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Overview Paper

Machine Learning for Wireless Communication: An Overview

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ABSTRACT

Over the past decades, machine learning techniques have demonstrated excellent superiorities in a wide range of fields, such as computer vision, natural language processing, etc. Through efficient utilization of a huge amount of data, machine learning techniques can solve problems that are hard or impossible for conventional model-based solutions, because the simplified models cannot effectively approximate actual scenarios while complicated models cannot be practically solved in a mathematically rigorous sense. In the meantime, future wireless communication systems are becoming increasingly complex due to diverse practical demands and communication applications. This makes it urgent to find alternatives to conventional solutions and warrants a paradigm shift towards the machine learning-driven direction. Although the convergence of wireless communication and machine learning is just unfolding, it has already achieved initial success in academic research and practical applications. This paper reviews the latest research of machine learning in wireless communications. We highlight key technologies of machine learning-driven signal processing, end-to-end communications and semantic communications, machine learning-based resource allocation, and

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federated learning of distributed systems. Furthermore, open challenges and potential opportunities in the convergence of machine learning and wireless communication are also illustrated.

Keywords: Machine learning, signal processing, end-to-end communication, resource allocation, federated learning.

1 Introduction

Along with the rapid growth of complicated wireless applications, future mobile communication presents the tendency of higher-capacity, higher-dimensions, and higher-density [59], which challenges conventional communication design wisdom. To meet the requirements of high rate and low latency, next-generation wireless communication systems pursue higher bandwidth and spectral efficiency, leading to higher frequency bands and more complex architectural designs. For example, millimeter-wave (mmWave) [12] and massive multiple-input multiple-output (MIMO) [43] are widely regarded as key technologies to future communications. However, the former faces serious path-loss and fading effects [25, 75] while the latter greatly increases the complexity [2]. Moreover, with the increase of frequency and mobility [50], various channel impairments, i.e., noise, fading, distortion, etc., and hardware impairments [19], such as non-linearity and frequency offset, become nonnegligible and seriously affect the performance of the system. Beyond the physical layer, heterogeneous and ultra-dense networks [11, 114] are introduced into wireless networks to improve performance and robustness, while also leading to increasing complexity for practical applications. Various requirements in different scenarios conflict with limited wireless resources, making resource allocation crucial [51]. For these challenges, conventional wireless communications adopt the model-based design and require mathematical models or expert knowledge [19]. However, any model is only an approximation of the actual scene, failing to accurately describe the reality, while inevitably increasing the system complexity. And expert knowledge is hard to obtain from various scenarios. Thus, new paradigms are necessary for wireless communication to further fulfill the requirements.

Recently, machine learning (ML) has made great achievements in various fields. In contrast to model-driven solutions, ML-driven technologies can learn the intricate inter-relationships of variables and train algorithms on vast amounts of data [28, 31], avoiding the need to build accurate mathematical models. Thus, those data-driven approaches can be effectively applied to many complicated scenarios, which are difficult to model. Compared to approximate models, ML-driven technologies may also provide better performance. For example, for areas supported by massive data, such as the computer vision (CV)

[112], natural language processing (NLP) [118], and intelligent recommendation [48], etc., ML-based schemes are demonstrated to outperform traditional solutions. This superiority makes ML a hotspot with great potential.

Inspired by the advantages mentioned above, ML has been widely used for wireless communications. Compared with conventional solutions, ML-driven wireless communication systems display their advantages in many fields, with the widely accepted aspects listed as follows. (i) Reducing the requirement for accurate modeling. With the development of communication systems over the past decades, the models have become increasingly complex, leading to over sophisticated modeling for conventional mathematical tools. Meanwhile, some underlying assumptions in models, e.g., linearity assumption and stationarity assumption, become questionable as the system evolves, resulting in the errors of existing models. However, the data-driven nature of ML reduces the demand for accurate models. They rely on massive communication data with a rough or no model to achieve their tasks, which fits modern communications with a vast amount of accessible data. (ii) Improving the performance and reducing the complexity. ML-driven wireless communication approaches can effectively explore the hidden inter-relationships of variables from data and utilize them to improve performance and reduce complexity. (iii) Breaking the limitation of traditional communication architectures. The ML-driven approaches are not limited to the independent block architecture in traditional transceivers or the bit-/symbol-level performance metrics. They can optimize the end-to-end (E2E) or semantic-level performance for specific applications to improve the quality of service.

For example, to achieve MIMO detection, various ML-driven schemes can be performed with fuzzy channel state information (CSI), i.e., inaccurate mathematical channel models [40, 105], and obtain superior bit-error-rate (BER) performance while reducing channel estimation overhead. For other physical layer communications, e.g., channel estimation [18, 64], channel decoding [66, 67], MIMO precoding [55, 79], etc., ML-driven solutions also demonstrate their superiority over conventional solutions in reducing errors, lowing complexity, or improving robustness. Especially, deep learning (DL)-driven end-to-end communication systems [24, 70, 71, 99] are proposed as new communication architectures, further improving end-to-end performance while reducing system complexity. Apart from the physical layer, in resource allocation [49, 106] and distributed network [44, 62], ML-based solutions also obtain better performance in many complicated scenarios, e.g. non-convex optimization problems [89], complex decision problems, etc. Currently, ML is becoming increasingly significant in wireless communications, and a paradigm shift is taking shape. The major differences between conventional and ML-driven solutions are summarized in Table 1. However, the “no free lunch” theorem [98] reveals that ML cannot apply to all complex applications. ML also faces its unique challenges in application in wireless communications

Table 1: Fundamental differences between conventional solutions and ML-based solutions.

	Conventional solutions	ML-based solutions solutions
Drive mode	Model-driven	Data-driven or data-model hybrid driven
Model	Accurate mathematical or physical models	Does not rely on accurate models
Interpretation	Mathematically or physically interpretable	“Black box”
Generalization ability	Widely applicable	Application-specific

compared with conventional solutions [86]. For example, the interpretability of results, the difficulty of getting enough traning data, the complexity, the long training time of some algorithms, etc., are limiting its deployment in wireless communications [65], which will be discussed in the Section 7. In addition, we should note that for some simple scenarios with typical solutions, the misuse of ML methods can also lead to unnecessary performance loss.

This paper will discuss the paradigm shift in wireless communication, focusing on some ML-driven applications. We will give a brief introduction of recent results from the aspects of ML-driven signal processing, end-to-end communications and semantic communications, ML-based resource allocation, federated learning of distributed systems, and other selected topics, and provide an overview of the recent development and achievement of ML technology in these areas, trying to describe and explain this paradigm shift. Moreover, we will also discuss the challenges of using ML in wireless systems and give some promising research questions and potential directions of ML-based wireless communications research.

2 ML Driven Signal Processing

Over the past decades, signal processing in the traditional communication system has gradually evolved into multi-module chain architectures, where multiple modules cooperate to complete the signal transmission and processing task. And the basis of this cooperation is that each module can effectively complete its function, which leads to the optimization of each module becoming a hot issue in wireless communication system research. For example, the channel estimator estimates the channel information and applies it to signal detection, where the accuracy of the estimated information directly affects the signal detector performance.

Currently, by abstracting communication scenarios into simple mathematical models, such as linear channel models [2], many studies have achieved great success, proposing various algorithms and optimization schemes, e.g., minimum mean-squared error (MMSE) for channel estimation and signal detection, Viterbi algorithm for channel decoding. However, with the development of communication technology, communication scenarios inevitably become complicated. The influences of non-linear, non-stationary, fading problems gradually become apparent, making algorithms and solutions based on traditional mathematical models and tools insufficient. Meanwhile, the increasing scale of communication systems and the limitation on energy consumption require us to control the complexity. Hardware defects ignored before are gradually exposed under high frequency and high-mobility conditions. These complex issues prompt us to find new solutions.

Since those purely model-driven approaches are no longer effective, more data-driven or data-model hybrid-driven solutions are considered by researchers, making ML algorithms promising for signal processing. It is worth noting that the data-driven ML utilizes a huge amount of labeled data to train the network without relying on a mathematical model and expert knowledge, while the model-driven ML combines conventional communication models with ML schemes. The models in the model-driven ML require no accurate modeling compared with the conventional analytical methods. They are utilized to capture domain knowledge to alleviate learning algorithm's reliance on a large amount of data. Through different neural networks (NN), ML algorithms can effectively characterize nonlinear models, adapting ML-driven signal processing to nonlinear scenarios caused by channel and hardware imperfections. Moreover, a well-trained neural network can reduce the computational complexity in practical applications, while maintaining or outperforming the performance of conventional solutions. And the effective robust designs also make ML-driven solutions more robust to various scenarios, improving the generality of the schemes. This section discusses the research of ML-driven signal processing from the aspects of channel estimation and CSI feedback, signal detection, learning-based precoding, and channel decoding.

2.1 Channel Estimation and CSI Feedback

CSI plays an essential role in the signal processing of typical wireless systems. To recover transmitted bits from distorted received signals, the receiver needs to estimate channel state to enable coherent detection and decoding. Meanwhile, through conveying the estimated CSI over a feedback link, the feedback information allows the transmitter to employ adaptive transmission techniques, providing significant gains in performance and efficiency. Therefore, how to accurately and effectively estimate the channel and compress the channel information for feedback on the bandwidth-limited channel becomes important.

However, with the increase in the number of antennas and complexity of channel scenarios, channel estimation and CSI feedback inevitably face many technical challenges. Due to the use of large-scale antennas, the overhead required by traditional channel estimation schemes, including computational overhead and pilot overhead, gradually becomes intolerable. The increasingly complex communication scenarios require more effective estimation schemes. In addition, limited by the bandwidth of the feedback channel and the latency requirement over the fast-varying channel, the feedback systems face challenges to transfer high-accuracy CSI estimates to the transmitter while using limited communication resources, which directly affects transmitter performance. On the other hand, the complexity of the channel scenarios and the large-scale antenna array make feedback CSI massive. Therefore, this pair of contradictions makes it critical to design a compression algorithm to compress the CSI with maintained accuracy. Based on the above requirements, ML-based channel estimation and CSI compression methods are studied.

