From Conventional to Semantic Communications based on Deep Learning

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Outline

- Overview
- DL-based Conventional Communications
  - * Block-Wise
  - * End-to-End
- DL-based Semantic Communications
- Conclusions

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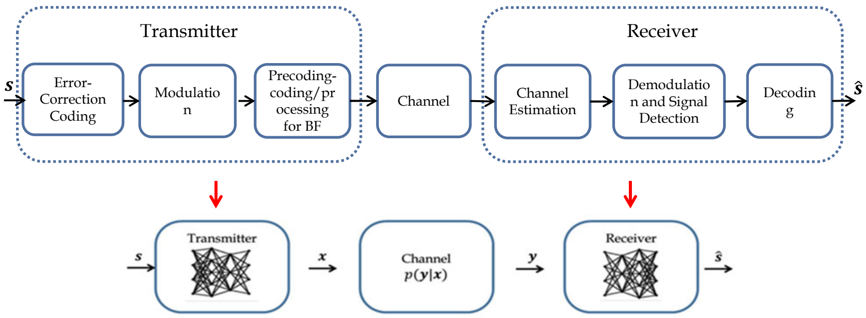
Motivation

- **Challenges in current/conventional communication systems**
  - Mathematical models versus practical imperfection
  - Block structures versus global optimality
  - Complexity and performance of optimization
  - Spectrum efficiency limited by Shannon capacity

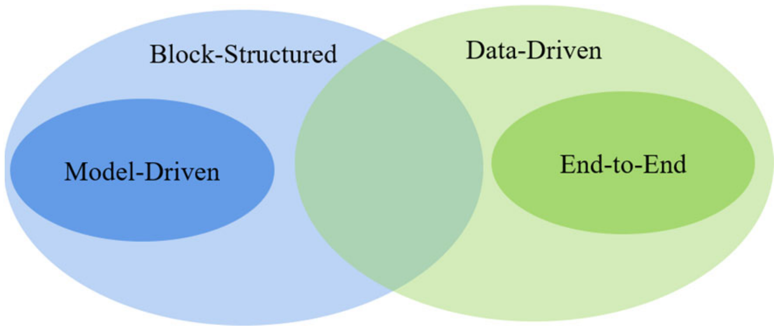
- **Why deep learning?**
  - No need for models for data-driven method
  - End-to-end loss optimization for global optimality
  - Deep learning enabled end-to-end and semantic communications

Block Structure or End-to-End for Conventional Communications

Conventional Communications:
Transmit symbols or bits, following Shannon Limit



DL in Physical Layer Conventional Communications



- 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
- 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.

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From Symbol to Semantic Transmission

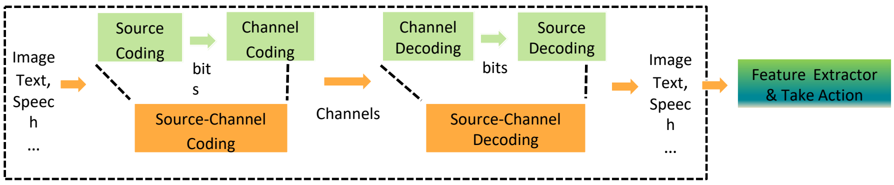
- **Three Levels of Communications: Shannon and Weaver**
  - **Transmission of symbols (Shannon Paradigm)**
    following Shannon limit & well-developed near limit
  - **Semantic exchange of source information**
    semantic communications (transmission of intelligence)
  - **Effects of semantic information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

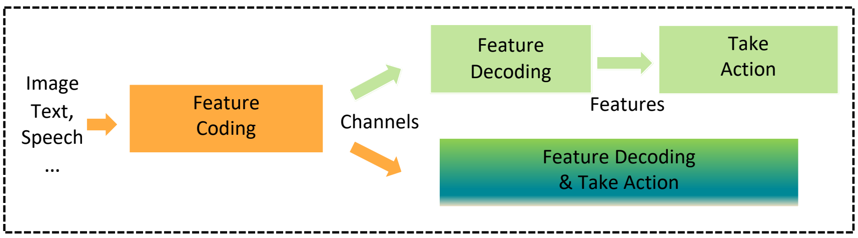
Conventional Communications

- Only consider the **data recovery accurately**
- Information redundancy are removed in **entropy-domain**
- All information (including **useless and irrelevant**) are transmitted to the receiver, part are useless for the target network



