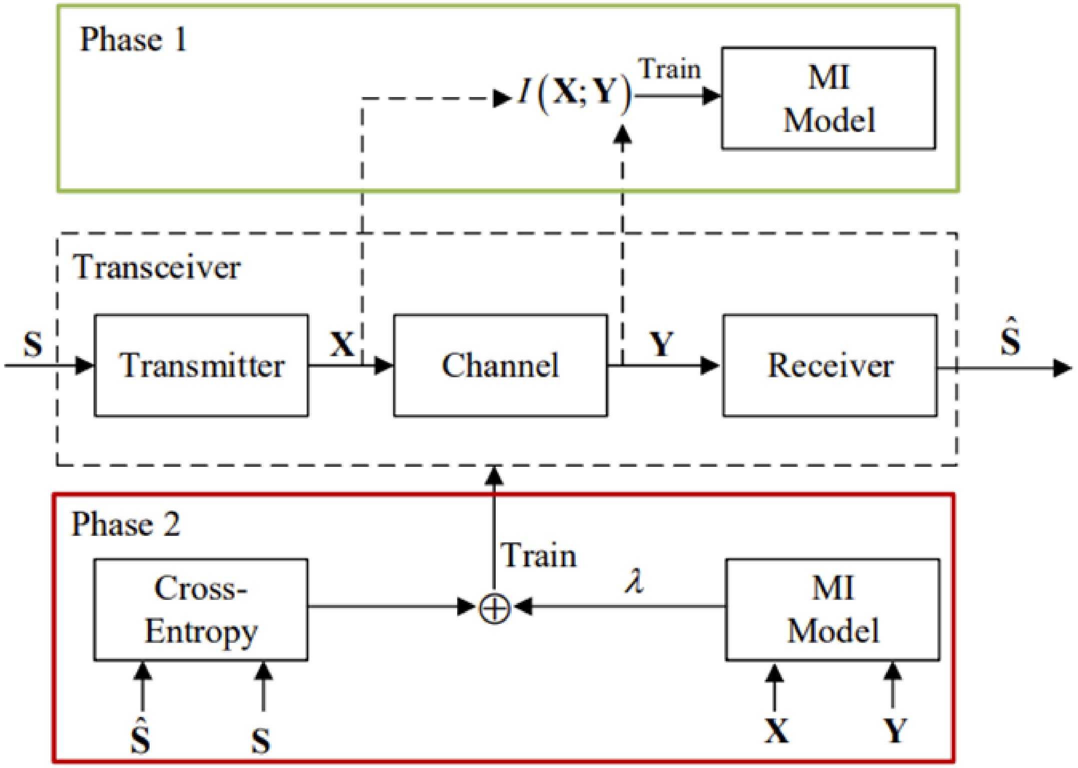
$$\mathcal{L}_{\text{CE}}(\mathbf{s}, \hat{\mathbf{s}}; \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\chi}, \boldsymbol{\delta}) = \\ -\sum_{i=1} q\left(w_i\right) \log\left(p\left(w_i\right)\right) + \left(1 - q\left(w_i\right)\right) \log\left(1 - p\left(w_i\right)\right)$$

- **Mutual Information**: maximizing achieved data rate

$$\mathcal{L}_{\text{MI}}(\mathbf{X}, \mathbf{Y}; T) = \mathbb{E}_{p(x,y)}\left[f_T\right] - \log\left(\mathbb{E}_{p(x)p(y)}\left[e^{f_T}\right]\right)$$

Two-Step Training

- Maximizing mutual information
- Train the whole model



S-SE based Resource Allocation

- **Semantic unit (*sut*)**
  - A measure of semantic information, the basic unit of semantic information
- **Semantic spectral efficiency (S-SE, *suts/s/Hz*)**
  - Taking text transmission for instance
  - Defined as the effectively transmitted semantic information per second, i.e.,

$$\Phi = \frac{I/L}{k}\xi$$

    - I : average amount of semantic information per sentence
    - L : average number of word per sentence
    - k : number of transmitted semantic symbols per word
    - ξ : semantic similarity

L. Yan, Z. Qin, R. Zhang, Y. Li, and G. Y. Li, "Resource allocation for text semantic communications," *IEEE Wireless Commun. Lett.*, vol. 11, no. 7, pp. 1394 – 1398, Jul. 2022.