For example, by combining convolutional neural network (CNN) with MMSE algorithms, the CNN-MMSE estimator in [69] outperforms traditional estimators over the single-path channel while reducing complexity. The ML-driven estimator for MIMO orthogonal frequency division multiplexing (OFDM) systems with fast fading channels in [18, 82] improves the robustness. Considering practical implementation issues, [26] proposes a DL architecture estimator for mixed analog-to-digital converters (ADCs) massive MIMO systems, and [63] investigates joint estimation of the channel, phase noise (PN), and in-phase (I) and quadrature-phase (Q) imbalance in multicarrier MIMO full-duplex wireless systems and develops a deep neural network (DNN). Moreover, [94] uses ML algorithms to compress CSI and significantly improves reconstruction quality. [93] considers time correlation of channels, further improves robustness of compression algorithms, and reduces complexity. Especially for specific communication scenarios, e.g., imperfect channel estimation, hardware limitation, etc., [52, 84, 85] propose several pertinent ML-driven compression algorithms to improve the accuracy of feedback CSI with higher efficiency and lower complexity.

2.1.1 ML Based Channel Estimation

Channel estimation is a process of estimating unknown channel parameters using received data and prior information. For typical pilot-based systems, the traditional methods, i.e., least square (LS) and MMSE, estimate the channel's response based on the pilots inserted in time/frequency domains. Specifically, for multipath channels or MIMO channels, consider a linear channel model,

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{N} \tag{1}$$

where $\mathbf{X}$ and $\mathbf{Y}$ are the pilot symbols and the received symbols respectively, and are assumed to be known to the receiver. $\mathbf{N}$ represents additive white Gaussian noise (AWGN). The LS and the MMSE estimation of channel can be written as

$$\hat{\mathbf{H}}_{LS} = \left(\mathbf{X}^H \mathbf{X}\right)^{-1} \mathbf{X}^H \mathbf{Y} \tag{2}$$

$$\hat{\mathbf{H}}_{MMSE} = \mathbf{R}_{\mathbf{HH}} \left(\mathbf{R}_{\mathbf{HH}} + \sigma^2 \mathbf{I}\right)^{-1} \hat{\mathbf{H}}_{LS} \tag{3}$$

where σ^2 is the noise variance. $\mathbf{I}$ represents the identity matrix. $\mathbf{R}_{\mathbf{HH}}$ denotes the channel correlation matrix.

According to the above results, the LS and MMSE algorithms contain the matrix inversion, whose complexity increases with the dimension of the matrix, i.e., the number of antennas for MIMO systems or the multipath latency for multipath channels. Meanwhile, rapidly varying channels can also lead to excessive pilot overhead, resulting in reduced transmission efficiency. These problems limit the performance of traditional algorithms.

Recently, ML-driven channel estimation has gained much attention. In [69], the channel is modelled as conditionally Gaussian distributed with a set of random hyperparameters. The distribution of those hyperparameters can be learned by a CNN-driven channel estimator from training data via stochastic gradient descent (SGD) methods. Once the CNN-MMSE estimator is learned, the complexity of channel estimation can be reduced to $\mathcal{O}(M \log M)$ with smaller estimation errors, where M represents the channel dimension.

By treating the time-frequency channel response of the fast-fading OFDM channel as a 2D image, a DL-based algorithm is developed in [82]. This scheme firstly models channel response as a low-resolution image based on the pilots and uses DL-based techniques to process the channel image to a high-resolution image. Then, the channel estimation can be easily achieved by converting the processed high-resolution image to the channel time-frequency response. When the channel statistics are perfectly known, the presented algorithm is comparable to the MMSE and outperforms the conventional approximation algorithms in MSE performance. A DL-based channel estimation scheme is proposed in [18] with fewer pilot symbols than transmit antennas. The method first uses DL to perform channel estimation based on pilots and then iterates data detection and channel estimation through a new DNN to reduce estimation errors further. For mmWave massive MIMO systems with a hybrid architecture, [20] utilizes the correlation of channels in spatial, frequency, and temporal domains to design channel estimators. The paper demonstrates all of three proposed methods, respectively named as spatial-frequency CNN (SF-CNN) estimation method, spatial-frequency-temporal CNN (SFT-CNN) estimation method, and spatial pilot-reduced CNN (SPR-CNN) estimation method, effectively improve the estimation accuracy.

Moreover, to reduce the complexity of channel estimation in MIMO-OFDM systems, a new architecture, called dual-CNN, is proposed in [38]. It contains two CNNs that perform channel estimation respectively from the angle-delay (AD) and spatial-frequency (SF) domains. By connecting these two CNNs, the dual-CNN outperforms conventional CNN-based channel estimators in the AD or SF domain with the same complexity. For example, for N transmission antennas and the channel matrix $\widehat{\mathbf{H}}_{\mathrm{LS}} \in \mathbb{C}^{M \times K}$, the structure of dual CNN is shown in Figure 1, where discrete Fourier transform and inverse discrete Fourier transform are used to realize domain transformations between the two CNNs. $D(\cdot)$ and $D^{-1}(\cdot)$ represent the domain transform processes.

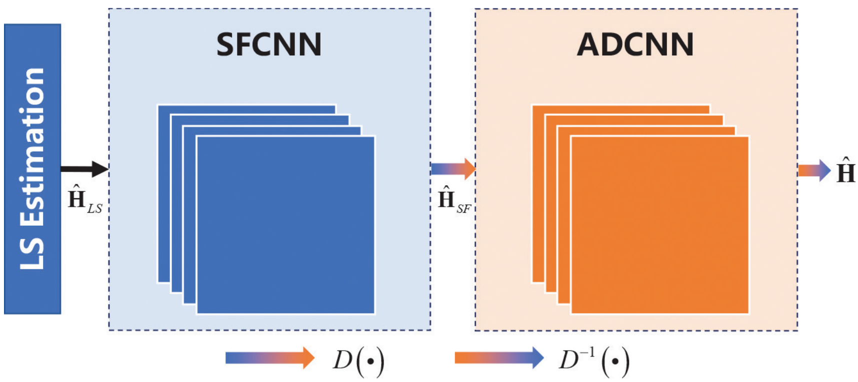

Figure 1: The structure of the dual CNN proposed in [38].

Considering practical implementation issues, in [26], DL is applied to estimate the uplink channels for massive MIMO systems equipped with ADCs of different resolutions. Specifically, it proposes a direct-input DNN to perform channel estimation and a selective-input prediction DNN to eliminate the impact of different ADCs. Additionally, to jointly estimate the channel, PN, and I/Q imbalance in multicarrier MIMO full-duplex wireless systems, [63] develops a DL-driven linear MMSE scheme, which has better MSE performance than traditional methods.

2.1.2 ML for CSI Feedback

The basic architecture of DL-based CSI feedback is shown in Figure 2, where the receiver transfers the estimated CSI to the transmitter through the feedback channel to improve downlink transmission performance. However, limited by the bandwidth and latency requirement of the feedback channel, it is essential to transfer high-accuracy CSI estimations with limited communication resources. Especially for massive MIMO systems, the CSI increases substantially with

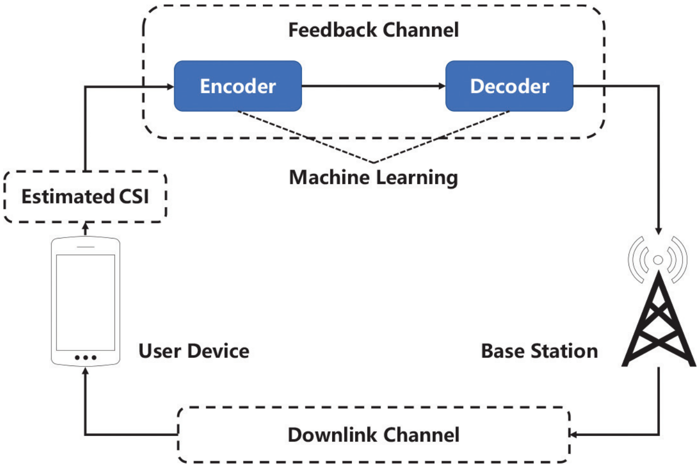

Figure 2: The ML-based CSI feedback.

the number of antennas while the communication resources of the feedback channel cannot be effectively improved.

Scalar and vector-based quantizations are two typical CSI feedback solutions. However, when the transmitter is highly sensitive to estimation accuracy, the feedback faces the overhead challenge since the simple scalar quantization cannot effectively utilize the spatial features of the channel. And for massive MIMO systems, the vector quantization reduction solutions [57] are also hard to handle the proportional growth of complexity with the expansion of codebook size. Moreover, compressive sensing (CS) utilizes the sparse features of the channel to compress CSI while still ignoring the correlations of antennas.

Recently, ML-driven schemes have demonstrated significant success in data compression [73, 77], which is comparable or even superior to state-of-the-art conventional compression techniques. DL technology is used in [94] to develop CsiNet, which can effectively learn to use channel structures from training samples and enable CSI sensing and recovery. Through a trained CNN, CsiNet can convert the original CSI into a small number of representations to realize compression. And then it can also recover the CSI matrix from compressed representations using a recovery network. The basic architecture of CsiNet is shown in Figure 3. The paper demonstrates that CsiNet significantly outperforms the traditional CS schemes in reconstruction performance and still works well at excessively low compression regions. By considering the time correlation of the channel, a DL-driven architecture, called CsiNet-long short-term memory (LSTM), is developed in [93] for real-time feedback. The CsiNet-LSTM enhances the robustness of compression ratio (CR) while maintaining superior reconstruction performance in the same complexity.

