Semantic Communications for 6G Future Internet: Fundamentals, Applications, and Challenges

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Abstract—With the increasing demand for intelligent services, the sixth-generation (6G) wireless networks will shift from a traditional architecture that focuses solely on high transmission rate to a new architecture that is based on the intelligent connection of everything. Semantic communication (SemCom), a revolutionary architecture that integrates user as well as application requirements and meaning of information into the data processing and transmission, is predicted to become a new core paradigm in 6G. While SemCom is expected to progress beyond the classical Shannon paradigm, several obstacles need to be overcome on the way to a SemCom-enabled smart wireless Internet. In this paper, we first highlight the motivations and compelling reasons of SemCom in 6G. Then, we outline the major 6G visions and key enabler techniques which lay the foundation of SemCom. Meanwhile, we highlight some benefits of SemCom-empowered 6G and present a SemCom-native 6G network architecture. Next, we show the evolution of SemCom from its introduction to classical SemCom related theory and modern AI-enabled SemCom. Following that, focusing on modern SemCom, we classify SemCom into three categories, i.e., semantic-oriented communication, goal-oriented communication, and semantic-aware communication, and introduce three types of semantic metrics. We then discuss the applications, the challenges and technologies related to semantics and communication. Finally, we introduce future research opportunities. In a nutshell, this paper investigates the fundamentals of SemCom, its applications in 6G networks, and the existing challenges and open issues for further direction.

Index Terms—Semantic communication, sixth-generation Internet, goal-oriented communication, effectiveness coding, artificial intelligence

I. INTRODUCTION

A. Motivation

The advent of the fifth-generation (5G) has brought about a breakthrough in communication network design [1], enabling a variety of services from digital twins, edge computing, the Internet of Things (IoT) and more, through the supporting pillars such as ultra-reliable and low-latency communications (URLLC) and enhanced mobile broadband (eMBB) communications.

As we revisit the development path from 1G to 5G, it is evident that the conventional focus has been to optimize data-oriented performance metrics, such as communication data rate and bit error probability, while ignoring service-, goal-, or semantic-related metrics. For example, 3G focuses on mobile broadband development and promises a thousand times data rate of 2G, whereas 4G unlocks high-speed Internet streaming through delivering a thousand times data rate of 3G. The motivation for this convention is traced back to the time when Shannon first demonstrated that reliable communication is possible in noisy channels in the classical information theory (CIT) literature [2]. Shannon believed that “the semantic aspects of communication should be regarded as irrelevant to the engineering problem”. The reason is that the meaning of a message can be related to “certain physical and conceptual entities” and that involving the meaning in a mathematical model may affect the generality of the theory [2].

Recently, content-centric data-driven communication architecture is increasingly seen as a barrier to providing end-users with services that demand high quality of experience (QoE). This is especially so given that the emerging applications of the 6G will be human-centric, data-, and resource-intensive. One such application is the Metaverse [3], which has been envisioned to be the future Internet. Just as we navigate the webpages of today’s Internet, we will soon explore the virtual worlds of the Metaverse through a head-mounted display (HMD) or navigate the augmented physical world through Augmented Reality (AR) glasses. The Metaverse is formed via the synchronization of the virtual and physical worlds, and the result is that one’s actions in the virtual and physical domains will be inextricably linked. Driven by Artificial Intelligence (AI), edge intelligence, virtual and augmented reality, as well as blockchain technology [4], [5], the user-centric QoE metrics required for the successful implementation of the Metaverse calls for a rethink of the CIT driven communication networks, because the massive data from new applications increases
TABLE I: A comparison of contribution between relevant surveys and our survey.

| Reference | Key contributions of the survey | How our survey differs |
|-----------|---------------------------------|------------------------|
| [9]       | Discuss the importance of SemCom and suggest a new architecture that facilitates an efficient cross-layer design capitalizing on the new levels. A vision paper whose goal is to motivate a paradigm shift from the mainstream research. | We present a comprehensive analysis of current technical papers that apply SemCom in the latest 6G networks, and detail the features of SemCom and 6G. |
| [6]       | Introduce the SemCom principles and two design approaches, i.e., layer-coupling design and end-to-end design using a neural network. Discuss specific techniques for different application areas of SemCom. | We classify the SemCom into three categories, which is more complete and covers the various ways how the SemCom is currently applied in 6G. The future research directions can also be inspired by our classification. |
| [10]      | Discuss SemCom with theory, frameworks, and system design enabled by deep learning. New performance metrics for SemCom are also discussed. | Instead of focusing mainly on AI-driven SemCom, we thoroughly consider the various forms of SemCom in 6G networks and study the application scenarios and challenges of 6G SemCom from both semantic and communication aspects. |
| [7]       | Review classical SemCom frameworks and then propose an architecture based on federated edge intelligence for supporting resource-efficient semantic-aware networking. | These papers focus on only a few aspects of SemCom, e.g., FL-enabled SemCom networks [7], task-oriented semantic systems [8], and DL-enabled E2E semantic networks [11]. However, in this paper, we give an exhaustive and comprehensive overview of SemCom systems, and we discuss the existing applications and the future potential of SemCom in the context of the latest developments in 6G. |
| [8]       | Apply SemCom to a communication scenario where the destination is tasked with real-time source reconstruction for the purpose of remote actuation. | |
| [11]      | An overview of the latest deep learning (DL) and end-to-end (E2E) communication based SemCom is given and open issues that need to be tackled is discussed explicitly. | |

significantly the processing latency of conventional communication networks.

In response, a novel paradigm known as semantic communication (SemCom) is inspired as a brand new technology in 6G to breakout the “Shannon’s trap”, which identifies and utilizes the meaning of messages during Internet communication. In contrast to conventional data-oriented communication networks, which improve the network capacity at the cost of system complexity, SemCom enables all communication participants to lighten the network burden via transmitting the most relevant information for the receivers or the goal of communication task after the pre-processing of the data based on the advanced AI technology [6]–[8]. The development of SemCom and the advancement of 6G are mutually reinforcing. On one hand, the availability as well as connectivity of distributed computation and ubiquitous AI networks that are brought about by 6G will allow SemCom to be feasibly deployed at scale [9]. On the other hand, SemCom transcends traditional communication constraints and will enable unprecedented improvements in network performance. Thus, after completing the training and deployment of SemCom, the visions of 6G, e.g., lower latency than 5G and enhanced reliability, can be fully realized. However, while the mutually reinforcing convergence properties in 6G and SemCom have attracted the attention of the academic community, there is not yet a comprehensive survey paper that provides a complete overview of the developments, challenges, and future trends for the SemCom-enabled 6G and Beyond networks. As SemCom is a relatively nascent topic, our survey aims to serve as a useful and effective guide for future studies for researchers and practitioners alike that look to incorporate SemCom concepts into future communication architectures.

B. Comparison and key contributions

Due to the recent attention in SemCom, some review papers exist. A comparison between our survey and the related reviews in the literature is shown in Table I. The authors in [9] give a detailed overview of the origin of the idea of SemCom and its development history and discuss the methods in which SemCom can be integrated into existing communication networks. However, as the authors state in [9], their main aim is to bring the SemCom paradigm to the attention of the academic community. Although the idea of SemCom is well described, the authors in [9] do not specifically discuss how to integrate SemCom with the 6G technologies. In our survey, we will extensively discuss how 6G technologies can drive the development of SemCom and how SemCom can enable the performance breakthrough of 6G networks.

The authors in [6] attempt to classify the SemCom literature into three broad areas namely human-to-machine (H2M), machine-to-machine (M2M), and knowledge graph based SemCom. The SemCom techniques for each category are then reviewed. However, the categories of classifications do not cover the full range of implementation challenges of SemCom networks. In our survey, we review the semantic-related challenges and communication-related challenges for SemCom implementation. We also provide insights into SemCom applications and implementations for 6G and beyond networks, and discuss the specific technical designs and future directions.

As a powerful driver for 6G, AI will certainly play an important role in the development of SemCom networks. As such, the authors in [10] discuss how deep learning can be used to empower efficient network design for SemCom. However, not enough attention is paid to the communication challenges. Considering that the design of the communica-
tion infrastructure can severely affect the overall network performance, we comprehensively discuss how SemCom can be used to assist the communication resources management and improve the performance of wireless transmission in 6G networks. Moreover, several other review papers [7], [8], [11] have provided insights from different perspectives with regards to the design of SemCom systems, e.g., FL-enabled SemCom networks [7], task-oriented SemCom systems [8], and DL-enabled E2E semantic networks [11]. However, these studies review the works from a limited perspective and do not provide a comprehensive review of the challenges and techniques.

In recognition of the fact that a successful implementation of SemCom systems must solve both the semantic-related challenges and communication-related challenges, our survey aims to provide readers with a multifaceted discussion on the challenges and techniques of SemCom. Moreover, the existing surveys have failed to reveal fully the relationship between SemCom and 6G networks. The rapid growth and development of 6G have resulted in a number of technologies that are (or can be) integrated with SemCom. Moreover, the features of SemCom can be instrumental towards advancing 6G and beyond communication networks. The key contributions of this survey are summarized as follows.

- We outline the major 6G visions and the key enablers which lay the foundation for SemCom system implementation. Meanwhile, we highlight some benefits of SemCom-empowered 6G and present a SemCom-native 6G network architecture. Our review aims to highlight the mutually reinforcing properties of 6G and SemCom.
- We present a holistic development of SemCom from the introduction of classical SemCom theory to modern AI-enabled SemCom. We provide three classifications of SemCom and highlight the main types of semantic metrics. Then, we discuss how the emerging applications of 6G can be enabled by SemCom. Our tutorial aims to provide readers with a holistic introduction to fundamental SemCom concepts and its most recent developments.
- We comprehensively review the semantic-related challenges for 6G SemCom, as well as communication-related challenges involved in SemCom. Our review of the available technologies leads to the identification of key challenging issues and limitations of the existing works. Our review of the literature aims to provide both researchers and practitioners alike with a knowledge of the state-of-the-art methods, while highlighting the unsolved challenges ahead.
- We identify and outline a series of directions for future research of SemCom in addition to the challenges ahead. Our discussion aims to shed light on the road ahead for SemCom research.