Problem Formulation

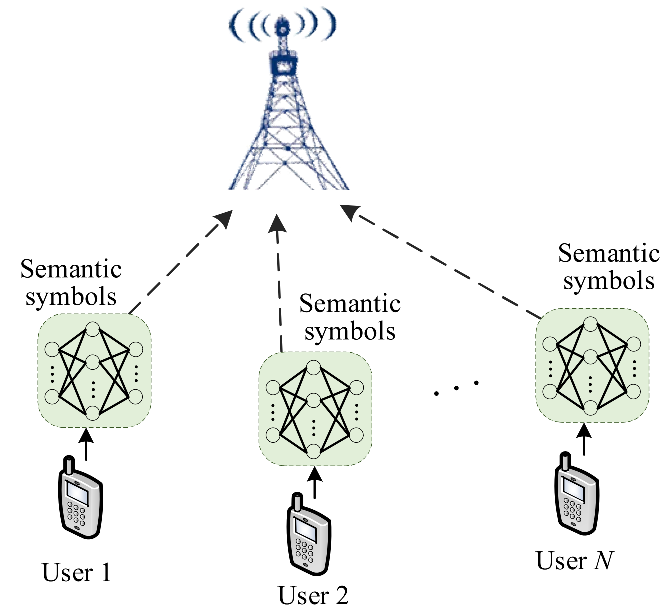
➢ S-SE maximization problem

$$\max_{\boldsymbol{\alpha}_n, k_n} \sum_{n=1}^{N} \sum_{m=1}^{M} \alpha_{n,m} \frac{I}{k_n L} \xi_{n,m}$$

$$\begin{aligned}
\text{s.t.}\ \ & \mathrm{C}_1: \alpha_{n,m} \in \{0,1\}, \forall n \in \mathcal{N}, \forall m \in \mathcal{M} \\
& \mathrm{C}_2: \sum_{n=1}^{N} \alpha_{n,m} \le 1, \forall m \in \mathcal{M} \\
& \mathrm{C}_3: \sum_{m=1}^{M} \alpha_{n,m} \le 1, \forall n \in \mathcal{N} \\
& \mathrm{C}_4: k_n \in \{1, 2, \ldots, K\} \\
& \mathrm{C}_5: \xi_{n,m} \ge \xi_{\mathrm{th}} \\
& \mathrm{C}_6: \Phi_{n,m} \ge \Phi_{\mathrm{th}}
\end{aligned}$$

➢ Solutions

- $\xi_{n,m}$ is obtained by running DeepSC
- I/L can be omitted for the same task
- Exhaustive searching and Hungarian algorithm