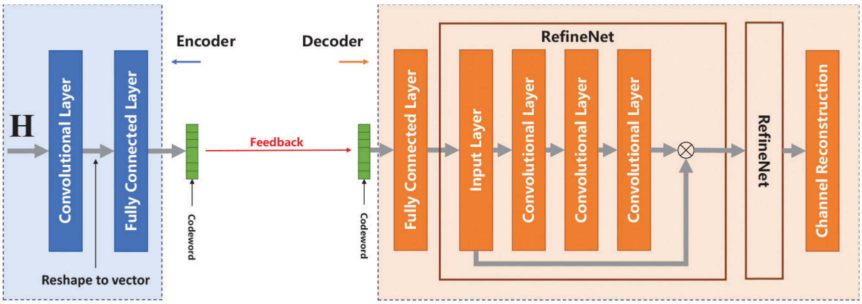

Figure 3: The basic architecture of CsiNet in [94].

Considering the non-ideal channel estimation and the limited bandwidth, the DL-driven method, called AnciNet, is proposed in [84] for CSI feedback. It can extract accurate features from the non-ideal estimation samples and compress the CSI. Additionally, for massive MIMO systems, the ML-driven CSI compression approach in [85], named ENet, utilizes the correlations of complex-valued CSI in the AD domain to reduce the size of the deep network while enhancing feedback performance. For the limitation of device memories, the DL-driven approach is proposed in [52], called CS-ReNet, to realize the CSI compression and recovery. Specifically, CS-ReNet uses the spatial pyramid pooling layer to fix the dimension of generated vectors regardless of the dimension of input vectors, which can effectively avoid overfitting and improve CSI recovery performance. Moreover, the DL-based denoise network, called DNNet, is developed in [110] to eliminate the influence of noises in feedback channels. The proposed method outperforms the conventional schemes in MSE performance, especially when the signal-to-noise (SNR) is low.

2.2 Signal Detection

By modeling signal detection as a classification problem, the current detectors adopt model-based solutions, where the channel model is constructed based on the estimated CSI at the receiver. Moreover, the estimated CSI is generally assumed to be perfect to simplify the detection problem. Based on this, the maximum likelihood detector has been demonstrated to optimally minimize the joint probability of error while detecting all the symbols [2]. However, the exponential growth of its computational complexity with the antenna size and modulation order limits its application in practical scenarios. Therefore, many suboptimal methods are developed to reduce complexity, i.e., the matched filter (MF), the zero-forcing (ZF) detector, the MMSE detector, etc. Unfortunately, there is an inevitable gap between these schemes and maximum likelihood performance. Therefore, finding a good trade-off of performance and complexity becomes the key to detector design.

Based on decision-feedback equalization (DFE), more advanced detection algorithms, such as approximate message passing (AMP) [100] and semidefinite relaxation (SDR) [97], are proposed recently, which have near-optimal performance with lower complexity than the maximum likelihood method. However, these methods still have shortcomings. With the development of communication systems, in addition to the trade-off of performance and complexity, other practical issues, e.g., ill-conditioned channels, CSI estimation errors, algorithm stability, etc., also become nonnegligible. For example, AMP can be easily implemented but is not robust enough for all scenarios while SDR is more robust but slower. Therefore, many ML-based detection methods are proposed to seek breakthroughs.

As in [76], a linear MIMO model $\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}$ is considered. The MIMO channel matrix $\mathbf{H}$ is assumed to be perfectly known by estimation. $\mathbf{n}$ represents the noise vector. The exact value of the vector $\mathbf{x}$ is unknown to the receiver while the symbols in $\mathbf{x}$ are assumed to be independent binary symbols with equal probabilities. Based on this model, the DNN framework for MIMO detection, named DetNet, is proposed in [76]. As a fast algorithm, DetNet utilizes the projected gradient descent method as the core algorithm to realize real-time detection while achieving near-optimal performance. Meanwhile, the robust design enables DetNet to generalize over different channels and handle ill-conditioned channels.

Based on the same MIMO model, a model-driven DNN for MIMO detection is developed in [53]. Through modifying the iterative detection algorithm [60] to DNN structure and mapping the L iterations to L-layer DNN, the network can be fast trained to improve performance. The flowchart of t-th layer is shown in Figure 4, where $\mathbf{H}$ and $\mathbf{y}$ are the channel matrix and the received symbols respectively. $\mathbf{D}$ is a diagonal matrix formed by the diagonal elements of $\mathbf{H}^T\mathbf{H}$. The input vector $\hat{\mathbf{x}}_t$ is the detection result from previous layer and $\mathbf{v}_t = \mathbf{D}^{-1}\left(\mathbf{H}^T\mathbf{y} - \mathbf{H}^T\mathbf{H}\hat{\mathbf{x}}_{t-1}\right)$ is the residual error vector. $\alpha_t^{(1)}$ and $\alpha_t^{(2)}$ are the parameters to be learned by DL. And "$Q\left[\cdot\right]$" is the quantizer. Over the AWGN channel, the proposed method outperforms existing algorithms significantly. Moreover, the model-driven DNN in [32], named OAMP-Net, introduces DL into the orthogonal AMP (OAMP) algorithm to improve detection performance. Since the optimization parameters of the net are few, OAMP-Net can be easily trained. The proposed method has better BER performance than the OAMP algorithm. Considering the temporal and spectral correlations in real channels, [41] utilizes these correlations to accelerate training and proposes MMNet as a new DL-driven detection scheme. It also introduces iterative soft-thresholding algorithms to improve the detection performance of the network. The simulation results in Figure 5 show that MMNet outperforms conventional methods in symbol-error-rate (SER) performance and has near-optimal performance on Gaussian channels.

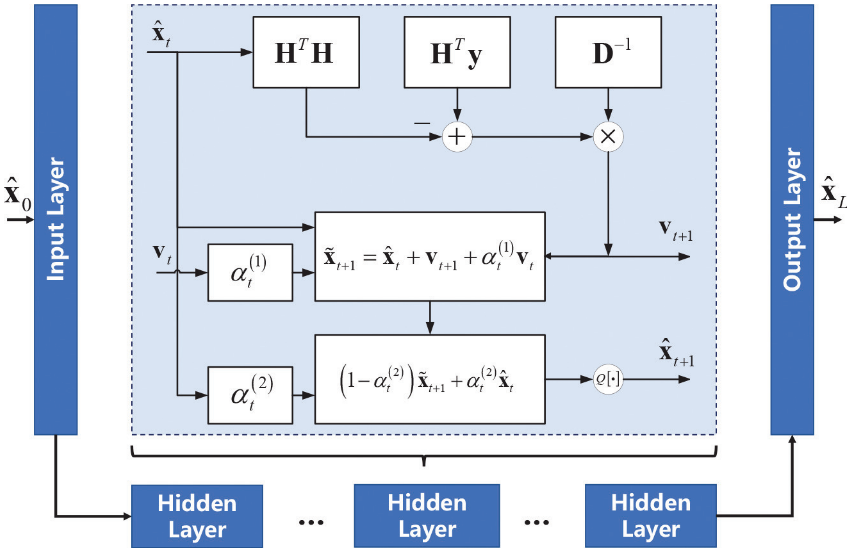

Figure 4: The flowchart representing one layer of the proposed algorithm in [53].

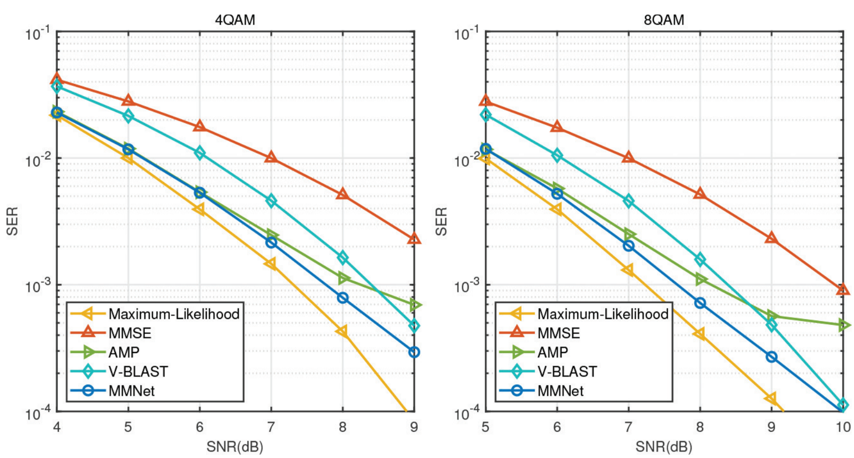

Figure 5: SER performance of different schemes for 4QAM and 8QAM with 16 transmitters, 32 receivers over Gaussian channels in [41].

Furthermore, for the system where CSI is completely or partially unknown, or CSI can only be implicitly estimated, DL-assisted detector is demonstrated to outperform traditional schemes. The sliding bidirectional recurrent neural network (SBRNN) in [23] is robust to changing channel conditions and requires no instantaneous CSI estimation. For mmWave systems with index modulation, the DL-assisted detector in [40] is trained to jointly detect the data and index information without accurate CSI. In addition, a fully-connected DNN (FC-DNN) is used in [105] to estimate CSI and detect transmitted symbols. The proposed scheme works well for fewer training pilots in cyclic prefix (CP) free OFDM systems. Later, the model-driven DL approach in [27], called ComNet, improves the estimation and detection performance of the CP-free OFDM system by dividing channel estimation and signal detection into two DNNs. The paper demonstrates that ComNet outperforms the FC-DNN, especially for high-order modulation systems. For the signal detection of CP-free MIMO-OFDM systems, a model-driven DL-based neural network is developed in [117]. It uses the DL-based approach to modify conventional OAMP detectors to reduce computational complexity while solving the CP-free problem.