C. Scope of the survey

As shown in Fig. 1, this paper is divided into the sections listed below. Section II begins by reviewing several potential key technologies in 6G and future visions, and then introduces the SemCom and its important role in 6G. In Section III, the development of SemCom from the classical SemCom to AI-enabled SemCom is reviewed. Then, we discuss the framework for the adoption of modern SemCom from the key performance metrics to the system models of SemCom. Section IV presents various applications of SemCom in the existing works and summarises corresponding improvements. In Section V and Section VI, the challenges and state-of-the-art techniques are reviewed in detail from the semantic-related and communication-related perspectives, respectively. Finally, Section VII presents the future research directions. Section VIII concludes the survey.

II. 6G NETWORK AND SEMCOM

In this section, we start by reviewing selected key enablers and corresponding visions for the 6G network. Then, we focus on the technology of SemCom, which is made possible by the 6G network, but is also beneficial for 6G network. Moreover, a general SemCom-empowered 6G architecture is given.

A. 6G VISIONS AND KEY ENABLERS

In the past few years, the capabilities of control, communication, computing, and AI capabilities that are integrated into the 5G network have enabled a new paradigm of intelligent Internet of Things [12], [13]. In this subsection, we present some key enablers and network visions, which can facilitate the implementation of SemCom or benefit from SemCom [14], [15], and highlight the underlying advantages and limitations of the corresponding technologies with SemCom as an example.

1) Computing force network: With the success of multi-access edge computing (MEC) deployment, the convergence of communication and computing has brought about a new paradigm known as computation oriented communications [16], [17]. Therefore, the computing force network (CFN) is proposed in 6G. The CFN is no longer solely responsible for the data exchange among the communication parties, but is expected to be an information system integrating the ubiquitous functions of communication, computing and, caching [18]. Meanwhile, more computing services, such as Amazon EC2, Azure IoT Edge, and Google Cloud Platform will be provided by the CFN for intelligent applications like smart home and intelligent transportation. The whole CFN can work as a brain to achieve mutual awareness, unprecedented levels of autonomous collaboration, as well as unified orchestration and management (O&M), which sets the stage for the fundamental infrastructure of SemCom’s implementation. More specifically, such a reshaped network architecture will bring three benefits as below [15]:

- **Real-time accurate computing force detection:** With real-time awareness of the network state and the position of computing force (CF) by the network layer, the available resources, whether on the edge or in the cloud, can be quickly detected and routed. This will help to improve the utilization of computing resources and load balancing
- **Flexible and dynamic scheduling of services:** Jointly considering the resource availability in terms of communication and computation as well as the user demand of service level agreement (SLA), the data traffic requested...
can be fast-matched to the optimal network node. Take SemCom as an example. The performance of SemCom heavily depends on the accuracy of the AI models employed to represent and infer semantic information, (which is detailed in Section V-A). Hence, the employed AI models need to be upgraded in time with evolving communication context. In this sense, the flexible and dynamic scheduling of services in CFN can provide timely updates of the semantic extraction model. Since it is possible to flexibly allocate the nearest available computing resources to the dataset for training, instead of sharing a fixed cloud centre with other services, the performance of SemCom can be enhanced.

- **Consistency of user experience:** The CFN provides ubiquitous computing coverage. Users need not worry about the location and deployment status of computing resources, because the collaborative scheduling of resources of network and computing can enable consistency of QoE. Especially for SemCom, both transmitter and receiver require sufficient computing resources to jointly

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**Fig. 1:** Structure of the survey.
ensure accurate semantic information processing. Insufficient computing resources on either side can lead to a failure of SemCom. Therefore, the consistency of user experience in CFN can facilitate the large-scale deployment of SemCom by mitigating the effects of imbalance in the distribution of computing resources.

To achieve the above benefits, CFN needs to feature new CF functions, such as CF service function, CF routing function, and O&M function. Three key technologies to be tackled are highlighted as follows:

- **CF measurement and modeling**: Nowadays, with the proliferation of high performance-intelligent computing, the computing forces show a trend toward heterogeneous processors, such as CPU, GPU, TPU, NPU, DPU, and FPGA [19]–[21]. Hence, accurate quantification of CF of these heterogeneous chips and effective sensing for their suitable service type and locations make the basis for providing CF services.

- **CF-awareness based CF routing**: Based on the measurement and modeling of CF, the CF information can be shared via the network control layer message for network decision making and guiding the full network routing.

- **In-network computing**: With the deployment of programmable network techniques, in-network computing can enable the share of CF within the network through the open programmable heterogeneous CF resources, which can accelerate the data process, reduce the response latency, and simplify the deployment process of applications.

2) **AI-native network**: With the impressive performance of AI in the past few years, treating AI as a cornerstone to enable “intelligence inclusion” has become the consensus for 6G networks [22]–[24]. Faced with the proliferation of intelligent devices and applications, such as the smartphones, tablets, and smart home, the 6G network is envisioned to accomplish the following transformations [15] to enhance data security and privacy, as well as to improve the overall performance and efficiency of the network [25], [26].

- **Data processing from the core to the edge**: As intelligent devices have become part of our daily lives, e.g., for entertainment, education, and healthcare purposes, significant volumes of personal and private data are captured by such devices. This results in an unprecedented burden on backhaul networks and central cloud servers. To this end, the data processing is expected to be moving from the cloud center to the edge to reduce the need for massive data exchange [27]. Avoiding data sharing in a central can help build a secure and private network. In SemCom, deriving an AI model for semantic information extraction requires lots of user private data. In this sense, edge computing combined with other distributed AI techniques (which is discussed in the next item about From cloud AI to distributed AI), can potentially facilitate SemCom, allowing users to alleviate concerns about private data. Meanwhile, edge computing can reduce the communication overhead associated with data sharing in the central cloud, reducing the network burden on the core network.

- **From cloud AI to distributed AI**: As the powerful heterogeneous CF progressively extends to the edge, the 6G network is envisioned to feature highly distributed AI [22]. In contrast to the traditional cloud AI, which mainly acts as an optimization tool or an over-the-top additional application, the distributed AI can be integrated into the future network design to enable more users to have the same capability to access intelligent services anytime and anywhere [15], [22]. Implementing AI in a distributed manner on the user side can further improve learning efficiency and address critical security issues for users [22]. Meanwhile, the coordination of the intelligence distributed in cloud, edge, devices, and network nodes can achieve the adaptation of resources such as spectrum, computing, and storage without human intervention, which can further enhance the overall network efficiency [15]. However, the distributed AI also generates massive extra data exchanges. In this regard, integrating the philosophy of SemCom, i.e., understanding the data before transmission and sending only the information that is considered important, into the intelligent agents can further enhance network efficiency by reducing communication overheads.

- **From connection-oriented communication to task-oriented communication**: The most typical service in conventional communication is establishing a connection between two specific terminals, wherein it is easy to tell an explicit pair of source and destination terminals according to the content they intend to communicate [22]. However, with the advent of intelligent applications based on distributed AI, such as full autonomous driving based on predictive quality of service (QoS) [28], connection-oriented communication will be transformed into task-oriented communication. In task-oriented communication, there are multiple explicit or implicit connections between different terminals and network nodes in a proactive or reactive manner [22]. As SemCom focuses on the transmission of the information that is relevant to the object of the communication rather than the data itself, applying SemCom to task-oriented communication can significantly reduce the data amount of information interaction among multiple agents, thereby achieving a higher degree of task completion compared to the transmission of source data or content-blind compressed data, in the case of limited communication resources.

To enable the above transformations, the AI-native network is proposed [14], [15], [22]. On one hand, the AI-native architecture aims to leverage the AI techniques to optimize network performance, enhance QoE, and achieve automated and customized network operations, i.e., AIaaS [14]. On the other hand, AI-native architecture can provide real-time AI services for a wide range of industries, i.e., Net4AI, which is also called AI-as-a-service (AIaaS) [14]. In the AIaaS platform, the techniques in terms of communication, information, and data are deeply integrated into wireless communication with large-scale distributed training, real-time edge inference,
and the ability to desensitize local data. To realize such AI-native network architecture, the following functions need to be implemented first [15].

- **O&M for network AI**: Different from the Cloud AI, the resources involved in network AI are distributed and heterogeneous at the cloud and edge network. In this sense, the AI framework and distributed learning paradigms need to be redesigned to cater to composite targets and scalability, where the model computational dependency and transfer as well as the fitness of the data amount of the AI layers to the transmission capacity of the network nodes should be taken into account.

- **Network function architecture for network AI**: The network function of network AI is in a layered integration manner, which consists of two layers: the global intelligent layer and the regional intelligence layer. The global intelligence layer is responsible for end-to-end control with coordination of edge intelligence, such as network routing. The regional intelligence layer is responsible for the immediate delivery of on-demand intelligent services, such as collaborative robots and hyper-intelligent IoT, to a high volume of devices, and achieving distributed intelligent collaboration via distributed learning.

3) **Ubiquitous connectivity**: The above new network architectures pave the way to achieve a highly efficient and flexible network O&M via building an intelligent network of intelligent things, and lay the foundation for the high-quality smart services like holographic videos and collaborative autonomous driving, which fully meet the personalized and high-end needs of users [16]. However, the massive volumes of data transmission will impose a significant burden to the resource-limited wireless communication networks. To meet the challenges, 6G networks are therefore aimed at enabling ubiquitous connectivity. Three key technologies are listed as below.