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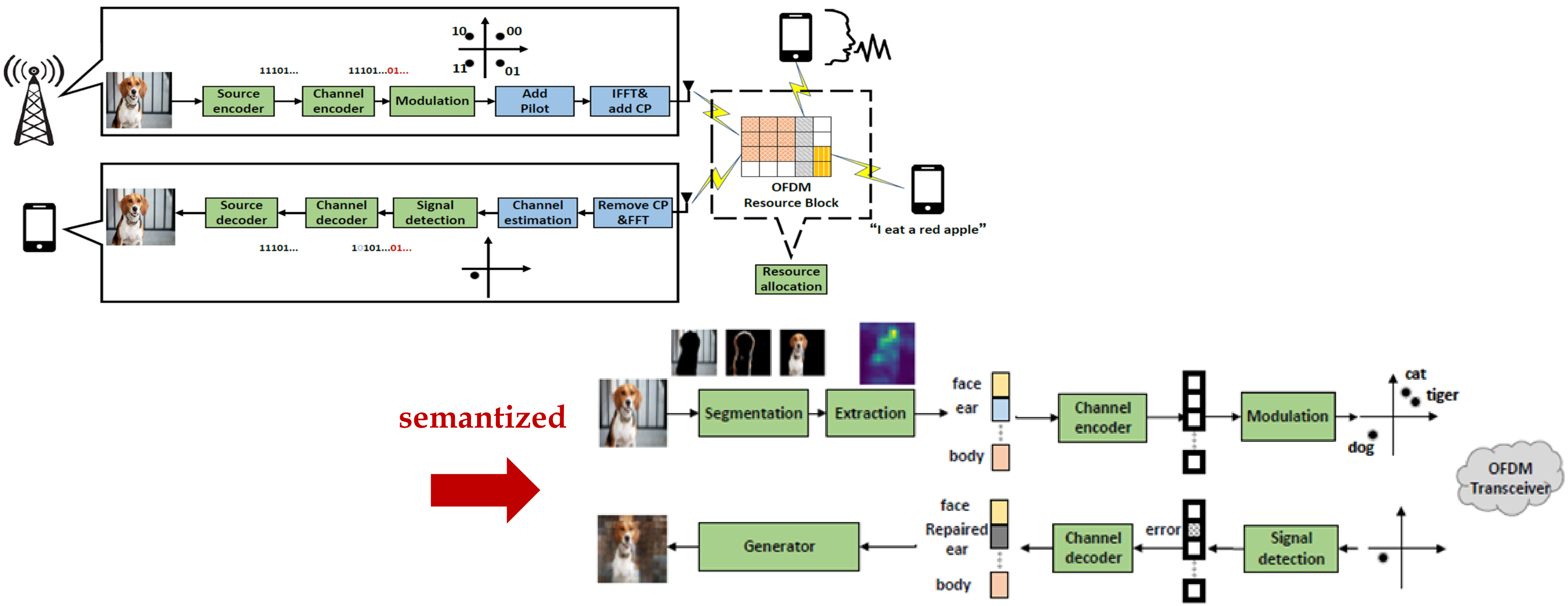
Revising Existing Modules

- Semantic Segmentation and Extraction for Source Coding
- Joint Design and Training for Channel Coding
- Minimizing Semantic Errors in Physical Modules
- Resource Allocation for Semantic Needs of Various Users



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P.-W. Jiang, C.-K. Wen, J. Shi, and G. Y. Li, "Wireless semantic transmission via revising modules in conventional communications," to appear in *IEEE Wireless Commun.*

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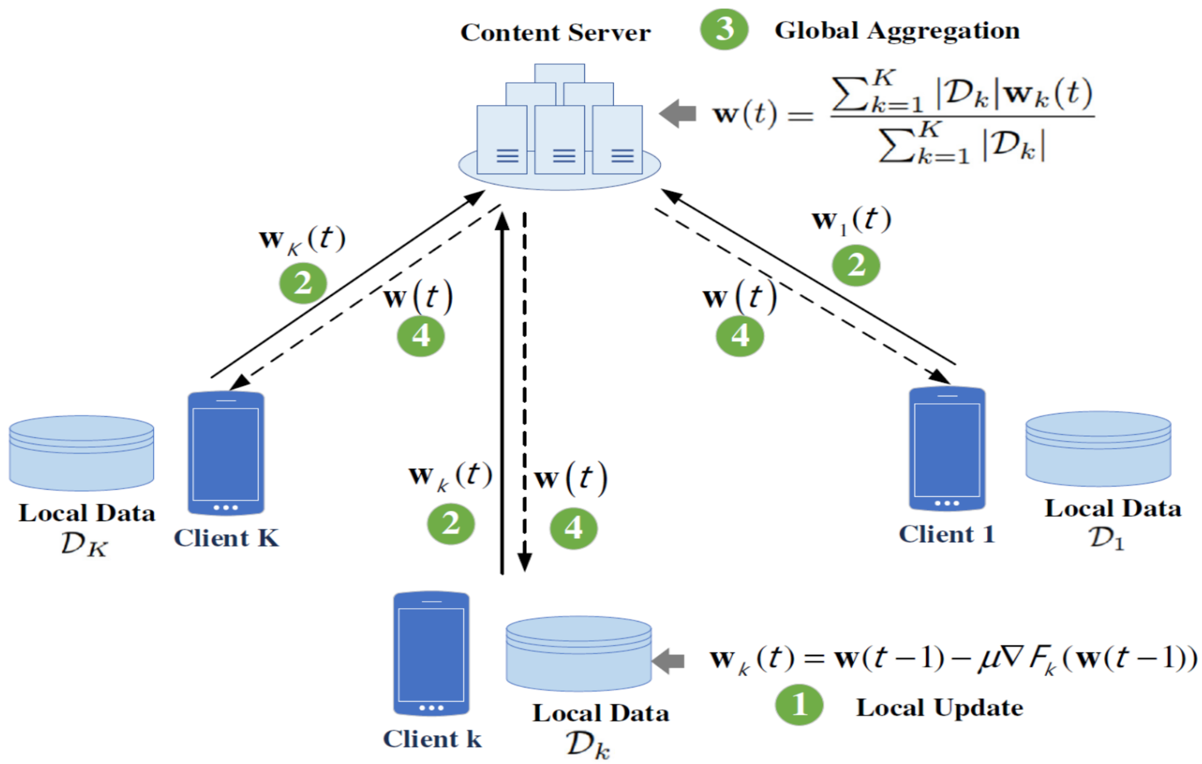
VI. Conclusion Remarks