2.3 Learning-Based Precoding

Similar to signal detection at the receiver, precoding can significantly improve transmission performance by utilizing CSI at the transmitter. Specifically, by precoding downlink data, the transmitter can concentrate each spatial signal at a specific receiver and improve the SNR or signal to interference plus noise ratio at the receiver. In general, the accuracy of instantaneous CSI at the transmitter (CSIT) can directly determine the precoding performance. In addition, some issues such as codebook design, beam training, hardware limitations, low-complexity design, etc. are also important topics in precoding research.

With accurate CSI feedback available at the transmitter, a DL-driven architecture, named auto-precoder is proposed in [47] for precoding. Through optimizing the compressive channel sensing vectors in an unsupervised learning way and constructing the beamforming vectors directly from the projected channel vector, the precoder can use a few training pilots to design precoding matrices. In [101], three beamforming neural networks (BNNs) are proposed to optimize beamforming performance for multiple-input single-output (MISO) systems. These new networks have better complexity and latency performance compared to the conventional iterative methods while achieving near-optimal beamforming. Moreover, a precoder based on a unified DNN for multi-target precoding is designed in [115], which can simultaneously optimize all objectives and significantly reduce computational complexity with near-optimal performance.

When the channel is fast varying or channel estimation is non-ideal, the transmitter cannot acquire perfect CSIT. Based on this scenario, a beamforming neural network is developed in [55] for beamforming design with imperfect CSI. After training, the proposed network is superior to conventional algorithms in performance and robustness. In [79], the precoding design is firstly modeled as an optimization problem to maximize the ergodic rate. Then to solve this problem, a DL-based scheme is developed, which uses a trained DNN to optimize Lagrange multipliers. Compared with conventional approaches, the proposed DL-based scheme has lower complexity. Later, exploiting this idea, the high-dimensional precoder design problem is transformed into a low-dimensional Lagrange multipliers design problem in [80], reducing the dimension of the problem while maintaining performance. The proposed framework for precoding is shown as Figure 6, where $\bar{\mathbf{h}}_k$ and $\boldsymbol{\omega}_k$ represent channel vectors, $\boldsymbol{\mu}_{\mathbf{h}}$ and $\boldsymbol{\mu}_{\omega}$ represent Lagrange multipliers, and $\boldsymbol{\rho}_{\mathbf{h}}$ and $\boldsymbol{\rho}_{\omega}$ are the power parameters. And the Lagrange multipliers design can be learned by a neural network, as shown in Figure 7, where $\boldsymbol{\Omega}_{\boldsymbol{\beta}} = [(1-\beta_1^2)\boldsymbol{\omega}_1, \ldots, (1-\beta_k^2)\boldsymbol{\omega}_K]^H$, $\bar{\mathbf{H}}_{\boldsymbol{\beta}} = [\beta_1\bar{\mathbf{h}}_1, \ldots, \beta_K\bar{\mathbf{h}}_K]^H$, β_k is the corresponding parameter.

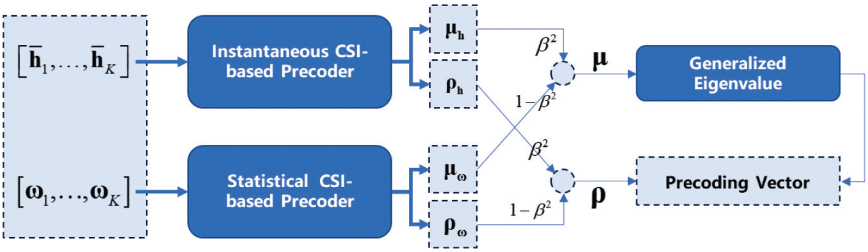

Figure 6: The low-complexity framework for robust precoder design in [80].

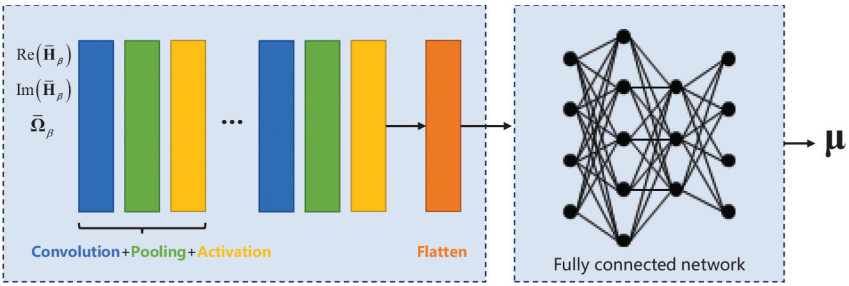

Figure 7: The proposed neural network for lagrange multipliers learning in [80].

Moreover, considering a downlink transmission hardware structure with low-resolution digital-to-analog converters (DACs) for each antenna, [33] develops a model-driven DNN with finite-alphabet precoding. Under the fading channel, the proposed DL-based precoder outperforms the conventional schemes in performance with lower complexity and is robust to imperfect channel estimation.

2.4 Channel Decoding

As a common approach in wireless communication, error correction codes (ECC) can effectively alleviate the influence of signal distortion caused by channels and improve transmission reliability. Similar to detection, decoding of codewords from a certain channel code is another classification problem. Currently, for different channel codes, such as Turbo codes, low-density parity-check codes (LDPC), polar codes, etc., some decoding algorithms, e.g., Viterbi algorithm, BCJR algorithm, belief propagation (BP) algorithm, have been proposed. However, with the increasing demands to reduce latency and complexity, traditional decoding algorithms faces challenges. And DL-based channel decoding gradually gains attention.

Considering the size of the classification problem increases exponentially with the length of the code block, early DL-driven decoders introduce DNNs to the conventional decoding approaches to avoid over-complexity problems for training. For example, an NN-based weighted BP method for low complexity decoding is proposed in [66], which incorporates DL methods into a conventional BP decoder to improve the performance of BP algorithms for short or moderate codes, especially in the high SNR regime. Later, by converting DNN-based BP decoders to recurrent neural network (RNN) architecture, the BP-RNN decoder in [67] introduces the successive relaxation method to the RNN decoder and reduces the number of parameters while maintaining the decoding performance.

DL can also be applied to other encoding methods. For polar codes, the polar encoding graph is partitioned into small blocks in [13] which are trained individually with NN to improve the performance of conventional iterative decoding. For Turbo codes, by incorporating DL into the conventional max-log-maximum a posterior (MAP) algorithm, TurboNet in [35] utilizes series-connected DNN decoding units to replace the iterative decoding process. The TurboNet architecture is shown in Figure 8. Each DNN decoding unit achieves one Turbo decoding with prior probabilities and received symbols as input and outputs priori probability log-likelihood ratios (LLR) for the next unit. The prior probabilities of the first unit are initialized to **0** while the last unit

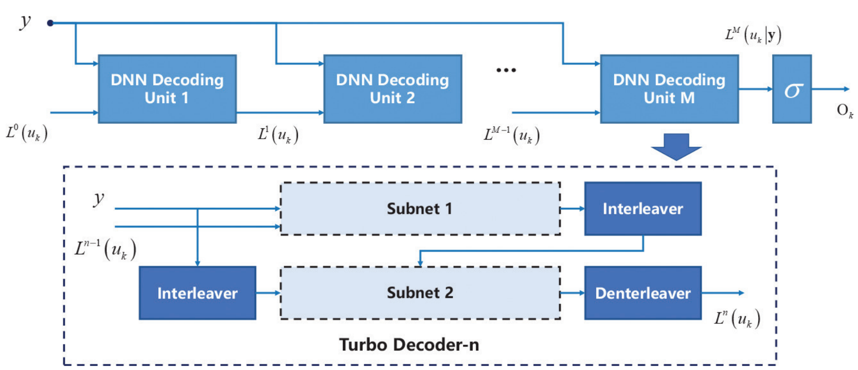

Figure 8: The TurboNet architecture in [35].

outputs posterior LLR vector $L^M(\mathbf{u}|\mathbf{y})$ rather than $L^M(\mathbf{u})$. The proposed TurboNet outperforms the conventional Turbo decoding methods and is robust to different SNRs. To further improve the performance of the TurboNet in complexity and training cost, TurboNet+ in [34] prunes the network and provides an effective training sheme to solve the overfitting issue.

Besides, a fully DNN-based channel decoder is considered in [29]. It utilizes a pure learning strategy to address channel decoding and achieves decoding without iterations by directly optimizing the FC-DNN. However, this method is limited to short blocklengths, i.e., $N \leq 64$.

3 End-to-End and Semantic Communications

In Section 2, we split the processing at the transmitter and the receiver into a series of multiple blocks. Some new communication architectures based on neural network structures have been recently introduced in many studies. This section focuses on two state-of-the-art ML-driven wireless communication architectures: end-to-end communications and semantic communications.

As described in Section 2, the conventional transmitter and receiver architecture are designed as a chained multi-module structure, with each module individually achieving a defined function, e.g., modulation, equalization, detection, decoding, etc., to address channel distortion and interference so that the data can be accurately recovered at the receiver. Based on this architecture, typical signal processing schemes, including typical ML-driven signal processing schemes, individually develop and optimize these modules to achieve overall performance improvement. However, such methods inevitably lead to compromised performance, when faced with a complex application scenario, such as the rapidly changing channel environment, nonlinear distortions in circuitry, etc. As a result, although this approach has achieved significant success in the wireless communication systems we have today, the multi-module chain-based communication architecture has its systematic defects and prevents us from obtaining the best possible end-to-end performance.