- **Space-air-ground integration**: Space-air-ground integrated networks (SAGINs) have gained significant attention in the past few years, and are considered as a promising architecture for ubiquitous connectivity [29], [30]. SAGIN is a multidimensional network, which consists of three main segments: space, air, and ground. The space network consists of satellites and constellations as well as the corresponding terrestrial infrastructures. According to the altitude, satellites can be classified into three categories: geostationary (GEO), medium earth orbit (MEO), and low earth orbit (LEO) satellites. The space network is mainly employed for the support of global information exchange, especially acting as a “last resort” for communicating in remote areas [29]. The air network can be regarded as an aerial mobile system that uses unmanned aerial vehicles (UAVs), airships and balloons, etc., as carriers for information acquisition, transmission, and processing. Compared with the ground network, the air network has the features of low cost, easy deployment, and large and flexible coverage [31], [32]. The ground network consists of the familiar cellular network, mobile ad hoc network (MANET), worldwide interoperability for microwave access (WiMAX), wireless local area networks (WLANs), and so on. The three segments can complement each other and form wide 3D communications networks that are based on ground networks and support multiple non-terrestrial communications, the in-depth convergence of which not only enables global broadband and IoT communication, but also allows the enhanced location navigation, real-time Earth observation, and other new capabilities to be integrated into the 6G network. However, the current research about SAGIN is still in its infancy. In short, the following issues remain to be addressed [15].

- Considering the topologies dynamics of space network and air network, strategic deployment of network function, as well as the integration and simplification of terrestrial and non-terrestrial networks in term of system architecture, interface protocols, etc., a flexible and efficient integrated network architecture needs to be identified.

- Since the topology of air network and space network is dynamic and the long distance causes high transmission latency, the robustness of the link between satellite nodes and terrestrial terminals is hard to guarantee. To this end, mobility/session management and routing techniques require further research.

- Uncertain delay and jitter, network topology, and frequent handovers of user links impose challenges to the QoS guarantee. To mitigate such issues, predictive QoS can be regarded as a promising approach, that is, introducing predictive delay, bandwidth, and other auxiliary tools like global navigation satellite system into resource allocation.

However, there is an inherent drawback to satellite communication that needs to be pointed out. Due to long distance, satellite communication can only accomplish the transmission of a small amount of data within the allowable delay [33]. In this sense, SemCom can be regarded as a promising complementary technology to allow long-distance communication for a wider range of services, as instead of sending raw data, sending useful semantic information will save significant amounts of bandwidth, energy, and transmission cost.

- **Tera-Hertz (THz) Communications**: To cope with the exponential growth in data volumes in 6G, THz communications are considered as a promising candidate to support ultra-broadband following millimeter wave (mmWave) communication and visible light communication (VLC) [14]. Moreover, the THz frequency band ranges from 0.1 THz to 10 THz, which bridges the gap between millimeter wave (mmWave) and optical frequency bands. THz communication can be treated as a beneficial supplement to incumbent transmission mechanisms, especially for holographic communications, small-scale communications, and short-range ultra-high-speed transmission [15]. In this sense, the full-band communications are expected to achieve system requirements for Tbps-class transmission rates and provide further guarantees for ubiquitous connectivity. In addition, the
high-frequency bands are also vital for scenarios such as integrated sensing and communication and intra-body communications [15]. However, there are still some challenges for THz communications, some of which are listed below.

- For the signal at the THz region, due to the free space path loss and atmospheric molecular absorption, the total signal loss is increased significantly. In addition, penetration through various materials and reflection from different surfaces are also to be taken into account.
- The current transceiver design is not suitable for THz frequency in terms of phase noise, nonlinear amplifier limited modulation index, etc. [34]. Hence, the novel transceiver technologies are urgent for the fabrication of state-of-the-art THz hardware, especially for the THz band which is higher than 300 GHz.
- THz radiation is regarded as a non-ionizing photon energy [35]. In this sense, the concern source with THz frequencies can be treated as a potential cause of cancer.

However, similar to satellite communication, there are also limitations to the application scenarios for THz communication. Due to the high-frequency feature, THz communication relies on line of sight communication, which means that the mobile user cannot maintain a reliable connection in the long term. To address this issue, SemCom can be employed to reduce the amount the data to be transmitted to save bandwidth and improve overall network performance.

- **Extreme multiple-input multiple-output (MIMO):** Extreme MIMO is an enhancement of the massive MIMO technology. With the continuous integration of antennas and chips, the scale of antenna arrays keeps increasing. Moreover, with the emergence of new materials and technologies, such as AI, reconfigurable intelligent surfaces, sensing technologies, and ultra-large aperture array, Extreme MIMO technology in 6G can overcome the high transmission loss in the THz frequency band and achieve higher spectral efficiency and higher energy efficiency in a wider frequency range, and apply to more scenarios, such as macro coverage, hotspot coverage, 3D coverage, high-speed mobility, and accurate positioning as well. However, extreme MIMO still faces many challenges, such as inaccurate channel measurement and modeling, the burden of signal processing load, limited fronthaul capacity, high reference signal overhead, and high costs [36].

4) **Trustworthiness-native network:** The trustworthy communication network has become a key requirement in 6G as a result of growing privacy and security concerns [16], [37]. However, with the evolution of the network architecture from centralized control to distributed processing and the in-depth convergence of AI technique, big data technique, 6G network foresees a huge exchange of data, which clearly poses some new challenges in terms of security, privacy, and trust. The traditional single-model security trust model is not sufficient anymore. 6G security requires multiple trust models such as centralized models, decentralized models, as well as third-party endorsements [15]. Moreover, as many user-centered services with multi-modal data like holographic communications and integrated sensing and communications emerge, this has necessitated a multi-mode and cross-domain security and trustworthiness system. Furthermore, the security architecture should support the techniques in terms of cryptographic application and key management that are compatible with the characteristics of the 6G network, such as monitoring of large-scale data flows, computational theory of privacy protection, encryption or decryption of high-throughput and high-concurrent data, as well as basic blockchain functions characterized by high throughput [15]. Moreover, since only the partial data or the pre-processed data needs to be transmitted in SemCom, SemCom has also been considered as a potential tool for secure communication [38], which is elaborated in Section III. Meanwhile, the trustworthiness-native network in 6G should take the access control model and topology dynamic change and WAN sharing mechanism, as well as the technologies of isolation and exchange into account [15]. In a nutshell, the trend of convergence and integration implies that 6G network will require a native security architecture with autonomous defense capabilities consisting of cryptographic technologies, intelligent and resilient defense systems, and security management architectures, and covering the entire lifecycle of 6G networks [15].

**B. SemCom-empowered 6G**

As stated in Section II-A3, some new techniques have been proposed for upgrading the network capability, facing the explosion of IoT devices and some new high-bandwidth services [39]. However, they still follow the traditional network design philosophy, i.e., broadening the available spectrum and increasing the density of access points and antennas [12], and have limited application scenarios. Thanks to the CFN and AI-native network stated in Section II-A1 and Section II-A2, they enable SemCom as a feasible revolutionary technology in
In this subsection, we highlight three potential benefits that SemCom can bring to 6G networks.

1) Lighten burden on the data transmission: Increasingly sophisticated AI models can allow the devices to acquire the human-like capability to capture and extract relevant information for different communication intents. Specifically, different from traditional intelligent agents only for decision making, intelligent agents in SemCom gain consciousness, which is a new type of computing employed before transmission, i.e., pre-processing for de-redundancy of data to be transmitted, to optimize user QoE or task performances based on the accumulated learned experience and background knowledge [12]. In other words, SemCom leads the 6G networks to a higher dimension, i.e., a four-dimension network of the ubiquity of communications, computing, control, and consciousness, thereby reducing the communication burden via the introduction of consciousness. As the example of image transmission in Fig. 2, in conventional communications, the replica or a content-blind approach simply compresses the original image that needs to be transmitted. In SemCom, the transmitters can filter out irrelevant image details for different tasks before transmission by performing the appropriate image processing techniques, thereby relieving the network burden without compromising the system performance.

2) Enhance efficiency of network control and management: In addition to the reduction of the transmission of redundant information in the network, SemCom can shed light on the design of the flexible protocol-function orchestration in 6G. With the convergence of the communication objects and transmission objects in SemCom, the inter-layer coupling is further enhanced [6]. The study of [40] introduces a semantic-effectiveness plane in the communication protocol architecture as shown in Fig. 3. The standardized application programming interfaces (APIs) provided by the semantic-effectiveness plane can access, on the one end, all layers of the radio access network protocol stack even with different technologies, and, on the other hand, users, sensors, and actuators. In such an architecture, the less important packets can be dropped in time by cross-checking against the state of the AI models or trusted distributed ledger technology tools such as blockchains and smart-contract ledgers, thus reducing overhead at all layers of the protocol stack when the available network resources are inadequate. Meanwhile, the semantic-effectiveness plane can control the operation of the communication protocol to achieve high utilization of communication and computing resources. Take immersive AR applications as an example, which is an application with the coexistence of video, audio, and haptic packets and requires high bandwidth and ultra-reliable low latency. For the haptic packets, the designer of the Medium Access Control frame usually reserves dedicated resources for ensuring that the delay QoS requirement is met. However, the request of the haptic packets is random and intermittent, which inevitably leads to wasted resources or transmission failures. In order to address the above issues, the semantic-effectiveness plane can play a role in jointly designing the transmission of all the types of traffic and adapting to current traffic conditions, such as detecting and removing the redundant data of the scene that the user does not interact with and freeing resources for low-latency traffic [40].

3) Promoting privacy and security in transmission: Beyond alleviating the transmission burden of data traffic and enhancing the efficiency of network management based on the computing force and AI-native network architecture, SemCom can also promote the privacy and security in transmission. Thanks to the pre-processing of the source data in SemCom, the communication parties only exchange semantic information extracted according to the communication tasks, instead of the complete source data, which can enhance the security of the network to a large extent. Moreover, as with human communication, wherein both parties need to understand the language and culture of each other, communication parties in SemCom need to share their background knowledge to infer the semantic information accurately. Considering that the available trust models in the 6G trustworthiness-native network pave the way for the implementation of security SemCom, it is not easy for an eavesdropper to interpret valid information from the intercepted data without knowing the knowledge background of the communication parties. To this end, SemCom can also be considered as a potential trustworthiness technique worth to be investigated in the future.