Federated Learning: Convergence Issues



- What if there are transmission errors in Step 2?
- Convergence if no aggregation in Step 2 for some clients due to communication issues?
- How to save communication resource?

FedGiA

Prior Arts

- Gradient descent (GD)-based FL: FedAvg [1], FedProx [2], ...
- ADMM-based FL: exact ADMM [3], inexact ADMM [4]
- **Strong assumptions** to guarantee convergence

A Novel Algorithm: FedGiA

- Communication and computation-efficient
- More private and realistic
- **Mild assumptions** to ensure **better** convergence

[1] B. McMahan, et al., “Communication-efficient learning of deep networks from decentralized data,” in AISTATS, 2017, pp. 1273-1282.
[2] T. Li, et al., “Federated optimization in heterogeneous networks,” Proc. - Int. Conf. Mach. Learn., vol. 2, pp. 429-450, 2020.
[3] Q. Li, et al., “Robust federated learning using ADMM in the presence of data falsifying byzantines” CoRR, 2017.
[4] S. Yue, et al., “Inexact-ADMM based federated meta-learning for fast and continual edge learning,” in ACM Mobihoc, 2021, pp. 91-100.

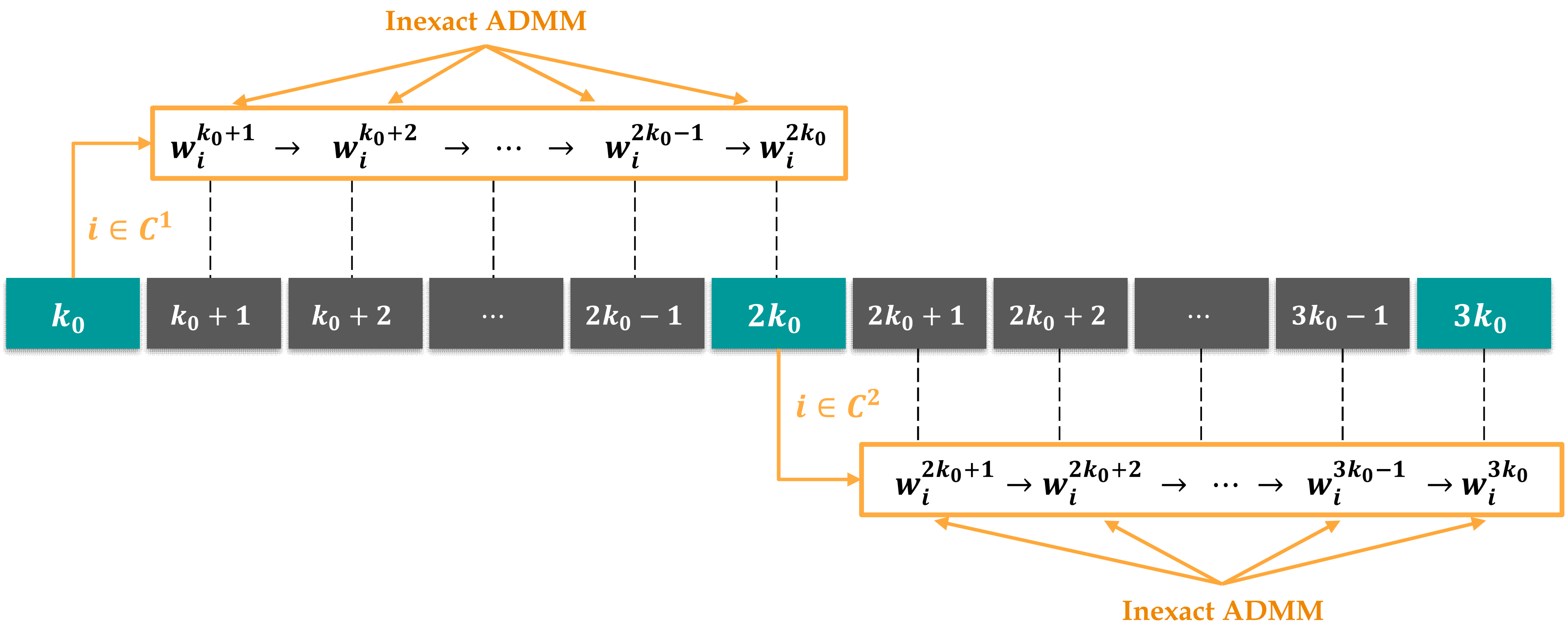
S.-L. Zhou and G. Y. Li, “FedGiA: An efficient hybrid algorithm for federated learning,” *IEEE Trans. Signal Process.*, vol. 71, pp. 1493-1508, 2023.