Correspondingly, a learned E2E communication system does not require such a rigid modular structure as shown in Figure 9(a). A typical autoencoder is mainly constructed by NN, i.e., an encoder network and a decoder network, as an alternative. During this transmission, the input data s is first processed into an embedding vector $\mathbf{x}$ by the encoder neural network at the transmitter, and the channel is modeled as a conditional probability density function $p(\mathbf{y}\,|\mathbf{x})$. For the receiver, the decoder neural network first converts the received vector $\mathbf{y}$ into a probability distribution vector, and then chooses the symbol with the maximum probability as the decoded symbol $\hat{s}$.

This new architecture breaks the boundaries of individual modules and enables end-to-end optimization, which can theoretically realize global optimal

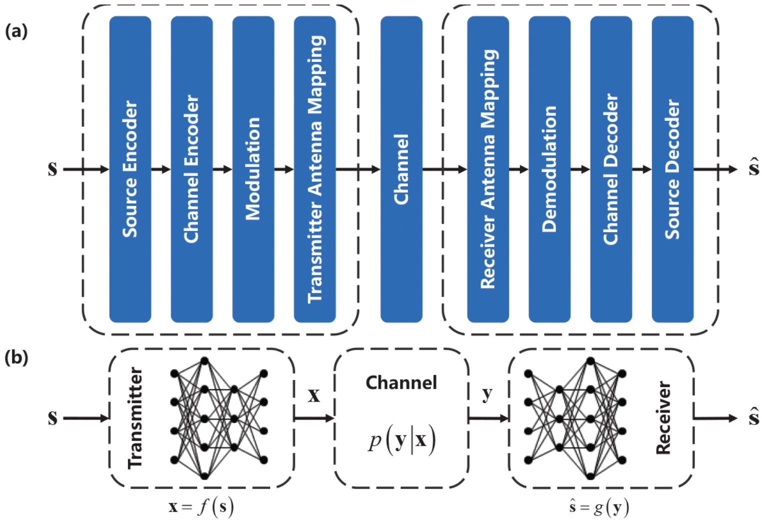

Figure 9: The structures of (a) a traditional wireless communication system and (b) an E2E learning based communication system.

performance. Besides, since the communication system is purely data-driven, the prior knowledge of the channels is not required. It is shown [71] that the basic architecture of E2E has similar or even superior performance to traditional modular systems. Later, [24, 70] further extend the architecture to MIMO and OFDM systems. To reduce complexity, and improve robustness and performance of the system under the E2E architecture, [21, 99, 113] introduce new neural network architectures to replace the DNN architecture and extend the application scenario to non-AWGN channels. Moreover, [6, 107–109] investigate how to learn E2E communication systems without prior knowledge of channel models and propose novel schemes.

Meanwhile, the E2E architecture also provides the basis for semantic communications, which are well adapted to semantic-based application scenarios, e.g., speech transmission, text transmission, etc. Semantic communication considers the meaning and veracity of source information since they can be both informative and factual, and is optimized to minimize semantic errors instead of BER or SER. According to Shannon and Weaver [78], communications can be divided into three levels:

- How accurate is the transmission of communication symbols?
- How exactly do the transmitted symbols convey the desired semantics?
- How effectively the received meaning influence behavior in the desired way?

The conventional communication systems always concentrate on the accuracy and efficiency at the symbol level and usually consider the BER/SER as the performance standard. However, although the bit-level optimization of the communication system has led to significant improvement in the transmission rate, it is approaching the Shannon limit and will be mismatched with the transmission data that is still growing. Besides, the growing requirements of massive connectivity and low latency over limited communication resources also challenge conventional coding approaches.

Unlike conventional communications, semantic communications process and transmit data at the semantic level to improve the accuracy of conveying semantics. Specifically, semantic communications can efficiently extract semantic information from original data while minimizing unessential information. By doing so, data can be further compressed while preserving the meanings, and the transmission data would be significantly reduced. Therefore, compared to conventional communication systems, semantic communication could be used at a lower SNR or bandwidth, or have better transmission performance under the same condition. In addition, since intelligent applications have become universal, semantic-irrelevant data is no longer common, which makes semantic communications more general in actual communication scenarios.

Although [30] demonstrates that semantic communication is theoretically feasible and superior over the noisy channel, the practical and effective design of semantic communication has remained unexplored for a long time since it is difficult to design and optimize individual modules at the semantic level under the conventional architecture. However, the E2E communication breaks the boundaries of individual modules and enables the semantic-level design and global optimization. Based on this architecture, the transceiver can be effectively optimized to reach the Nash equilibrium while minimizing the average semantic errors [9]. And inspired by E2E communication and DL-based NLP, different types of E2E semantic communication systems are proposed [95, 96, 102, 103], which outperform traditional architectures in various scenarios, especially when SNR is low.

3.1 End-to-End Communications

Unlike conventional communication systems that are always divided into several individual modules, a simple E2E communication system can be viewed as an autoencoder. Through learning, the autoencoder can find an optimal function to map the messages $\mathbf{s}$ to symbols $\mathbf{x}$ at the transmitter that can overcome channel distortion and interference, and recover the original messages with a small probability of error from distorted received symbols $\mathbf{y}$ at the receiver. In other words, by adding redundancy, the autoencoder learns an intermediate representation robust to channel impairments.

Specifically, as shown in Figure 10, the typical E2E transmitter utilizes a feedforward neural network with multiple dense layers to approximate the mapping function and a normalization layer to achieve energy constraint. Meanwhile, the input vector $\mathbf{s}$ is transformed into a one-hot vector $\mathbf{1}_s \in \mathbb{R}^M$, where the s-th element equals one while others are zero. The channel is assumed to be an AWGN channel and is represented by an additive noise layer. The receiver also uses a feedforward neural network, followed by a softmax activation with an output vector $\mathbf{p} \in (0,1)^M$, whose elements represent the probability of all possible messages. By selecting the element with the highest probability in $\mathbf{p}$, the transmitted message can be decoded as $\hat{\mathbf{s}}$. In addition, using specific methods, e.g., SGD, the E2E communication transceiver can be properly trained.

At present, the autoencoder based on the above architecture, proposed by [71], has been proved to have similar or even superior performance than traditional modular systems. And based on it, [24, 70] further extend E2E architecture to the OFDM system and MIMO system respectively by treating the channel as a group of independent sub-channels divided in frequency or space.

And different from typical E2E communications with DNN structure, some new methods based on other NN have also been proposed. In [99], a CNN-based autoencoder is proposed for both AWGN and Rayleigh fading channels. The proposed CNN-based autoencoder can work with any input length and flexible data rate while achieving optimal performance of block-error-rate (BLER). Besides, [21] uses generative adversarial networks (GAN) to treat physical impairments in E2E communication systems and embeds conditional Wasserstein GAN into an autoencoder architecture to further improve training stability.

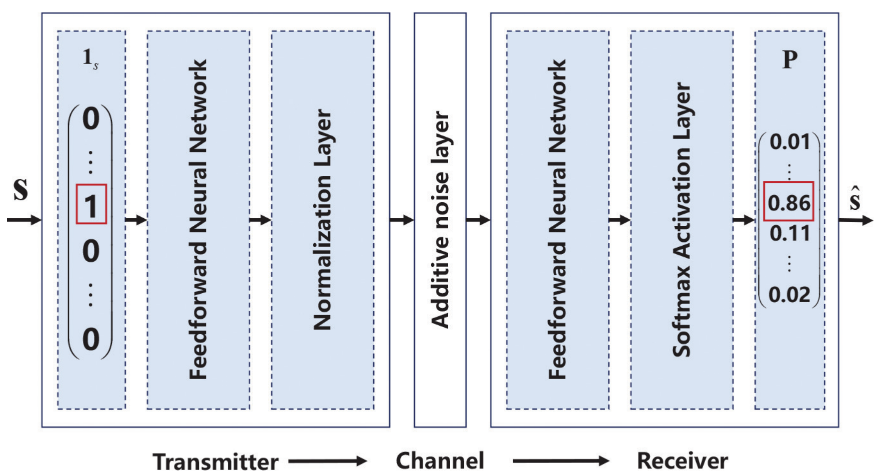

Figure 10: The communications system over an AWGN channel represented as an autoencoder.

And the proposed training strategy requires a simpler training data acquisition process when compared to reinforcement learning based training. Considering the data is generally transmitted in block or sequence form over the fading channel, [113] proposes a DL E2E communication system constituted by LSTM units and residual networks (ResNet). The LSTM units can help the neural network process information sequentially when information bits are transmitted in blocks or sequences, while ResNets are added to accelerate the convergence.

Recently, new architectures and learning strategies of an E2E communication system have been investigated when the prior knowledge of channel models is unknown. In [107], a conditional GAN-based approach is introduced into the E2E communication system to solve the channel-agnostic problem. By utilizing a conditional GAN to learn the channel effects, the proposed method can iteratively train the channel GAN and transceiver DNN to minimize end-to-end loss. However, due to the curse of dimensionality, [107] is only suitable for small block sizes. Based on this, [108] uses convolutional layers to solve the dimensionality problem for large blocks and expands application scenarios. Besides, [6] presents a novel learning algorithm for unknown channel models with non-differentiable components and demonstrates practical viability on software-defined radios. A training procedure with mini-batches of input samples is proposed in [109] for pilot-free E2E communications. The proposed autoencoder has a good E2E performance while reducing pilot overhead.

3.2 Semantic Communications

The typical semantic communication model consists of two levels: semantic level and transmission level, as shown in Figure 11 from [103]. The semantic level extracts and interprets semantic information from messages based on the same background knowledge through encoding and decoding semantic information. The transmission level transfer signal in a specific way to guarantee that semantic information can be transmitted accurately. Considering different physical channels, the background knowledge of the transmitter and the receiver is different, which could be inferred by training data or other prior knowledge.