As aforementioned, SemCom impacts the 6G network in multiple ways, which is simultaneously driving the evolution of the network architecture. In the next subsection, we will present a new SemCom-powered 6G architecture [41].

C. SemCom-native 6G architecture

In the conventional communication network, the network nodes are not concerned with what the data is trying to convey. The information exchanged between the inter-and intra-layer nodes in the network can be generally seen as homogeneous Bit sequences. However, in the SemCom architecture with ubiquitous consciousness, the information representation can achieve a higher level. In line with the concept of “Bit” in Shannon’s information theory, the authors in [41] introduce a new concept called “Seb” for semantic information. To clarify the differences between Bit and Seb, they compare the communication process to that of the construction process. In the conventional communication system, Bit serves as brick, and reconstructing the message at the receiver is similar to constructing a building in a brick-by-brick manner. Conversely, the recovering of the message in SemCom is similar to...
constructing a building using the laminboard and integrated window or door. A SemCom system dimensioned by Seb is highly modulated as compared to conventional communication systems, which calls for a simplified network architecture design to efficiently carry SemCom.

In [41], the authors introduce a novel intelligent and efficient SemCom (IE-SC) architecture, as shown in Fig. 4. In their proposed IE-SC architecture, the network is divided into three semantic-empowered layers: semantic application-intent (S-AI) layer, semantic network-protocol (S-NP) layer, and semantic physical-bearing (S-PB) layer. Meanwhile, a separated semantic intelligence (SI) plane is introduced to coordinate the three layers as well as the physical environment via the semantic information flow (S-IF).

The S-AI layer is responsible for decomposing and translating the users’ intent into the network’s deployment, configuration, or control policies. The intent is related to the goal of communication or task. The three main functions within the S-AI layer are highlighted below.

- **Intent mining**: The S-AI layer is responsible for extracting, analyzing, aggregating, and synthesizing the original intents received from users or applications.
- **Intent decomposition**: The obtained intents after intent mining is decomposed into a set of sub-intents for guiding the implementation of the various layers of functionality.
- **Semantic representation**: Based on the sub-intent set, the S-AI layer represents intent for the decision-making in the SI plane.

The S-NP layer aims to efficiently serve the intents of upper-layer applications with intelligent network protocols. The design of this layer mainly concentrates on the strategies of semantic interaction, which includes experience accumulation for learning (e.g., multiple rounds of dialogues), real-time knowledge sharing, and simplified semantic interaction. In this sense, some key modules should be included in the S-NP layer:

- **Semantic information computation**: This module is for identifying the intent information on the S-IF to obtain knowledge from the counterparts.
- **Semantic protocol parsing**: This module is used to analyze the functions available for the existing protocol.
- **Semantic protocol formation**: This module is responsible for optimizing the existing protocol or forming a new one to adapt to the intent of the application.
- **Semantic information conversion**: This module is responsible for completing the semantic information encapsulation based on the generated protocol.

The S-PB layer is responsible for converting semantic information from the upper layers into physical signals. Different from conventional communication, SemCom aims to deliver semantic information instead of source data, so the traditional source encoding/decoding and channel encoding/decoding are to be replaced. Some semantic-related counterpart modules should be integrated into the S-PB layer:

- **Semantic encoding/decoding**: Following the modular design method, the modules of semantic encoding and decoding are designed separately from other modules, such as channel coding.
- **Semantic extraction/utilization of channel information**: Integrate the channel information in terms of fading, signal-to-noise ratio (SNR), and interference into semantic encoding and decoding.
- **Semantic-aware joint source-channel encoding/decoding**: Following the integrated design method, channel encoding and decoding can be jointly integrated into the modules of semantic encoding/decoding.

As coordinator of the entire IE-SC network, the SI plane contains three main functions:

- **Semantic environment representation**: This function deals with the extraction of semantic information from the internal and external environmental information based on...
the intent information provided by the S-AI layer. The environment representation is then derived following semantic classification. Meanwhile, the SI plane generates the semantic instructions and maps them to the functions of each layer, and semantic information is embedded into the S-IF to flow in the network through the SI plane and the interfaces of different layers.

- **Background knowledge management:** The background knowledge of different layers and various network nodes, such as the communication context and the network environment, have an impact on the performance in each network layer. The SI plane serves as a coordinator, which is in charge of classification, integration and, storage of the extracted semantic information, and then shares it via S-IF.

- **Semantic decision and deduction:** The SI plane is also responsible for evaluating the achievable performance according to the results of the intent analysis fed by the S-AI layer and performing decision-making for all network layers.

As research on SemCom has just emerged, there is still relatively little research on the S-AI layer and S-NP layer. Therefore, the “SemCom” that we discuss in the subsequent sections refers to the SemCom in the S-PB layer, and the works we review in this paper are all within the scope of the S-PB layer and related functions in the SI plane.

### III. Fundamentals of SemCom

In this section, we first review the development of the classical SemCom theory and then introduce the general system model adopted in the modern SemCom.

#### A. Classical SemCom related theory

The concept of *semantics* is initially introduced in the studies on semiotics [73]. In [74], the authors define semiotics as a triple combination of *syntactics, semantics*, and *pragmatics*. Syntactics focuses on the interrelation of the formal features for signs (visual and linguistic) without considering the meaning. Semantics specializes in the meaning of the signs at different levels. Pragmatics concentrates in the relationship between the utility of the signs with respect to the user in the sign system [73], [75]. Comparable to the triple-definition for the signs, Weaver [76] identify three levels of communication as below to further characterize the syntactic, semantic, and pragmatic features of communications [41].

**Level A** How accurately can the symbols of communication be transmitted? (The technical level.)

**Level B** How precisely do the transmitted symbols convey the desired meaning? (The semantic level.)

**Level C** How effectively does the received meaning affect conduct in the desired way? (The effectiveness level.)

Shannon’s CIT achieves a big success in deriving a rigorous mathematical theory of communication based on probabilistic models, wherein the concept of *information* is defined as *what can be used to remove uncertainty* and the analysis is based on mutual information in the *entropy* domain. However, CIT focuses only on the technical level. Therefore, some researchers follow Shannon’s work and made an attempt to extend it to the semantic level and effectiveness level. The development of classical SemCom has been highlighted in Fig. 5.

1) **Semantic-oriented communications:** The authors in [77], [78] make the first effort in contributing to the *Theory of semantic information* (TSI) in 1950s. They propose an ideal language model which consists of $n$ nouns and $k$ adjectives. An arbitrary noun $A$ and an arbitrary adjective $a$ can be conjugated via a verb. For instance, $Aa$ means “$A$ is $a$” or “$A$ has property $a$”. Besides, there exists five connects in the proposed model: $\sim$ (Not), $\lor$ (Or), $\land$ (And), $\rightarrow$ (If ... then), and $\equiv$ (If and only if). In this sense, many sentences can be generated based on the above conjunctions. Following the definition of *information* in CIT, the amount of semantic information for a word can be defined as a function of the number of sentences that the word can imply in the considered language model, i.e., the more sentences a word can imply in the language model, the more semantic information the word contains [73]. Moreover, to quantify the amount of information of a sentence $x$, they further propose a concept named “*state descriptor* $Z$”, which is defined as the conjunction of one noun and one adjective (positive or negative) [73]. Furthermore, they define a subset of the description set $\mathcal{Z}$ with $|\mathcal{Z}| = 2^{kn}$, wherein the sentence $x$ is valid, as *range* for sentence $x$ denoted by $R(x)$. By introducing a measurement function for a description denoted by $m(\mathcal{Z})$, where $0 \leq m(\mathcal{Z}) \leq 1$, $\sum m(\mathcal{Z}) = 1$ [73], the measurement for a sentences $m(x)$ equals the sum of all $m(\mathcal{Z})$ within $R(x)$ and, similar to Shannon theory of syntactic information, the amount of semantic information for a sentence can be calculated as its entropy, i.e., $I(i) = -\log_2 m(x)$.

By this point, one significant limitation can be found that it completely ignores the motivation and purpose of the communication at hand. In fact, there is no radical difference between TSI and CIT [73]. In this sense, a false sentence that happens to say much may also be highly informative, as the semantic information, in such a measurement for semantic information amount, is not meant as implying truth [77].

To address the above issue, The study of [79] develops a *Theory of Strongly Semantic Information* (TSSI). Compared to the “weakly” TSI, the truth values play a role in TSSI. Define $f(s)$ as the degree of discrepancy of statement $s$ from the actual situation. The author in [79] stipulates five conditions that any feasible and satisfactory metric should satisfy as below.

- **C 1** For a true $s$ that conforms most precisely and accurately to the actual situation, $f(s) = 0$.
- **C 2** For an $s$ that is made true by every situation, i.e., a tautology, $f(s) = 1$.
- **C 3** For an $s$ that is made true in no situation, i.e., a contradiction, $f(s) = -1$.
- **C 4** For a contingently false $s$, $-1 < f(s) < 0$.
- **C 5** For a contingently true $s$ that is also made true by situations other than the actual one, $0 < f(s) < 1$.