Semantic Communications

- **Feature** networks and **action** networks considered
- Information redundancy removed in **semantic domain**
- Only **useful and relevant** information transmitted to the receiver
- The features can serve **different** action networks



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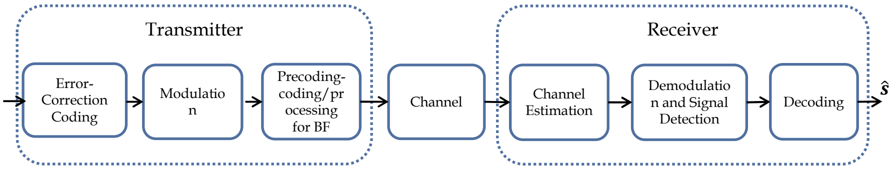
Channel Estimation (CE) and Signal Detection (SD)



➢ **Related works:**
- MMSE for channel estimation
- Neural networks and DL in equalization and decoding

➢ **Challenges:**
- Nonlinear distortion and interference

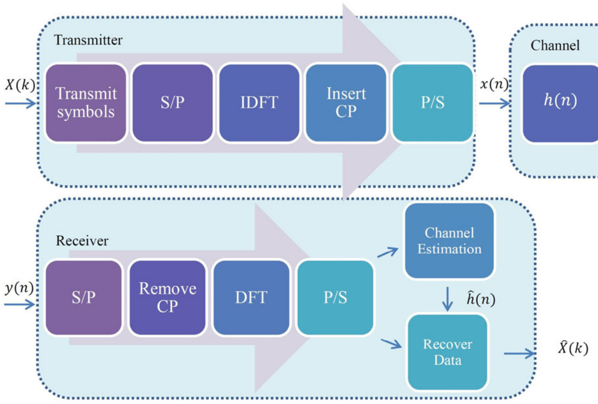
➢ **Innovations:**
- DL for joint channel estimation and symbol detection
- DL-based method: robust and insensitive to nonlinear distortion and interference

902 IEEE TRANSACTIONS ON COMMUNICATIONS, VOL. 46, NO. 7, JULY 1998

Traditional CE and SD

Robust Channel Estimation for OFDM Systems with Rapid Dispersive Fading Channels

Ye (Geoffrey) Li, *Senior Member, IEEE*, Leonard J. Cimini, Jr., *Senior Member, IEEE*,



I. INTRODUCTION

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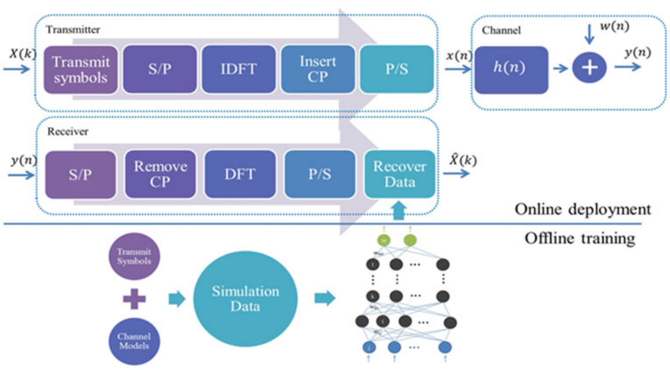
DL-based CE and SD



- 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.

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DL-based CE and SD: DNN Model Training

- Training DNN to predict transmit data
- Training with received OFDM samples corresponding to pilots and data
- Generating label data under diverse channel conditions
- Optimizing model parameters to minimize L_2 loss function

$$L_2 = \frac{1}{N}\sum_k (\hat{X}(k) - X(k))^2$$

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Model-Driven DL

- ❑ Relying on relatively accurate model
- ❑ Exploiting rich domain/expert knowledge
- ❑ Easy to train with a small amount of data
- ❑ Explainable and predictable neural networks
- ❑ **Deep unfolding**: a popular model-driven approach

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.**
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.**

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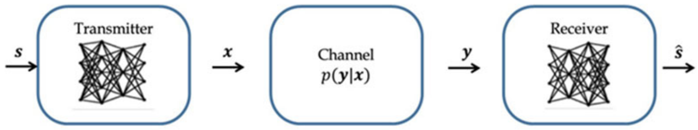
Why End-to-End Learning?