The goal of semantic communication is to minimize semantic errors with fewer transmission symbols. To achieve this goal, the system requires to design joint semantic-channel coding and transmit information at the semantic level. Based on the background knowledge, this joint coding method mainly focuses on the semantic information that needs to be transmitted while ignoring other irrelevant information, so as to realize the training of NN for semantics.

[30] formulates the semantic communication problem both as a static Bayesian game with a Bayesian-Nash equilibrium and as a dynamic game with imperfect information characterized as a sequential equilibrium. Through this approach, it demonstrates that transmission in the semantic domain improves the communication accuracy of desired meanings under noisy conditions and

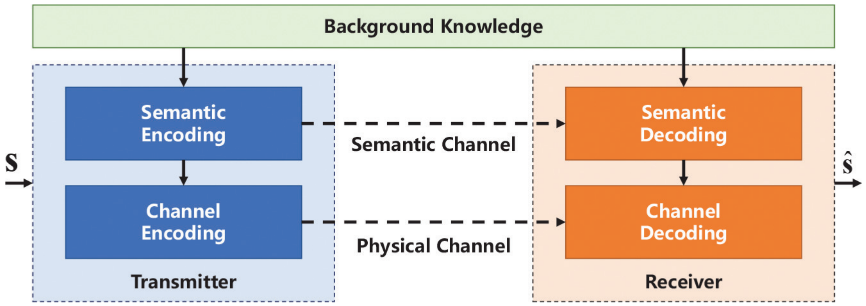

Figure 11: The typical framework of semantic communication system from [103].

defines a semantic error metric as a paradigm for semantic communication design.

In [103], a DL-based E2E semantic communication system, called DeepSC, is proposed for text transmission. Inspired by the NLP approach, DeepSC can address semantic information from transmission data under noisy conditions. And based on the analysis of language texts, DeepSC focuses on minimizing transmission errors at the semantic level, rather than bit-level or symbol-level in conventional communications. Compared with the traditional schemes, DeepSC has superior transmission performance, especially when the SNR is low.

Based on DeepSC, a semantic communication system, called DeepSC-S, is proposed in [96] to transmit speech signals. By adopting squeeze-and-excitation (SE) networks, DeepSC-S can learn to address speech information efficiently. The paper shows that DeepSC-S outperforms the conventional systems in reducing the semantic error of speech. Later, a general model is developed in [95] to improve DeepSC-S performance in dynamic channel scenarios. The proposed model is robust to various channels and maintains good performance without retraining when the channel changes. Moreover, considering the limitation of computing power in the Internet of Things (IoTs) scenarios, the lite distributed semantic communication system, called L-DeepSC, is designed in [102] for low complexity text transmission. By pruning the redundancy of the model and reducing resolution, L-DeepSC can be applied at IoTs devices and efficiency transmit text information at the semantic level.

Furthermore, by combining semantic communications with existing technologies, many new works have been developed to improve the performance of semantic communications. For example, hybrid automatic repeat request (HARQ) is introduced into semantic transmissions in [37] to improve transmission efficiency. It combines semantic coding with HARQ and develops an E2E architecture, named SCHARQ, to reduce transmission bits and received semantic errors. In [116], knowledge graphs are used to enable the cognitive ability of semantic communication systems. Based on knowledge graphs, the proposed framework only transmits important parts of semantic information, while the receiver can detect semantic information and correct errors. Compared with conventional systems, this framework has a higher compression rate and transmission reliability.

4 ML Based Resource Allocation

In the era of 5G and future 6G, the data traffic of mobile devices is exploding, making it of great importance to improve the capacity of communication networks. Furthermore, the 5G mobile communication technologies are expected to be applied to some cases that demand lower latency, higher reliability, and wider coverage, such as mobile health, internet of vehicles, industry control, and so on. To further guarantee and improve the required performance, resource allocation is catching more and more attention.

4.1 Traditional Resource Allocation Solutions

For generic resource allocation, the problems are modeled under certain constraints set by limited communication resources, such as spectrum and energy resources, etc., and are oriented towards improving the performance of the system, e.g., maximizing throughput or minimizing interference. Conventionally, we deal with these optimization problems by mathematical programming methods. However, in many cases, we do not have a precise system model, or the optimal solution to the optimization problems is too complex to obtaining by traditional methods.

To be specific, in many situations, the optimization problems for wireless communication tend to be non-convex and thus are subject to local optima. A typical approach to deal with the non-convex problem is to transform it into convex problems, which, however, may impair accuracy. On the other hand, due to the complexity of wireless channels, we usually cannot get accurate CSI by channel estimation. In addition, based on the traditional methods, the computing process can be too complex to be applied in practical situations. For instance, the weighted MMSE (WMMSE) algorithm [17] is a common approach to maximize the weighted sum rate. It needs many iterations for convergence and each iteration may contain many complex operations like matrix inversions.

4.2 ML-Based Resource Allocation Solutions

Considering the limitation of conventional solutions and the excellent performance of ML in other fields, applying ML for resource allocation problems has gained recent interests. There are mainly two application situations. One is to regard the optimization problems as a "black box", where we only focus on the mapping from the input to the output by ML without knowing channel states. The other is to incorporate ML with an existing algorithm to accelerate optimization.

In the first case, ML is applied to reduce the computation complexity compared to the traditional algorithms. For example, for multi-cell networks, a supervised DL model based on the genetic algorithm is proposed in [1] to allocate the sub-band and power efficiently. After training, the proposed model can compute the optimal allocation solution with high probability while accelerating the computing process. However, a large amount of labeled data (around 17,000 samples in [1]) is needed in supervised learning, which can be hard to obtain from practical environments. Therefore, to avoid the large labeling overhead of supervised learning, [36] adopts the unsupervised learning mechanism, where no labels are required. By training the DNN with unsupervised learning, the proposed scheme can optimize beamforming design with lower complexity and incur no performance loss compared to the WMMSE algorithm.

Reinforcement learning is another effective approach to resource allocation, where the design objective can be directly treated through proper reward shaping. Through reinforcement learning, the agents of the system can learn to find the best actions based on the observation of the state space to maximize its long-term reward. For resource allocation problems, the action is the resource allocation decision, and the reward is related to the design objective, e.g., average delay, the system's cost, resource utilization, etc. And based on the learning model, the system can find the optimal policy to allocate communication resources.

For instance, for vehicle-to-vehicle (V2V) networks, a decentralized resource allocation scheme is developed in [106]. To allocate the sub-band and power in V2V communications, the proposed method utilizes deep reinforcement learning to learn the optimal allocation solution decentralized. After training, each agent in the V2V network can effectively learn how to minimize the interference under the latency constraints. Besides, considering a dynamic multichannel access problem in multichannel networks, [91] develops a dynamic access algorithm based on the deep Q-learning network. After training, users can find a good policy for channel selection to maximize successful transmissions even when the channel dynamic is unknown.

Furthermore, as part of the overall algorithm structure, ML can be used to assist in resource association. For example, [58] investigates a joint design of positions of unmanned aerial vehicles (UAV), UAV-user equipment (UE) associations, and transmit beamforming in the downlink of a multi-UAV-assisted wireless network. After modeling the association problem into a mixed-integer nonlinear programming problem, [58] respectively develops a deep Q-learning approach to determine the positions of all UAVs and a difference of convex algorithm to design transmit beamforming and UAV-UE associations. By iterating between two methods, the association problem can be efficiently solved with significant improvement in convergence compared with the conventional algorithms.

5 Federated Learning for Distributed Systems

As a distributed ML paradigm in wireless communication, federated learning (FL), also known as federated ML, is proposed to coordinate multiple clients to solve ML problems. This paradigm allows clients to train a model based on the local data and upload the updated part of the model to the central server for aggregation, avoiding the transmission of massive original data and effectively protecting user privacy.

Specifically, FL performs training on distributed participating clients (e.g., mobile phones), each of which has part of the training data and then a central server aggregates these training models collected through information exchange. The clients and the central server only exchange the model parameters rather than the original data to protect privacy of the clients. Therefore, users benefit from shared models based on data collected by all clients while avoiding data leaks.

In contrast to traditional distributed systems, in FL, the computing nodes have full control and privacy and can stop computation and communication anytime. However, there still exist many problems, such as the system and statistical heterogeneity, robustness, personalization, and the tradeoff between communication resources and performance optimization. In this section, we first introduce the basic architecture of FL and then we discuss the challenges and the related solutions.

5.1 Basic Architecture of Distributed and Federated Learning

Typically, there are two main architectures of FL systems based on the network topology [39, 44], namely centralized FL systems and fully decentralized FL systems.

5.1.1 Centralized FL

In centralized FL [61], a central server coordinates multiple clients to solve the learning task. Each client has a local training dataset to train a ML model and only transmits an update to the server for global model aggregation. Meanwhile, for privacy protection, the local training dataset is stored in each client and is never uploaded to the server.

To be specific, as shown in Figure 12, a typical FL architecture consists of several clients and a central server. And the FL training process can be summarized into the following three steps.