The details about calculations for the degree of inaccuracy and vacuity in C4 and C5 can be referred to [79]. Based on the degree of discrepancy, the degrees of informativeness for
| Ref   | Applications             | Related technologies          | Key improvements                                                        |
|-------|--------------------------|-------------------------------|------------------------------------------------------------------------|
| [42]  | text transmission        | DL, LSTM, JSCC                | Lower word error rate with the same BER                                 |
| [43]  | text transmission        | DL, TL, Transformer, JSCC    | Higher system capacity; adaptable to various environments              |
| [44]  | text transmission        | DL, Transformer, HARQ, JSCC  | Higher reliability; changeable code length networking.                 |
| [45]  | text transmission        | DL, Transformer, NN compression | A small size of DL model; power and latency bound                       |
| [46]  | text transmission        | RL, LSTM, JSCC                | A system to learn from non-differentiable metrics                      |
| [47]  | text transmission        | RL, Transformer, JSNC         | A confidence-based distillation mechanism JSNC                         |
| [48]  | text transmission        | DL, Transformer, Auto-encoder | A SF protocol for mismatch issue of BK                                 |
| [49]  | text transmission        | DL, Transformer               | A flexible Transformer by introducing ACM                              |
| [50]  | energy harvesting        | DL, Transformer               | Economic energy valuation and allocation                               |
| [51]  | audio transmission       | DL, SE, JSCC                  | A SemCom system for speech transmission                                |
| [52]  | audio transmission       | DL, SE, JSCC                  | Verification of model adaptation with practical scenarios             |
| [53]  | audio transmission       | DL, FL, CNN                   | SE with high convergence rate                                          |
| [54]  | audio transmission       | DL, CNN, RNN                  | A SemCom system for speech recognition                                 |
| [55]  | visual transmission      | DL, CNN, JSCC                | A graceful performance degradation with variable SNR                   |
| [56]  | visual transmission      | DL, ResNet, JSCC              | Good recognition performance at the very low SNR                       |
| [57]  | visual transmission      | DL, JSCC, AF module           | Good adaptability, robustness and versatility.                         |
| [58]  | visual transmission      | DL, MAE, ViT, codebook        | A robust SemCom system for image transmission                          |
| [59]  | visual transmission      | DL, HARQ, facial keypoints    | A keypoint-based SemCom framework for video conference                |
| [60]  | VQA task                 | DL, ResNet, CNN, LSTM         | A novel multi-modal data SemCom system                                 |
| [61]  | object detection         | DL, CNN, KB                   | An architecture for task-aware SE                                     |
| [62]  | object detection         | DL, CNN, HEVC                 | A V2I RA scheme based on QoC                                           |
| [63]  | referential game          | DL, CNN, HEVC, MARL           | A V2X RA scheme with spectrum multiplexing                             |
| [64]  | referential game          | MARL                          | A strategy for grounding agents’ code into natural language           |
| [65]  | referential game          | DL, CNN, RNN                  | A method of logical operations for emergent languages                  |
| [66]  | traffic control           | MARL                          | A general networked MARL setting                                       |
| [67]  | traffic control           | Convex optimization           | An AoII-optimal policy with performance advantages                     |
| [68]  | FL                        | FL, DSGD                      | A novel analog communication scheme called CA-DSGD                     |
| [69]  | CDRL                      | Heterogeneous federated DRL, KG | Selection of semantically relevant agents for collaboration             |
| [70]  | remote monitoring         | SL, Koopman operator theory   | An Koopman autoencoder for non-linear dynamical system                 |
| [71]  | UAV                       | MADRL, GAXNet                 | Lower inter-UAV collisions                                            |
| [72]  | wearable sensing          | Random Forest, SVM            | A framework for on-board classification of activities                   |

A statement $s$ is calculated as $g(s) = 1 - f(s)^2$. Clearly, the more a statement deviates from 0, the more informative it is, which is more in line with the instincts of people. However, it can only perform the quantitative analysis for the complete class of propositions in logical space and fails to provide rigorous metrics. The authors in [80] further improved this work based on the available works on truthlikeness, which measures the degree of being similar to the truth [81], via extending the quantitative analysis to the semantic concepts of the quantity of misinformation, wherein \textit{semantic information} is defined as true semantic content and \textit{semantic misinformation} is defined as false semantic content. The related concept of information is rooted in semantic information framework using information flow [82]. By employing prior works on truthlikeness for classical systems [83], [84], the proposed semantic information quantifying method can support a broader range of use cases. However, how to deal with the non-classical systems is still an open issue. Nevertheless, the transformation of the measurement from uncertainty into message content in [79], [80] has made a milestone step in the development of semantic information theory.

The authors in [85] initially put forward a \textit{Theory of Semantic Communication} based on semantic information quantifying method [77], aiming to achieve semantic-level communications. They propose a SemCom model for a basic type source that can just make factual statements in propositional logic. In their model, the source and destination are modeled as a 4-tuple of < world model $W$, background knowledge $K$, infer-
ence \( I \), message interpreter. Moreover, the Shannon entropy \( H(W) \) is employed to quantify the information amount of the source, i.e., semantic entropy. Furthermore, they consider a finite set of allowed messages \( X \), which can be seen as the set of available semantic codes. In this regard, semantic coding is the process of mapping from the observed values of the world model to a specific message. The strategy is a conditional probabilistic distribution \( P(X|W) \), and a deterministic coding is encoding the observed value \( w \) into \( x \) with the highest \( P(x|w) \). Furthermore, the relationship between the semantic entropy and message entropy is \( H(X) = H(W) + H(X|W) - H(W|X) \), where \( H(X|W) \) measures semantic redundancy of coding, and \( H(W|X) \) measures semantic ambiguity of the coding [85]. The major difference from CIT is that the semantic information measure is based on the logical probabilities which are determined by the background knowledge and inference, instead of statistical probabilities. Secondly, the side information, i.e., the destination’s prior knowledge about the source, can also be considered in the coding process to reduce the code length. More detail about encoding method based semantic entropy can be found in [38]. Moreover, by denoting the received message by \( y \), the semantic channel can be characterized by the distribution of \( p(y|x) \). Furthermore, different from the CIT, the semantic channel capacity for the discrete memoryless channel is dependent on three elements. The first one is the mutual information \( I(X;Y) \) between \( X \) and \( Y \), which is also the channel capacity for CIT. The second one is the degree of semantic ambiguity introduced in semantic encoding with \( K_s \) and \( I_s \), i.e., \( H_{K_s,I_s}(W|X) \). The last one is the average logical information of the received messages, which is determined by \( K_d \) and \( I_d \), i.e., \( H_{K_d,I_d}(Y) \). If \( K_s(I_s) \) and \( K_d(I_d) \) do not match, excessive semantic noise be generated. For deriving the limit of semantic channel capacity, the authors in [85] simplify the model by assuming \( K_s = K_d \) and \( I_s = I_d \), and the upper bound is given as \( C = \sup_{P(X|W)} \left\{ I(X;Y) - H(W|X) + H(Y) \right\} \).

These works can be seen as an initial but pioneering exploration of SemCom. However, it is only a model-theoretical framework, which could be unrealistic for the practical communication scenarios. More relevantly, in the above work, the information amount is merely quantified based on classical Shannon entropy, which has no concerns with the essence of semantic information, the meaning factor, and thus is inconsistent with the original vision of SemCom.

2) Goal-oriented communications: In contrast to the study of [77], which focuses on the extension of Shannon’s CIT, the study of [86] focuses on the development of the classical communication system model. In both Shannon’s classical system model and the SemCom model [85], all the communication parties need to have a common language or background. Faced with the increasing interaction among the diversified computers at that time, the study of [86] tried to make an attempt to make progress on the universal SemCom, wherein the communication parties are expected to obtain a common understanding via learning each other’s behavior without any prior common language. In [86], the authors focus on a particular communication model between Alice and Bob, where Bob is a probabilistic polynomial time bounded interactive machine with the goal to solve a hard computational problem, and Alice has unbounded computational power and is willing to help Bob. Meanwhile, they speak different languages and expect to discuss via some binary channel. To solve this problem, the authors introduce a “trusted third party”, which knows both languages of Alice and Bob and can give finite encoding rules to translate for this discussion. The results of the theoretical analysis show that Alice can help Bob if and only if the problem that Bob wants to solve is in PSPACE [87], (i.e., the solutions to the problem are verifiable for Bob). Although the above assertions are in a restricted setting, it first highlights that communication is not an end in itself, but rather a means to achieve some general goals among the communicating parties.

Based on the formulated communication model in [86], the authors make an extension to study the general goals of communication and first propose the conception of “goal-oriented communication” in [88]. In this work, they clarify two definitions related to the goals in communication. One is meta-goal, which captures the intents of communicating agents, and the other is syntactic goal, which captures effects that can be observed by an agent. The results show that the meta-goals with different syntactic versions are also achievable, i.e., two communicators do not (necessarily) share a common language under some technical conditions. Based on this, a novel architecture could be enabled for the communication among multiple agents with different protocols, wherein the trusted party called “interpreter” played an essential role. It should be noted that in the above communication model, while the
communication parties did not share a common language, they are assumed to be “sufficiently helpful”. In [89], the authors further generalize the above work. At this level of generality, misunderstandings might occur between the communication parties. In this work, the third party is renamed as referee, which hypothetically monitors the conversation between communication parties and assesses whether or not the goal has been achieved. Moreover, they identify and highlight a new concept called sensing, which captures the communication parties’ ability to simulate the referee’s assessment. Based on the concept, they propose a design principle for communication systems, which could achieve polynomial overhead in the description length of the desired strategy. In [90], the authors claim that the construction of universal users from such sensing functions is equivalent to the design of an on-line learning algorithm. However, the above works mostly rely on “try and check” paradigm. They can only provide guidance on the design of the protocol or strategy for the simplistic communication system, such as the conversation between a server and a printer. Although the series of works only focus on a mathematical theory of goal-oriented communication for traditional computer communication models, the system model proposed in their work has laid the foundation for modern goal-oriented communication.

B. Modern AI-enabled SemCom

In contrast to the early studies of classical SemCom, which are limited to the ideal language model and simplest communication scenarios, the research of modern SemCom has emerged in multiple applications owing to the powerful AI techniques. In this survey, we will mainly focus on the modern SemCom, for which the terms “SemCom” in the subsequent text refer to “modern SemCom” for brevity. Before presenting the available and potential applications for SemCom and discussing the challenges and related technologies in detail, we first provide a brief introduction of the general system models in the existing works and the main types of semantic metrics which differ from the traditional metrics for communication performance evaluation.