FL via Inexact ADMM

- **Similarity and Dissimilarity with FedGiA**
  - **Similarity**:
    Aggregation only at certain iterations
    ADMM update for a subset of users (ADMM clients)
  - **Dissimilarity**:
    Partial device participation: No parameter updating for non-ADMM clients
    Solving subproblem inexactly for ADMM clients
- **Convergence: under the same assumptions**
  - Two assumptions as FedGiA, plus
  - A new assumption: ADMM clients selected with a certain probability
- **Potential Application**
  - Over-the-Air Computing: no aggregation for bad channel clients)

S.-L. Zhou and G. Y. Li, "Federated learning via inexact ADMM," ***IEEE Trans. Pattern Anal. Mach. Intell.,*** **early access.**

FL via Inexact ADMM – Algorithm



Partial device participation:

Much more realistic but more challenging to establish the convergence !!!

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FL via Inexact ADMM – Convergence

- **Assumptions**
  - Every F_i: gradient Lipschitz continuous with constant r_i
  - Level set $\{w: F(w) \leq c\}$: bounded by a given constant c
  - Every client chosen at least once for $s_0 k_0$ steps, where s_0 is a given integer

Can be ensured in a high probability !!!

- **Global convergence**

  Let w^* *be any accumulating point of sequence* $\{w^{\tau_k}\}$ *and* $\sigma > \max_i 3r_i/m$. *Then*

  - $\nabla F(w^*) = 0$, implying w^* is optimal if F is convex
  - $F(w^{\tau_k}) \to F(w^*)$
  - $\min_{j=1,\ldots,k} ||\nabla F(w^{\tau_j})||^2 = O(k_0/k)$
- **Impact and implication**
  - **No need for convexity,** thus enabling to process more applications
  - Providing a lower bound for setting parameter σ
  - k_0 should not be chosen too large for quick convergence

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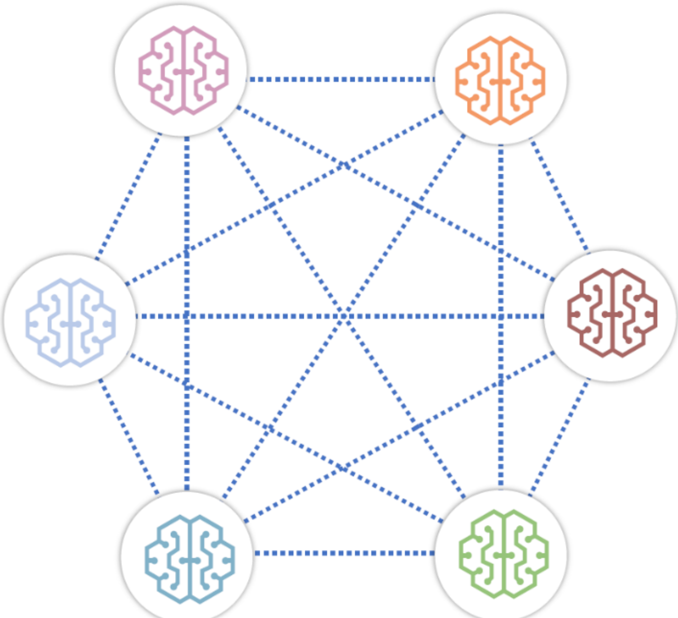
Decentralized Federated Learning