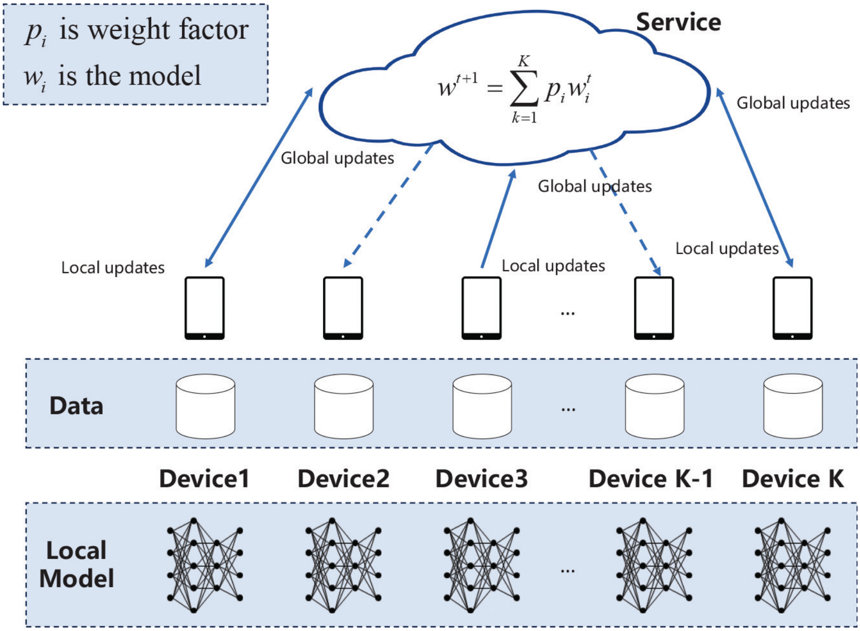

Figure 12: The typical architecture of a centralized FL system.

- Step 1 (Initialization): The central server determines the data requirements and training parameters and broadcasts them to the selected clients with an initialized global model and corresponding training task on the broadcast channel.

- Step 2 (Local training and update): Each client participating in FL trains and updates its local model based on the received global model and the local data according to training requirements. Then the client sends the updated part of the model parameters to the server.

- Step 3 (Global aggregation and update): The central server performs global aggregation on the updates from all participants to produce a higher quality global model.

The process iterates until a pre-set training accuracy is satisfied.

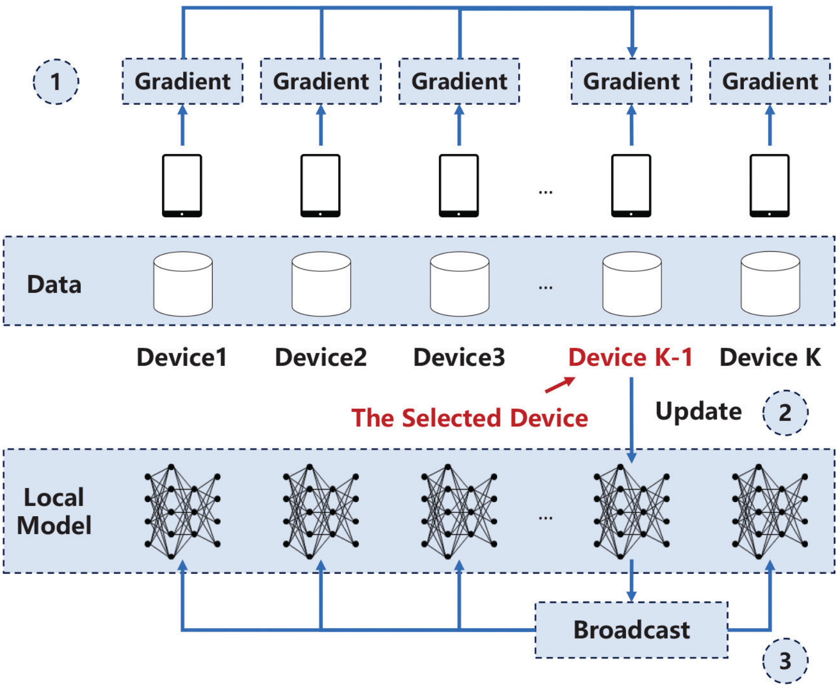

Figure 13: The typical architecture of a fully decentralized FL system.

5.1.2 *Fully Decentralized FL*

In fully decentralized FL [39, 44], there is no central server and all communications take place between the participants, as shown in Figure 13, which makes stronger encryption and decryption operations required. In each iteration, participants first update the gradients based on their local data and send those gradients to a selected data holder participating in the joint training. Then, the selected data holder updates the model based on the received gradients and the local data and broadcasts the model to all participants. The iteration stops when each participant is selected for updating the model for about the same number of rounds to utilize all data and guarantee fairness for all participants.

5.2 *Key Problems for Federated Learning in Wireless Communications*

5.2.1 *Heterogeneity in Federated Networks*

Distributed ML allows all clients at different locations to participate in model training in parallel while protecting privacy. However, the participants may differ in structure and performance in practical applications, leading to system and statistical heterogeneity problems [45]. Specifically, system heterogeneity refers to the differences in storage, computing power and communication performance of each participant because of the differences in hardware, network connectivity, power, and so on. And statistical heterogeneity refers to non-independent and identical distribution (non-IID) data generated and collected by the clients. Moreover, it has been found in [104] that heterogeneity can impact FL on the accuracy and training convergence, causing significant performance degradation in FL tasks. The Federated Averaging (FedAvg) algorithm proposed in [61] firstly deals with the heterogeneity by averaging local SGD updates and is demonstrated to work well for non-IID data and unbalanced systems.

However, FedAvg cannot provide convergence guarantees. Therefore, [46] proposes FedProx to deal with the convergence problem by integrating device lag signal updates. Since ignoring or partly combining the information of stragglers can lead to slower convergence, FedProx introduces a proximal term to the objective to improve method stability. Compared to FedAvg, FedProx can dramatically improve convergence of practical heterogeneous networks.

5.2.2 Privacy and Security

Privacy is the primary concern in FL since the original intention of FL is to train models under the premise of protecting user data privacy by transmitting model updates rather than the original data. However, this decentralized training approach risks exposing model parameters, which may make FL vulnerable to various attacks. The typical privacy and security assurance schemes are secure aggregation (SA) and differential privacy (DP).

To prevent local model updates from being tracked, SA requires the central server to compute the sum of the local gradient updates of the clients without revealing the contribution of each client. There are mainly three SA techniques, namely homomorphic encryption, secure multiparty computation (SMC), and Blockchain. Specifically, homomorphic encryption directly encrypts original text and performs operations on the ciphertext. While in SMC, multiple participants with their secret input collaborate to compute an agreed function, ensuring that each party only infers its results. And in blockchain, data is stored, verified, and transmitted through specific distributed nodes owned by the first party to ensure security.

Different from SA, DP tends to be a tradeoff between privacy and accuracy by adding noise intentionally to obfuscate the source of data. [10] first proposes the concept in FL to protect the clients' privacy from differential attacks by adding noise to sensitive information to hide the clients' contributions during training. Meanwhile, the model performance loss caused by the added noise is controlled at a low level.

5.2.3 Gradient Compression for Efficient Transmission

Communication is a critical bottleneck in FL compared to computation due to the large scale of FL networks and the multiple iterations during the training process [45], prompting researchers to investigate efficient transmission in FL.

Considering most of the gradient exchanges in distributed SGD are found to be redundant [56], a large number of studies have shown that transmitting the updated gradient by sparsification, quantization, subsampling, encoding, and some other compression strategies significantly improves the performance of FL [5, 62]. [56] proposes a deep gradient compression (DGC) scheme to reduce the required communication bandwidth. It is shown to compress the gradient by a factor of 270-600 for a wide range of CNNs and RNNs without losing accuracy. Two distributed SGD (DSGD) based methods are proposed in [5] over the noisy fading wireless channel, where one is digital DSGD (D-DSGD) and the other is compressed analog DSGD (CA-DSGD). Considering the separation of communication and computation, in each iteration, D-DSGD selects the device according to the channel state, then quantizes the estimated gradients to a certain number of bits based on the channel condition and sends these bits to the server. CA-DSGD considers the similarity of estimated gradients at different devices, projects the sparsity gradient estimates to a low-dimensional vector, and then only transmits the important gradient entries for bandwidth reduction. The paper demonstrates that CA-SDGD outperforms D-SDGD with non-IID data and is robust to imperfect CSI.

5.2.4 Some Other Issues

In addition to compressing the gradient for efficient transmission in FL, recently, more and more researchers pay attention to jointly optimizing FL and communication resources for better performance. For example, a joint communication and FL framework has been developed in [16]. It formulates the distributed learning, communication resource allocation, and user selection problem as an optimization problem. Based on the expected convergence rate of FL, it develops an algorithm to find the optimal allocation solution of the user selection and the transmit power allocation to minimize FL performance loss. Considering a noisy downlink, the convergence of FL has further been investigated in [4]. It provides effective transmission schemes for digital and analog downlinks, and analyzes the convergence of the analog downlink scheme over imperfect downlink channels. [90] studies the resource allocation problems to reduce the convergence time of FL and develops a deep Q network-based approach to optimize convergence time with limited wireless resources. Besides, considering the tradeoff between energy consumption, learning time, and learning accuracy, [87] develops an optimization problem and provides a globally optimal solution. Moreover, [92] focuses on the tradeoff between local

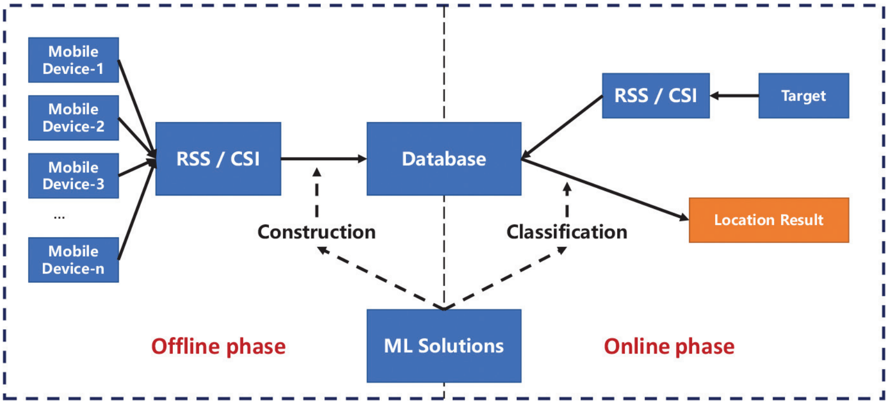

Figure 14: The architecture of fingerprinting-based localization.

update and global aggregation and proposes a control algorithm to optimize the frequency of global aggregation with limited communication resources.