1) System models for SemCom: As mentioned at the beginning of Section III-A, the classical communication systems only focus on the first level (i.e., technical level) in the three levels of communications identified by Weaver and Shannon. SemCom is proposed to integrate the remaining two higher levels into the design of communication systems. The available works for SemCom can be mainly divided into two main categories: semantic-oriented communications, which focus on the semantic level, and goal-oriented communications which focus on effectiveness level [9]. The comparison of the three communication models can be shown in Fig. 6. Next, we describe the details of the general system models for SemCom.

- **Semantic-oriented communications:** Different from the content-blind classical communication systems, what matters in semantic-oriented communication design is the accuracy of the semantic content of source data, instead of the average information associated with the possibilities of source data that can be emitted by a source [9]. As such, the main changes in the semantic-oriented communication system lie in the data processing phase before sending and after receiving. The conventional source encoding is designed to find a method to convert source data into short code. Meanwhile, since the
transmitted message is blind to the underlying meaning, a good source encoding method means that it can cope with more possibilities of source data, which is in line with the information quantification in CIT. However, in SemCom, the definition of “information” needs to be modified. As stated in [91], information is the commodity capable of yielding knowledge, and the information that a signal carries is what we can learn from it. In this sense, a module of “semantic representation” is introduced before encoding in SemCom, which is responsible for capturing core information embedded in source data and filtering out the unnecessary redundancy information. In many studies, the function of “semantic representation” and “semantic encoding” are integrated into one module called semantic encoding, which jointly plays a similar role to source encoding in conventional communications. Similarly, the combined role of semantic inference and semantic decoding is equivalent to that of source decoding. In general SemCom scenarios, decoding is the inverse process of encoding, which is determined based on the AI technologies, such as Transformer and auto-encoder which are powerful with prior knowledge. Since the objective of SemCom is to enable the receiver to successfully access semantic information, we regard the joint semantic encoding and decoding process as semantic extraction (SE). Moreover, as with human conversation, effective conversation requires common knowledge of each other’s language and culture. In SemCom, the local knowledge of the communication parties needs to be shared in real time to ensure that the processes of understanding and inference can be well matched for all the source data. If the local knowledge fails to match, semantic noise generates, which leads to semantic ambiguity, even in the absence of syntactic errors during the transmission in physical transmission.

- **Goal-oriented communication**: On the basis of semantic-oriented communication, goal-oriented communications aim to enable the involved communication parties to accomplish a joint communication goal or task [9]. Recall the triple definition for signs, i.e., syntactics, semantics, and pragmatics. In the above semantic-oriented communications, SE mainly focuses on semantic information, whereas in goal-oriented communication, it is necessary to capture pragmatic information. In [73], the authors illustrate the mutual relationship of the three information types. As shown in Fig. 7, the pragmatic information can be treated as part of all the semantic information that can be conveyed by syntactic information, which is only relevant to the specific goal of communication. For convenience, we also refer to pragmatic information as semantic information. Differently, in goal-oriented communication, the goal or task needs to play an important role in SE as well since the construction of the local knowledge for further filtering out the irrelevant semantic information in each transmission is especially essential for various scenarios, where the communication target changes frequently. Recall from the semantic-oriented communication example of image transmission in the transportation scenario as shown in Fig. 2, the results inferred by the receiver may be a combination of feature maps similar to the ones on the right of Fig. 2. Whereas, in goal-oriented communication, the output of the inference module is the action execution instruction, such as acceleration, braking, the angle for the steering wheel, and flashing headlights, to respond to pedestrians, roadblocks, and traffic signal status changes. In summary, goal-oriented communication focuses on the effective level and aims to accomplish the task in a desired way given limited network resources, rather than the semantic information accuracy focused on by the semantic level in semantic-oriented communication. Moreover, similar to semantic-oriented communication, the local knowledge and communication goal of all the communication parties need to be maintained to be consistent, otherwise, the resulting semantic noise may cause the task to fail.

In addition to the above communication paradigms, there are also some communication paradigms that introduce the concept of “semantic” but do not have the “inference” module. For such a communication paradigm, we call it semantic-aware communication. More specifically, the existing semantic-aware communications fall into two main categories. One category concentrates on a reliable and efficient transmission by reducing the length of bits flow, in fact, which merely accomplishes a source compression [68]. The other category usually applies to the scenarios with multiple intelligent agents, wherein the extracted semantic information is mainly used to facilitate multi-agent cooperation and is not directly linked to the task of the agents themselves [69]. The details about the challenges and techniques of SE and semantic noise can be found in Section V-A and Section V-C, respectively.

2) **Main concerns for semantic metrics**: In conventional communication, the metrics of bit-error-rate (BER), symbol-error rate (SER), delay, and throughput are widely used to evaluate the network performance. As the redundancy information usually exists in various kinds of sources, treating all the bits, symbols, and packets equally by the above metrics inevitably leads to a waste of resources. Moreover, to compensate for the limitation of the above metrics, some metrics applied in the higher communication layer, such as QoE, are proposed to evaluate the communication performance in the view of end users. Multi-metric based network optimization imposes challenges to network resource management. Thanks to SemCom, it enhances the interlayer coupling in the system design, which improves the effectiveness and efficiency of communication networks. In this sense, some new semantic metrics should be proposed in SemCom. Here, we highlight three main concerns in semantic metric design, that is, semantic error, age of information (AoI), and value of information (VoI). Accordingly, semantic metrics can be divided into three basic categories as shown in Fig. 8, which are discussed in Section V-B.

- **Semantic error**: Different from the conventional communications which pursue the accuracy of each bit transmission, SemCom is concerned with whether the destination can recover equivalent meaning from the received message to that in the transmitted message or the accuracy
of action execution. For example, the similarity between the sentence “I have just brought a yellow banana” and the sentence “I have brought a banana.” is much higher in semantic understanding than that between the former sentence and the sentence “I have just brought a yellow banner” with smaller technical errors [46]. In this regard, quantifying semantic errors is crucial in the design of semantic metrics. Since the study on SemCom is still in its infancy, most semantic metrics are from natural language processing (NLP) and speech signal processing, which focus on text and audio transmissions. They avoid treating packets equally, and measure the differences in the meaning conveyed by the received sentence and transmitted sentence.

- **AoI**: The difference between semantic information in communication and that of other fields such as semantic web and semantic segmentation lies in its emphasis on time sensitivity. This feature introduces new dimensions to the accuracy of semantic information, i.e., the right time [92]. Especially for some applications, such as location tracking, control, and situational awareness, the freshness of information have a significant influence on the action execution at the receivers. In this regard, some metrics focusing on timeliness are required. In fact, taking AoI into account in performance evaluation can be considered as an initial attempt at SemCom. Different from the metric of delay, which primarily measures the transmission performance without concern for the content of the packets, AoI-based metrics are utilized to quantify the staleness of the information received at the destination. The scheduling schemes based on AoI minimization can highlight the importance of the freshness of the data packets and filter out the irrelevant or less important packets given the bandwidth constraints. Meanwhile, from the degree of fulfillment for the communication goal or task, AoI largely determines the effectiveness of actions made on the received information. In this sense, AoI-based metrics play an important role in both semantic-oriented and goal-oriented communications.

- **VoI**: VoI measures the benefit of the data packets to be transmitted for the communication goal, which considers not only the content of the packet itself, such as the bursts and exceptions in monitor systems but the cost of transmission [92]. For the resource-limited cases, where the benefits of the data packets to be transmitted are evaluated to be important for the system objective, the VoI is of more concern than accuracy. In this sense, VoI-based metrics are a better fit for goal-oriented communications than error-based metrics. However, the definition of VoI is largely task-dependent, and it is challenging to derive a deterministic and explicit function for VoI. Hence, so far, there has been relatively insufficient research diving into VoI-based metrics.

Most of the available semantic metrics fall into one of the above three basic types, each of which has its own limitations. To this end, some researchers have worked on the design of semantic metrics considering multiple concerns [67]. Meanwhile, in the existing works for goal-oriented communication, the performance evaluation is based on the degree of completion of communication tasks, such as recognition accuracy. More details about the available semantic metrics in different applications and their remaining limitations are discussed in Section V-B.

IV. **SemCom for 6G Applications**

After a brief overview of SemCom, in this section, we discuss some potential applications for SemCom in 6G. Moreover, the technologies used in the various applications in the existing works and corresponding improvements have been summarized in Table II.

A. **Classical multimedia transmission**

Multimedia is today’s dominant focus of communication that includes different content forms such as text, audio, images, animation, and video. Most existing SemCom studies can fall into the above types. Among them, text is the type of source data that has received the most attention, which can be sensed from speaking and typing [45]. In their works, they usually adopt semantic symbols to represent semantics [93], wherein a semantic symbol represents a subset of data including words, phrases, and sentences. For example, the words “car” and “automobile”, and the phrase “a wheeled motor vehicle used for transportation” can be mapped into one semantic symbol, which is the main reason that SemCom can considerably reduce the bandwidth [93]. However, this also inevitably results in some loss of information. In this sense, the compression ratio of semantic encoding should be determined by the specific application scenario. The above ideas still apply in SemCom for audio data transmission. Moreover, in recent years, with the rise of voice-controlled smart home applications, audio communications are no longer limited to human-to-human conversations [53]. Speech recognition has also become a prevalent application. Compared to text data, audio data contain more characteristics such as speaking speed and tone. In some studies of SemCom for speech recognition, the speech signal is first converted into text data before SE [51], thus avoiding the influence of other speech features. Furthermore, the communication tasks are more varied for visual data, such as image classification, object identification, or video conferencing. Different from the generalized traditional image and video compression and encoding, SE is tailor-made to the communication task and the characteristics of source data. Take video conferencing as an example. Since the background of the frames in video conferencing is almost static, the study of [59] integrate the technique of keypoint-based video restoring in SemCom. In their work, only the keypoints, such as the information about the changes in facial expression and manner, are encoded and transmitted to the receivers in real time. The other information about background picture and the appearance features of the speaker is shared to the receivers just at the beginning of conferencing. In this way, a high compression ratio is achieved while maintaining a high level of resolution. Since SemCom allows for more relevant data to be transmitted within a limited bandwidth, SemCom
tends to achieve higher performance compared to conventional communications. Despite the proliferation of new applications for 6G, multimedia services continue to be an important part of 6G network traffic, wherein the advantages of SemCom also become more apparent in comparison to the available 5G network.