- **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

Channel Agnostic End-to-End Learning

- **Related Works:**
  - End-to-end communication for AWGN
  - End-to-end communication in OFDM
  - End-to-end communication with hardware impairment
- **Challenges:**
  - Back-propagation of the gradients is blocked by the unknown channel
  - Channel is time-varying
- **Approaches:**
  - Reinforcement Learning (following references)
  - Conditional *Generative Adversarial Net* (GAN) (our approach)

- T. O'Shea and J. Hoydis, "An introduction to deep learning for the physical layer," *IEEE Trans. on Cogn. Commun. Netw.*, vol. 3, no. 4, pp. 563-575, Dec. 2017.
- S. Dorner, S. Cammerer, J. Hoydis, S. ten Brink, "Deep learning-based communication over the air", *IEEE J. Select. Topics Signal Process.*, vol.12, no. 1, pp. 132-143, Feb. 2018.
- A. Felix, S. Cammerer, S. Dorner, J. Hoydis, and S. ten Brink, "OFDM autoencoder for end-to-end learning of communications systems," in *Proc. IEEE Int. Workshop Signal Proc. Adv. Wireless Commun.(SPAWC)*, Jun. 2018.
- F. Aoudia, and J. Hoydis. "End-to-end learning of communications systems without a channel model," *arXiv preprint arXiv: 1804.02276*

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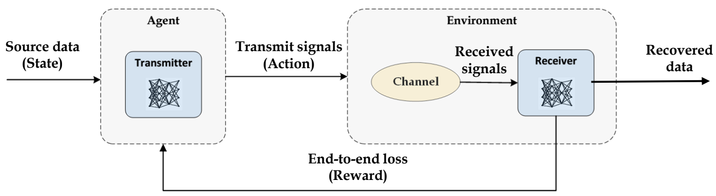
E2E based on Reinforcement Learning



- **Reinforcement Learning Formation:**
  - Agent: transmitter
  - Environment: channel + receiver
  - States: source data
  - Actions: transmit signals
- **Advantage and Disadvantage:**
  - Unnecessary for channel modeling
  - Hard for continuous action in reinforcement learning

F. Aoudia, and J. Hoydis. "End-to-end learning of communications systems without a channel model," ***arXiv preprint arXiv: 1804.02276***

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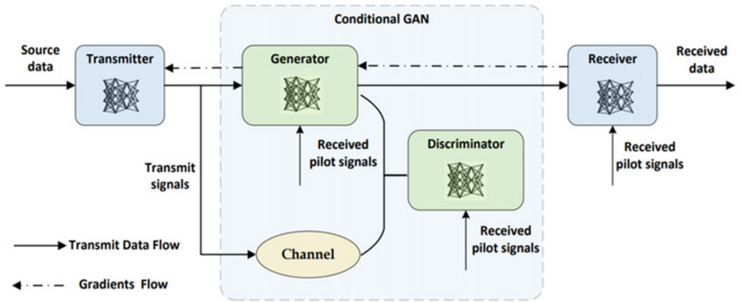
E2E based on Conditional GAN

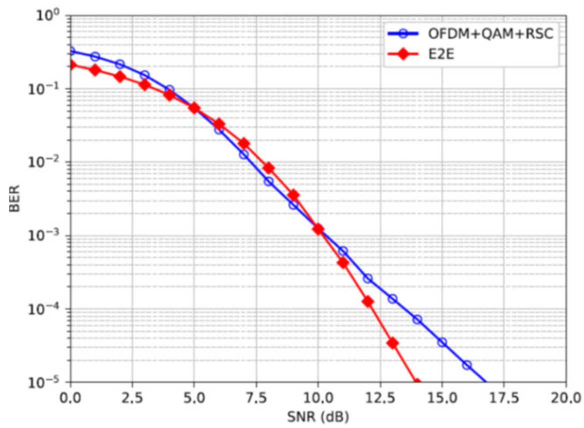


- Using CNN to address curse of dimentionity
- Conditional GAN: modelling the channel output distribution
- Surrogate of real channel when training the transmitter
- Received pilots as a part of conditioning for unknown channel