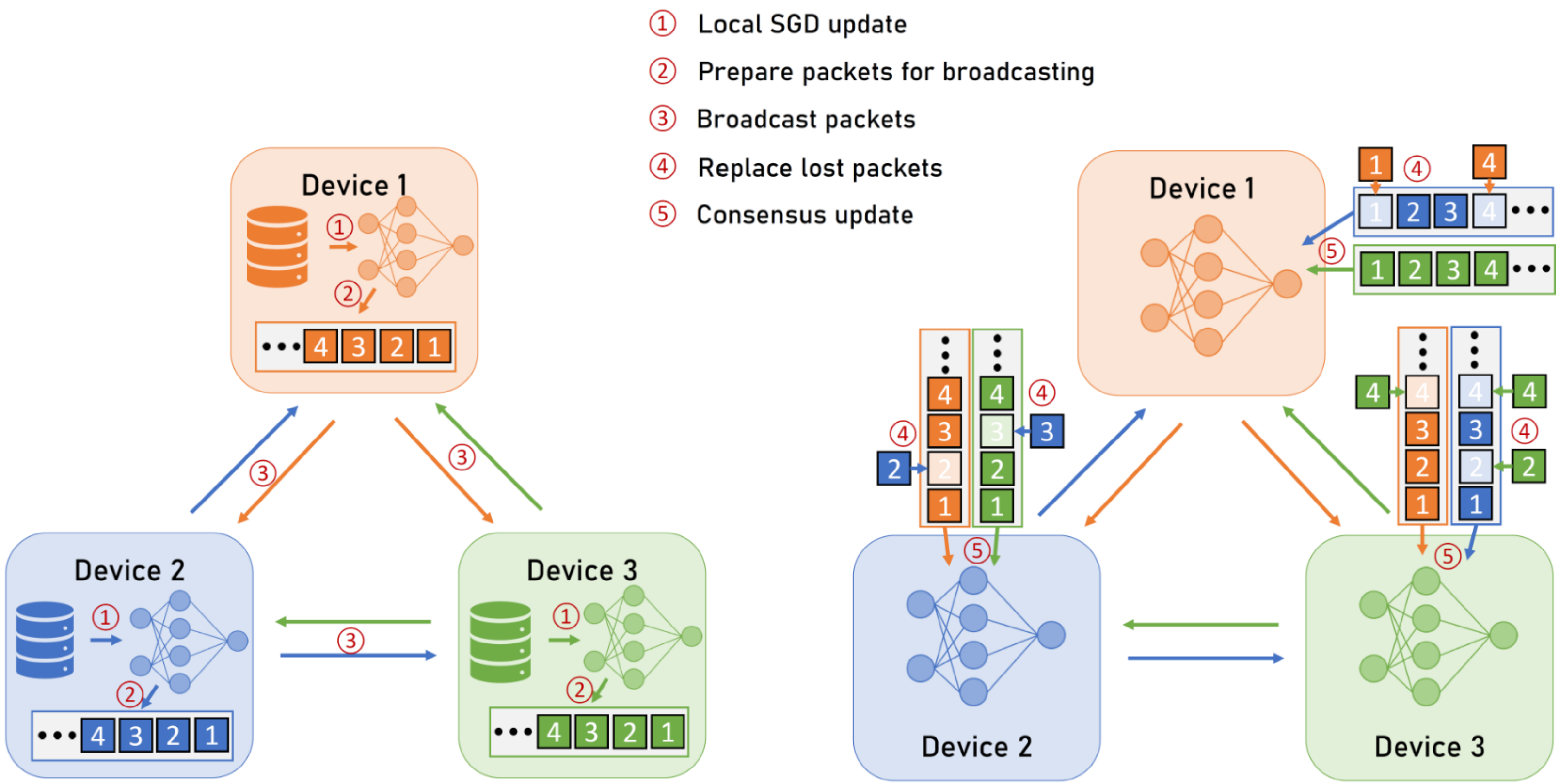
(a) Centralized FL



(b) Decentralized FL

H. Ye, L. Liang, and G. Y. Li, "Decentralized learning with unreliable communications," *IEEE J. Select. Topics in Signal Process.*, vol. 16, no. 3, pp. 487 – 500, April 2022.

Soft DSGD



Before communication

After communication

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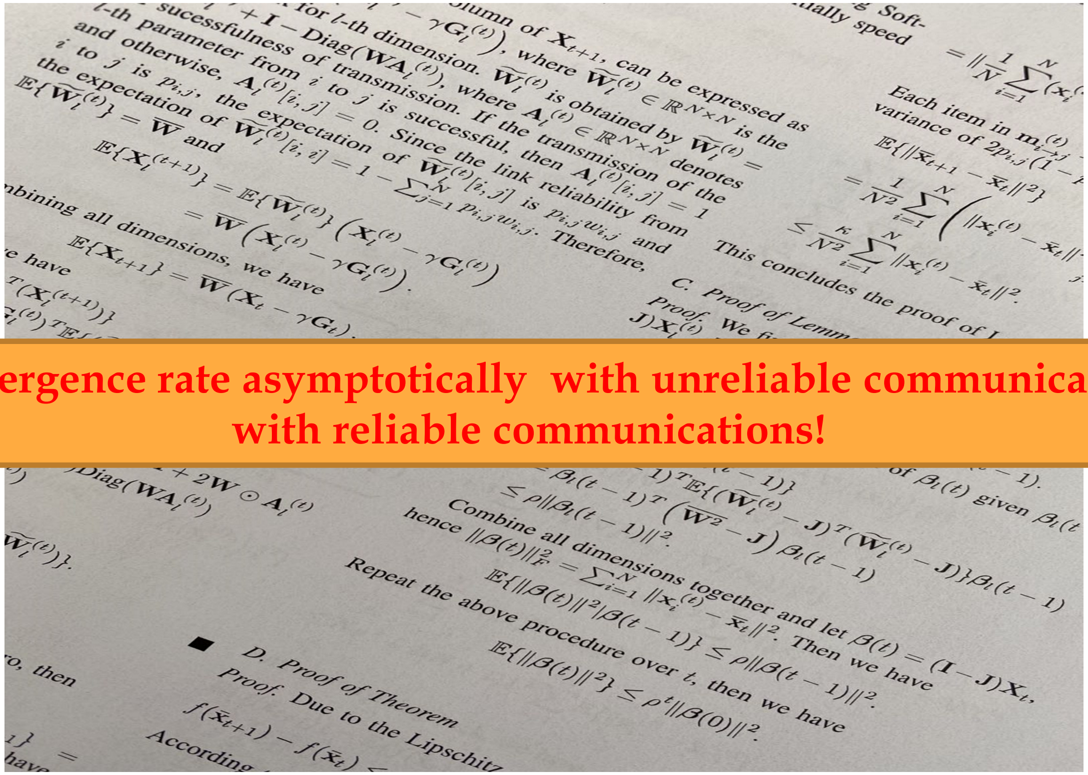
Asymptotic Convergence Rate



Same convergence rate asymptotically with unreliable communications and with reliable communications!

Soft-DSGD with unreliable commun. needs fewer commun. rounds than DSGD with reliable commun. since reliable commun. requires retransmission!

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Outline

I. Motivation

II. Physical Layer Processing

III. Resource Allocation

IV. DL-enabled Semantic Communications

V. Communications and Federated Learning

VI. Conclusion Remarks

Conclusion Remarks

- Lots of Work in the past 5 years
- Semantic Communications: a Popular Area
- Future Trend: AI for wireless → Wireless for AI