**B. Machine learning**

As a typical and widely used new form of applications, various deep learning-based AI techniques have penetrated all aspects of people’s lives [94], such as medical diagnosis and cyberattack detection. With increased computing power on end devices and growing privacy concerns of users, distributed learning, such as federated learning (FL) has become a dominant paradigm for privacy-preserving machine learning [95]. In the FL framework, the task initialization and local model training are performed on the end devices. After the local parameter updates, the model or gradients are transmitted to a server for parameter aggregation. Then the server sends the updated global model parameters back to the individual end devices [96]. As deep neural networks (DNNs) usually contain millions of weight parameters, the frequent exchanges of DNN models or gradients incur costly communication overheads, which poses challenges for communication networks, especially for the uncertain wireless environment and limited wireless resources. In this regard, SemCom has been identified to be a key enabler to achieving model/gradient compression, e.g., through only communicating the important weights [68]. Meanwhile, there are also some autonomous systems, such as autonomous driving and drone navigation, that require intelligent agents with computing and learning capabilities to perform real-time decision-making in dynamic environments based on deep reinforcement learning (DRL). However, DRL still faces some challenges in practical applications, such as slow convergence [97], overfitting problems [98], and poor exploration in complex environments [99]. Collaborative DRL (CDRL) is treated as a promising solution to the above issues, wherein the agents can share their experiences and collaboratively learn the optimal policy for their task [69]. Whereas, as the agents have different environments, tasks, and action spaces, it is challenging to filter the helpful agents. In this sense, some works integrated the semantic awareness (i.e., the useful information about the relationship between tasks of the different agents) in the agent-selection scheme [69], [100] to choose an optimal subset of semantically-related DRL agents for collaboration.

**C. Extended Reality and the Metaverse**

In 5G, AR, Virtual Reality (VR) as well as Tactile Internet have been applied in many cases, such as entertainment, autonomous vehicles, and healthcare [101]. Extended reality (XR) is an umbrella term that encompasses VR, AR, Mixed Reality (MR), and other immersive environments that have not yet been invented [102], [103]. In the past few years, the development of sensing technology and computing power has led to tremendous advances in all aspects of XR hardware. Due to the economies of scale of the massively growing XR market, these devices are now available at reasonable prices [104]. In the near future, XR could become a powerful tool in many new use cases, wherein the remote collaboration among multiple users needs to take place in a virtual environment [105], or when the users need to carry out tasks that would be dangerous [102].

The possibility of synchronization of the physical and virtual world through XR has also led to the birth of the Metaverse, which has been dubbed as the successor to the Internet. The performance of XR is heavily dependent on the collection and processing of data that reflects or describes human movements and changes of surroundings, which can guide XR server operations, e.g., shifting rendered targets, displaying particular videos, and giving the corresponding tactile feedback. To guarantee the ideal immersive experience for users, the end-to-end latency and data rates requirements have to be strictly met [3], [106]. In this regard, effective tracking and accurate prediction are key to reducing transmission and computation latency and ensuring a smooth user experience. To this end, SemCom can be seen as an enabler for the Metaverse [107]. In the SemCom paradigm, the data tracked by the end devices, such as head movement, arm swing, gestures, and speeches, need to be extracted semantically first. This allows the end device to transmit the information concerned by the XR server for operation after understanding and filtering out the irrelevant information to save bandwidth and reduce computing latency at the XR server. Meanwhile, the XR server can also extract semantic information for video based on the user’s preference, ignoring irrelevant details in the face of bandwidth constraints, thus reducing downlink pressure.

**D. Holographic telepresence**

Holographic telepresence (HT) can project realistic, full-motion, real-time three-dimensional (3D) images of distant human beings or physical objects with a high level of realism rivaling of the physical presence [106], [108]. It can be applied not only to 3D video conferencing, TED talk like applications, and the realm of entertainment, but also to remote repair, and remote surgery [106], [109]. Holographic communication is based on multi-view camera image communication. The captured footage of remote people and surrounding objects in different locations is first compressed locally, and then transmitted to the receiver. Then, the receiver’ ends decompress and project the footage information with the aid of laser beams [108]. Like the immersive XR application, to ensure a real-enough virtual and seamless experience, holographic communication also imposes stringent QoS. As reported in [106], the end-to-end latency reaches 0.1 ms, and the data rate is up to 2-4 Tbps, which is beyond the capabilities of 5G networks. Moreover, almost all the human senses, such as smell and taste, are expected to be transmitted through future networks for a fully immersive remote experience. For such communication-and-computation intensive services, the traditional content-blind communication paradigm results in a waste of bandwidth resources and computing resources. To this end, the understanding-before-transmission paradigm
of SemCom can be regarded as a promising method to alleviate the pressure of bandwidth and the receiver’s end processing. This is attributable to the fact that SemCom allows the semantic information extraction that is adaptive to network conditions and enhances transmission reliability, so that changes in the network conditions cannot be perceived by users, thus improving user QoE.

**E. Autonomous driving**

In recent years, with the development of hardware in vehicles and vehicular infrastructures, vehicles can be considered as intelligent agents with greater computing, caching and data storage capacities [110], [111]. Meanwhile, the traditional vehicular ad hoc network is expected to be transformed into the Internet of autonomous vehicles (IoAV) [112], [113], wherein the autonomous driving and cooperative vehicle networks can be achieved without the need of human involvement. The IoAV that has benefited from the vehicle-related operations paves the way for future 6G Intelligent Transport System and intelligent V2X communications, which has attracted a great deal of attention from both industries and academia [106]. However, autonomous vehicles heavily rely on reliable real-time communication, autonomous interactions, and timely computations to complete route planning and traffic congestion control, accident warnings, and other operations. To this end, timely and accurate updates are of vital importance in mission-critical decision-making [114]. The delayed or ambiguous information can lead to misjudgments which may cause large disturbances and, in some worst situations, loss of money and even loss of life [112]. In this sense, the traditional content-blind communications that seek only the lowest latency are no longer sustainable for IoAV. Fortunately, SemCom can be treated as a promising solution, which is concerned with the semantics of information, such as significance, goal-oriented usefulness, and contextual value, to leverage the synergy of source data processing, information transmission, and signal reconstruction [115]. Moreover, content-aware performance metrics, such as AoI and VoI, can also play important roles in SE and resource allocation.

**F. Unmanned aerial vehicles**

UAVs have attracted lots of attention especially while being served as aerial base stations (BSs) or as relays [30], [116], [117]. Unlike static ground BSs or relays, UAVs can be flexibly deployed to satisfy various QoS requirements and balance load amongst users. When the UAVs are being served as BSs, ultra-reliable and low-latency communication (URLLC) can be achieved by managing multiple UAVs in real time. However, the energy constraints of UAVs impede their abilities to facilitate long-term communication. Fortunately, because SemCom can reduce the amount of information that needs to be transmitted, an efficient communication framework among UAVs can be implemented. A novel centralized training and decentralized execution (CTDE) of multi-agent DRL (MADRL) framework is proposed for UAV-assisted URLLC [71]. Compared to the state-of-the-art CTDE method, the proposed solution, graph attention exchange network (GAXNet), achieves 6.5x lower latency with the target $10^{-7}$ error rate by exchanging semantically meaningful attention weights [118]. When the UAVs are being served as relays, diversity gain can be achieved with the help of cooperative communication protocols, such as decode-and-forward (DF) and amplify-and-forward (AF) [119]. The authors are motivated to propose a novel forward method which is called semantic process-and-forward. As shown in Fig. 2, the semantic decoder is typically deployed at the receiver. However, if the receivers are edge nodes which have insufficient extra memory or computing power, an efficient method is to deploy the semantic decoder on the UAV as the edge node. Overall, with the help of the flexibility of UAVs in the physical world and the efficiency of SemCom for information exchange, the UAV-aided SemCom opens up new research directions toward efficient and reliable network designs [120], [121].

**G. Collaborative robots**

A group of cooperative robots can explore, interact with, and perceive the environments far more efficiently than a single robot working alone [122]. In scenarios such as disaster management, warehouse automation, and surveillance, the application of collaborative robots is rapidly increasing. However, the limited computation capability of each robot limits the widespread deployment in computation intensive tasks [123]. One promising solution is to apply the SemCom techniques to achieve efficient data exchanging and processing. SEMIoTICS, a new SemCom-based control system architecture is proposed in [124], which enables the utilization of logic-based reasoning over declarative language models to reduce the decision-making time. In [124], SEMIoTICS is deployed in a building that consists of 15 IoT components for temperature regulation control. The results show that the overall control processing time can be maintained in 6 minutes, which is only 24% of that of the traditional fuzzy logic control-based method [125]. To further reduce the communication overhead among collaborative robots, a lite distributed SemCom system, named $L$-DeepSC [45], can be used. When the communication environment among collaborative robots experiences low SNR, $L$-DeepSC can enable efficient information exchange. In particular, with $L$-DeepSC, the amount of data needed to interact among robots can be compressed to 2.5% of the information that is needed by the traditional method.