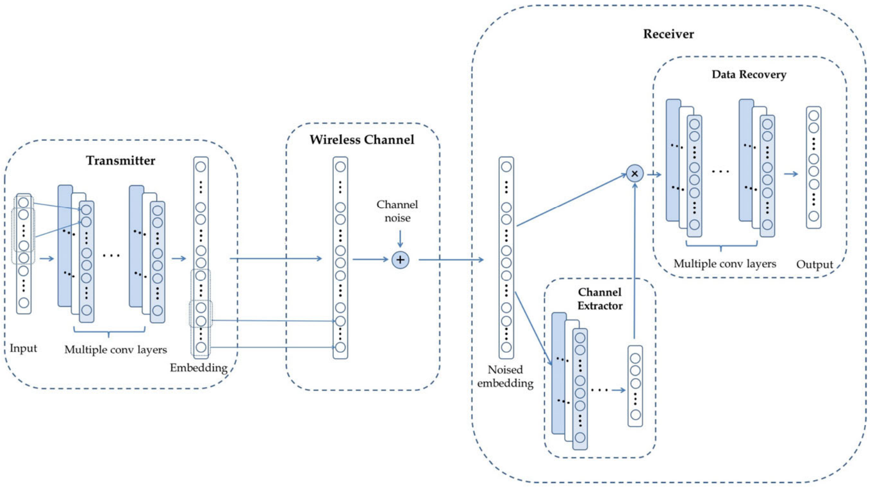
H. Ye, L. Liang, G. Y. Li, and B.-H. F. Juang, "Deep learning based end-to-end wireless communication systems with GAN as unknown channel," *IEEE Trans. Wireless Commun.*, vol. 19, no. 5, pp. 3133-3143, May 2020.

Performance for WINNER II Channels

- Similar BER at low SNR
- Better at high SNR



E2E without Pilot



H. Ye, L. Liang, G. Y. Li, and B.-H. F. Juang, "Deep learning based end-to-end wireless communication systems without pilots," *IEEE Trans. Cognitive Commun. and Netw.*, vol. 7, no. 3, pp. 702 – 714, September 2021.

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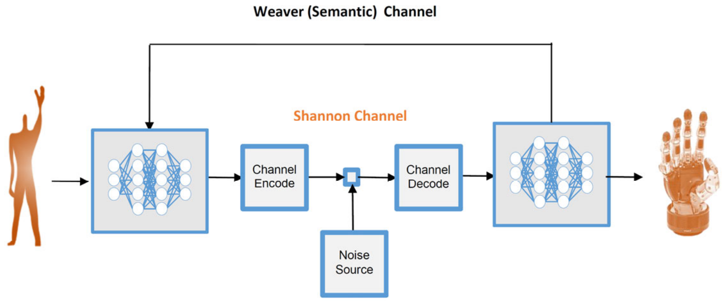
Example on Semantic Communications



W. Tong and G. Y. Li "Nine critical issues in AI and wireless communications to ensure successful 6G," to appear in *IEEE Wireless Commun.*, also at https://arxiv.org/abs/2109.11320, Aug. 2021.

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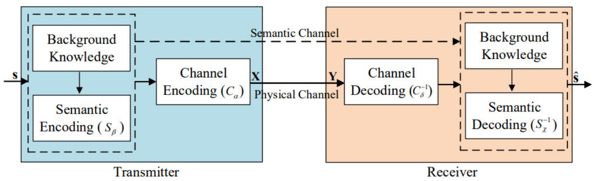
Semantic Transceiver

- **Transceiver**
  - Transmitter
    $\mathbf{X} = C_{\alpha}(S_{\beta}(\mathbf{s}))$,
  - Receiver
    $\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{N}$,
    $\hat{\mathbf{s}} = S_{\chi}^{-1}(C_{\delta}^{-1}(\mathbf{Y}))$



- **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.