6 Selected Topics for ML Wireless Communications

This section briefly discusses several topics of ML-based wireless communications that are uncovered in the preceding sections. The topics include wireless indoor localization, ultra-dense hyper-cellular network, and DeepNOMA.

6.1 Wireless Indoor Localization

Unlike outdoor positioning, where satellite constellations, e.g. GPS and BeiDou, can be used, wireless indoor localization faces more challenges, such as shadowing, multipath effect, etc. For this problem, fingerprinting-based localization is currently one of the state-of-the-art solutions.

As shown in Figure 14, fingerprinting-based localization usually consists of two basic phases: the offline training phase and the online test phase. The training phase is used for database construction, preprocessing survey data related to the position marks. In this stage, the received signal strength (RSS) samples of each transmitter are collected by the sensors of smartphones at different reference points as a database. Then by comparing the received power samples on the target location with the database, the target can be located according to matching approaches in the online phase.

Based on this model, [42] proposes a novel ML-driven algorithm for indoor localization, where an autoencoder-based deep extreme learning machine is utilized to improve the feature extraction capability. Later, [88] further extends the fingerprint-based positioning to MIMO systems and utilizes a deep CNN to learn the sparse structure of massive MIMO channels for localization. For Wi-Fi systems, [15] proposes the first CNN-based Wi-Fi localization algorithm, called ConFi. Considering CSI contains more location information than RSS, it uses a CNN to extract position features from CSI for localization and improves localization performance.

6.2 Ultra-Dense Hyper-Cellular Network

To further increase system capacity and improve the quality of service, the ultra-dense network introduces a large number of small cells to the conventional communication network, significantly reducing the transmission distance between users and base stations (BSs) and improving spectrum utilization. However, with the reduction of the transmission distance and the increase of the number of BSs, the densified network faces several challenges, e.g., the strong interference among densely deployed BSs, the allocation of resources, etc. Recently, ML-driven methods are introduced to the ultra-dense hyper-cellular network.

For interference management, [83] proposes a parameterized coordinated beamforming scheme considering the balanced strategy in ultra-dense networks. The optimal balancing coefficients are learned by the deep reinforcement learning method to design the beamforming vectors.

For resource allocation, [14] proposes an unsupervised learning approach to design the optimal network topology, which can balance energy consumption and increase the lifetime of devices. Considering the ultra-dense network with a limited amount of CSI, [54] utilizes deep reinforcement learning methods to allocate the subcarrier selection and the transmission power for the best tradeoff between spectrum efficiency, energy efficiency, and fairness.

6.3 DL-Driven NOMA

Non-orthogonal multiple access (NOMA) can potentially provide massive connectivity for future IoTs. However, the non-orthogonality of NOMA makes it tricky for traditional communication methods to process. Therefore, the DL-driven NOMA currently become a research hotspot.

For example, the DL-based multi-user detection algorithm in [68] can recover symbols of all users in a one-shot process without the explicit channel estimation and outperforms traditional methods in robustness and SER performance.

To significantly reduce the overhead of control signals and the transmission latency, a finite-alphabet signature is designed in [111] for the grant-free NOMA with random and nonuniform user activations. The proposed scheme outperforms the conventional ones, especially when the users have unequal activation probabilities.

7 Open Challenges and Opportunities

In this section, we will discuss some open issues and identity potential opportunities in the area of ML for wireless communications.

7.1 Open Challenges

Although ML algorithms have achieved significant improvements in various fields of wireless communications as mentioned above, there are still some open issues to be investigated.

7.1.1 The Interpretability Problem

The "black-box" nature of the ML-driven methods is a major resistance for the deep convergence of ML and wireless communication. Over the past decades, communication engineers usually provide performance guarantees on specific performance parameters, e.g., error probability, MSE, system latency, etc. Those guarantees are supported by the reliable mathematical or physical system models. Their validity is depended on the accuracy of these models. However, the data-driven methods are trained on data rather than dependent on a specific model, leading to the inability to guarantee system performance. Although many ML-driven wireless communication methods have achieved great success, how to explain the reasons behind the success credibly is still an important problem to research.

7.1.2 Limited Availability of Data

Unlike in CV, language processing, or intelligent recommendation, standard datasets for different application scenarios are generally lacking in wireless communication, making it difficult to train or test the proposed ML-based methods. Thus, more public and standardized datasets are expected for the community. That said, we have witnessed some initial efforts in this direction, e.g., the DL dataset for mmWave and massive MIMO applications [3], datasets for semantic communication [72], and datasets for indoor positioning [7], etc., available to the public.

7.1.3 Non-stationary Communication Scenarios

Along with the convergence of wireless communication and ML, ML-driven algorithms are used in a wider range of communication scenarios. However, in the communication scenarios with high frequency or high mobility, e.g., mmWave communication, V2V communication, high-speed train communication, etc., wireless channels are often non-stationary in time or frequency, which means wireless channels in different frequencies or times may exhibit different statistical characteristics. In those scenarios, offline training based on certain datasets may not promise satisfactory performances in other channel conditions. And online training is required to improve system robustness. However, according to current research results, the online training time of machine learning may still be unacceptable for the timescales of communication systems.

7.1.4 Complexity Challenges

Since data-driven algorithms require massive datasets and computing resources, many successes with ML-based methods are supported by machinery with excellent computing power. However, for wireless communication, most mobile devices have limited computing and storage resources due to their portable sizes and power sources, which may limit the power of ML-based techniques. In addition, limited by the transmission bandwidth and energy consumption, it is hard to opportunely transmit massive data between the processor and the mobile terminal, resulting in each wireless UE typically having only a small amount of data, further limiting the learning capabilities. Therefore, it is necessary to investigate distributed learning and low-complexity ML-based algorithms in the wireless setting.

7.2 Potential Opportunities

This section discusses the potential opportunities and research directions of ML-based wireless communications.

7.2.1 Multiagent Cooperation

Along with the incredible growth of agents in industrial networks and vehicular networks, the issues of communication and cooperation between agents gradually become nonnegligible. In these networks, data is generated and stored across different devices, e.g., vehicles, industrial sensors, remote servers, etc. Meanwhile, different units cooperate and coordinate with each other through information sharing to reach system-level optimal performance. Such scenarios can be technically regarded as a multiagent system, where each agent can obtain information from the environment while jointly optimizing the performance with other participants. Based on ML, each agent can learn what to share and perceive and how to act in the next step, with optimal network transmission overhead.

Furthermore, conventional multiagent learning systems generally ignore the communications costs to simplify the models, by assuming the information sharing process is error- and delay-free. However, with the expansion of application scenarios, the actual wireless channels become intricate, where some harsh issues, e.g., channel fading and interference, should be considered since they actually constrain the cooperation. And the limitations of wireless resources, e.g., channel bandwidth and transmission power, also cause errors and delays in multi-agent communication. Therefore, designing efficient multiagent cooperation mechanisms under the constraints of wireless communications is an ongoing research topic.

7.2.2 Knowledge Driven ML

Due to the nature of wireless communication, data-driven ML-based algorithms face many challenges as described in the previous section, such as interpretability problems, limitation of data, complexity challenges, etc. To meet these challenges, a potential solution is the additional integration of prior knowledge, e.g., encapsulating domain knowledge in the form of heuristics, data structures, semantic models, etc., into the ML architecture to assist learning. Compared with conventional ML, knowledge-driven ML (KDML) has a unique module to understand prior knowledge and utilizes the knowledge to simplify the network's structure and training process and improve interpretability. However, how to effectively integrate KDML into wireless system design remains unclear and warrants further study.

7.2.3 Security Communication

Since the shared and broadcast nature of the wireless medium, the security and privacy of wireless communication have gradually gained more attention in recent years. Once a module in a complex communication system is attacked, the entire communication system will be affected. Therefore, ML-based methods can be considered to improve wireless communication security. For example, [81] proposes an adversarial DL-based scheme to defend against exploratory attacks on cognitive radio transmissions in wireless communication. And [22] develops a DL-driven method by interfering with the attacker's predictions to defend against intelligent jamming attacks in wireless communications.

Moreover, ML also brings huge potential risks by itself. When there is maliciously designed noise or rewards, ML-driven algorithms can also be easily deceived [8, 74], leading to incorrect decisions or output. As a result, it is crucial to improve the robustness and security of ML, especially for safety-sensitive areas. Due to the massive data transmission and communication in ML-based algorithms, data privacy is also a key issue for ML applications. Based on this, it is important to consider data privacy in learning-enabled wireless system design, such as authentication/authorization, regulatory requirements, rotation of keys/certificates, etc.

8 Conclusion

In this paper, we have investigated the paradigm shift of wireless communication from conventional schemes to ML-driven solutions. Modern wireless communications have a growing demand for higher data rates, improved reliability, and lower latency, while also embracing more spectrum in the high-frequency band. This poses significant challenges to the wireless system design, thus calling for revolutionized changes in the design principles and objectives. In the meantime, allocating and trade-off the limited but diverse resources in wireless communication systems is also a challenge. ML is widely recognized to be a promising solution to those challenges since its satisfactory performance in various areas. We have provided some examples of applying such tools from the aspects of ML-driven signal processing, end-to-end and semantic communications, ML-based resource allocation, federated learning of distributed systems, and other focused topics, and tried to explain the motivation behind the paradigm shift. Additionally, we have further discussed some open issues and potential directions for future research.

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