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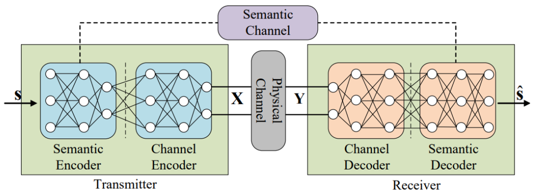
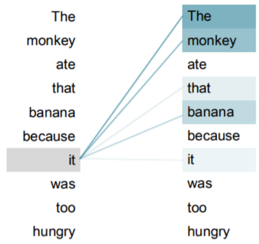
Transceiver Structure

Transformer based semantic communication

- Merge the traditional communication and semantic into DNNs
- Transformer can learn the semantic in text
  - e.g., “it” completes pronoun reference “the animal”





A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, “Attention is all you need,” in *Advances Neural Info. Process. Systems (NIPS’17)*, Long Beach, CA, USA. Dec. 2017, pp. 5998–6008.

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 CE, the network can learn the syntax, phrase, the meaning of words

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

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

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

Performance Metrics

- **BLEU score**
  - Compare the difference between words in two sentences

$$\log \text{BLEU} = \min\left(1 - \frac{l_{\hat{\mathbf{s}}}}{l_{\mathbf{s}}}, 0\right) + \sum_{n=1}^{N} u_n \log p_n,$$

  - $l_{\mathbf{s}}$ is the length of sentence $\mathbf{s}$, $l_{\hat{\mathbf{s}}}$ is the length of sentence $\hat{\mathbf{s}}$
  - p_n is the n-grams score, u_n is the weights of n-grams
- **Sentence Similarity**
  - Use siamese network to compute the semantic similarity

$$\text{match}(\hat{\mathbf{s}}, \mathbf{s}) = \frac{\boldsymbol{B}_{\boldsymbol{\Phi}}(\mathbf{s}) \cdot \boldsymbol{B}_{\boldsymbol{\Phi}}(\hat{\mathbf{s}})^T}{\|\boldsymbol{B}_{\boldsymbol{\Phi}}(\mathbf{s})\| \, \|\boldsymbol{B}_{\boldsymbol{\Phi}}(\hat{\mathbf{s}})\|}$$

  - $\mathbf{B}_{\Phi}(\bullet)$ is the BERT model
  - Sentence, $\mathbf{s}$, will be mapped into **semantic vector space**, $\mathbf{B}_{\Phi}(\mathbf{s})$, by BERT model
  - Similarity is computed by measuring **distance** between $\mathbf{B}_{\Phi}(\mathbf{s})$ and $\mathbf{B}_{\Phi}(\hat{\mathbf{s}})$

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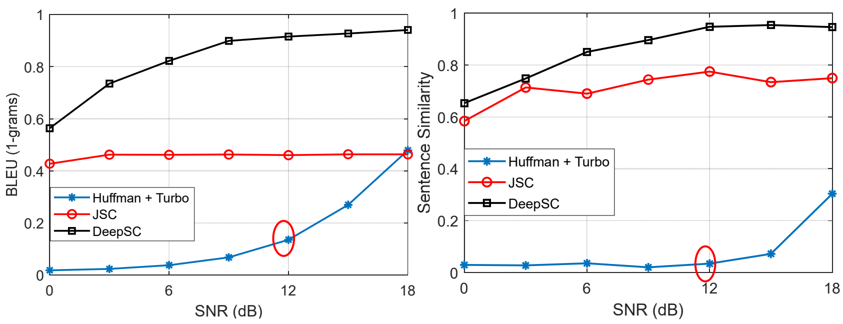
Simulation Results



- All deep learning approaches are more competitive in the low SNR regime.
- The tendency in sentence similarity is much closer to human judgment.
  - In SNR = 12 dB, 20% BLEU score = approximate 0 sentence similarity
  - People are usually unable to understand the meaning of texts full of errors

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Conclusions

❑ For Conventional Communications
*Robust to nonlinear distortion, interference, & frequency selectivity
*Improving performance of iterative detectors and adapt to complicated channels

❑ End-to-end Communication Architecture
* Enabling global optimization of transceiver
* Potentially reducing the complexity

❑ Semantic Communications
*Significantly improving transmission efficiency
*Future of wireless communications

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