**H. Personalized body area networks**

Personal data management as well as transmission of wearable devices are future trends that will affect how personal services and procedures develop. An important element is the wireless body area network (WBAN). Defined formally by the IEEE 802.15 (Task group 6) as a communication standard optimized for low-power devices, the WBAN can serve a variety of applications such as medical, consumer electronics, and personal entertainment [126]. Because of the energy constrained power supplies of tiny sensor nodes, effective energy consumption is a key challenge in WBAN. SemCom prompts us to think about whether we can save energy and increase...
the lifetime of wearable devices by reducing the number of actual bits transmitted. In WBAN, it has been shown that
the on-board extraction of features on modern low-power wearables is both feasible and beneficial for system lifetime
improvement [127]. Although a resource-constrained sensing system needs to strike the balance between the accuracy
of the semantic features output and the cost of analyzing the data for extraction, the benefits from reducing the radio duty cycle
which is used for transmission, vastly outweigh the cost of increasing the processor duty cycle which is used for semantic
features extraction [72]. As knowledge extraction from the raw data can significantly reduce the information that needs
to be transmitted, the SemCom-based method increases the lifetime of the wearable device by one order of magnitude,
at the cost of approximately 5% degradation of classification accuracy [72]. The development of SemCom and the deeper
integration with WBAN will give rise to longer-lasting and more convenient wearable devices.

I. Hyper-intelligent IoT

Hyper-Intelligence (HI) refers to higher- and super-intelligent abilities to accomplish complex tasks. The com-

bination of HI and IoT will lead to a smarter and data-driven society [128], [129]. A general and reasonably predictable
trend in the next a few years will be a rise in the native intelligence of networks, network nodes, and linked devices.
Devices that are formerly utilized merely as sense-and-transmit entities will be endowed with various levels of embedded
intelligence that operate directly on the data acquired. The necessity for progressively smarter communication parties
opens the door to the creation of “smarter” content to exchange and reason, as well as innovative methods for ensuring that
it is done effectively and accurately [130], which coincides with the booming development of SemCom. With the help
of SemCom, only the most useful data is transmitted, and therefore the communication effort is optimized. To deploy the
SemCom techniques in HT IoT to promote efficiency, a potential solution would be to consider whatever enables the
receiver to effectively execute a given task, while relying on SemCom that extracts only the necessary information from
the data. By giving HI the ability to process and reason information at the semantic and even effective level, the HI
IoT will be more connected, further advancing the construction of an interlinked and connected society.

V. SEMANTIC-RELATED CHALLENGES AND TECHNIQUES FOR 6G SEMCOM

Although SemCom has been considered as a powerful 6G technique for many emerging techniques, there are still many
challenges to be resolved. From this section, we discuss the common challenges and corresponding available methodolo-
gies and technologies in SemCom for different applications. For clarity, we focus on the semantic-related challenges and

\[
\begin{array}{|c|c|c|}
\hline
\text{Addressed} & \text{Semantic extraction} & \text{Key} \\
\text{issues} & \text{methods employed} & \text{challenges} \\
\hline
\text{Achieve a replication} & \text{Absence of} & \text{Reduce the redundant} \\
\text{of message sent by} & \text{semantic} & \text{information generated} \\
\text{transmitter at receiver} & \text{extraction} & \text{beyond what is desired} \\
\hline
\text{Enhance the system} & \text{DL-based} & \text{Touch only the semantic} \\
\text{robustness at low SNR} & \text{semantic} & \text{coding problem without} \\
\text{with shorter bit-flow} & \text{extraction} & \text{semantic understanding} \\
\hline
\text{Develop a generalized} & \text{RL-based} & \text{Inflexibility in semantic} \\
\text{mechanism for sophisti-
\text{cated semantic metrics} & \text{semantic} & \text{extraction for goal-} \\
\text{cation} & \text{extraction} & \text{variable communication} \\
\hline
\text{Achieve goal-based} & \text{KB-assisted} & \text{Lack of self-adaptability} \\
\text{semantic extraction} & \text{semantic} & \text{for evolution of the} \\
\text{without retraining} & \text{extraction} & \text{communication goal} \\
\hline
\text{Empower transceivers} & \text{Semantic-native} & \text{Still be a theoretical} \\
\text{with contextual} & \text{semantic} & \text{model and be hard to} \\
\text{reasoning capability} & \text{extraction} & \text{generalized in practical} \\
\hline
\end{array}
\]

Shannon limit and the remaining available spectrum resources are becoming increasingly scarce [43] [132]. The key to
SemCom being pushed forward to address the bandwidth bottlenecks lies in that it converts the transmission-before-
understanding communication paradigm to the understanding-before-transmission communication paradigm. In this way, SE
can be integrated into the communication model to achieve SemCom [6], [41], which allows only the information of
interest to the receiver for transmission, rather than raw data, thereby alleviating bandwidth pressure and enhancing privacy
preservation by reducing and hiding the redundant data to be exchanged. However, there are still some challenges for SE
hindering the implementation of SemCom.

In fact, SE is not a brand-new topic, but it has been evolving [133], [134]. Some comparable works have been explored
in other research fields, such as semantic segmentation in computer vision, which is used to cluster parts of images
together which belong to the same object class [135], semantic computing, which addresses the derivation and matching of
the semantics of computational content and that of user intentions to retrieve, use, manipulate, or even create the
content [136], and semantic web, which can be considered as a knowledge graph formed by combining the linked data
with intelligent content and is widely used in recommendation systems to facilitate intelligent and integrated user experi-
ence [137], [138]. On the other hand, compared to [135]–[138], SemCom is another key field for SE. In this field, all
the communication parties have to be highly aligned in semantic representation and interpretation, which imposes challenges
for SE, especially for the communication parties whose context may evolve individually. In addition, information in the 6G
communication system features a strong time-sensitive nature and is highly demanding in terms of accuracy [139]. Hence,
in the following, we concentrate on the challenges unique to the SE in SemCom. The main methods available for SE along with corresponding addressed and unsolved problems are highlighted in Fig. 9. Next, we discuss these SE methods in the specific application in detail.

1) DL-based SE: Following the success of DL in the individual block optimization in the physical layer [140]–[144], DL-based end-to-end communication systems has emerged as another potential direction outperforming the conventional communication structure in block error rate (BLER) and BER performance [145]–[147]. Inspired by this, some researchers further introduce the DL-enabled method in fields of computer vision (CV) [148]–[150], NLP [151]–[153] and speech processing [154]–[156] into end-to-end communication system as SE approaches, which pioneered the modern SemCom study [157].

With the large amount of image data, the authors in [56] first focus on an image transmission scenario, where an IoT device transmits images to the server to perform recognition. The IoT device maintains a direct, point-to-point wireless link to the server, where both the additive white Gaussian noise (AWGN) model and the Rayleigh fading channel are considered. Different from the conventional communication models where multiple modules are cascaded, they propose a DL-constructed joint transmission-recognition scheme with the design metric of recognition accuracy. In the designed scheme, the ResNet architecture [158] is employed due to its favorable performance and few parameters. In order to complete feature extraction before transmission, the DNN of ResNet is split into two parts. The first few layers function as a feature extractor (i.e., semantic extractor) at the transmitter, and the rest of the layers serve as a recognizer at the receiver. Furthermore, to achieving the adaptive semantic extraction in noisy channels, the joint semantic-channel coding (JSCC) is implemented by using the DNN as channel encoders and decoders, which is discussed in detail in Section IV. To demonstrate the effectiveness of the proposed scheme, the authors in [56] compare the DNN-constructed joint transmission-recognition scheme with three other cascaded compression-and-recognition schemes given the similar compression ratio of 0.04 in both analog transmission and digital transmission. Specifically, the three baseline schemes are JPEG-compressed scheme, compressed sensing with direct recognition, and compressed sensing with reconstruction, which are denoted by “JPEG”, “CS-DR”, and “CS-R”, respectively. From the results, it can be seen that the proposed scheme has the best performance in recognition accuracy and complexity (in terms of runtime). With the effective semantic extraction, the recognition accuracy of the proposed scheme can achieve 0.9, when the SNR is higher than 0 dB in both modes of transmission. In contrast, due to the high compression rate, it is hard to reconstruct the original images for recognition from compressed sensing, the recognition accuracy of the CS-R scheme is only around 0.1 even with high SNR. Moreover, since it is unnecessary to reconstruct the images before recognition in the CS-DR scheme, the CS-DR scheme performs better than the CS-R scheme. However, the highest recognition accuracy of the CS-DR scheme is only around 0.45, which is achieved in the digital transmission with channel coding codes of LDPC. Meanwhile, for the scheme of JPEG, as small changes in

1Here the analog transmission means that the data values are directly used to modulate the signal without going through the steps of quantization. The digital transmission means the data values need to be quantized and converted to bits before modulation and transmission.
JPEG values during the analog transmission can destroy the JPEG structure, the JPEG scheme performs as poor as the CS-R scheme. Although the performance of the JPEG scheme is improved in digital transmission with LDPC codes, the recognition accuracy can reach 0.7 when the SNR is higher than 5 dB, which is still much worse than the performance of the proposed DNN-constructed joint transmission-recognition scheme. Furthermore, using the well-trained DNN model, the runtime of the proposed scheme is lower than $10^{-4}$ in the analog transmission, whereas the lowest runtime of the JPEG scheme is around $10^{-2}$s in digital transmission. However, this scheme is only designed to operate under a specific SNR level. In conventional communication system, the general source encoders and channel decoders can achieve an adaptive compression ratio and the channel coding rate according to the SNR to achieve the optimal performance given the limited bandwidth. To address this issue, the authors in [57] consider a point-to-point image transmission system with SNR feedback. They integrated the attention mechanism [148], [150] that is widely used in CV into SE. The attention mechanism adopts an additional neural network to rigidly select certain features or assign different weights to different features in the original neural network. In their proposed design, the joint semantic-channel encoding is performed by a single network, which consists of two parts: a feature learning module and an attention feature module. The feature learning module is used to learn features from the input images. The attention feature module then takes the output of the feature learning module and SNR as its input and produces a sequence of scaling parameters. The product of the outputs of the feature learning module and the attention feature module can be seen as a filtered version of the feature learning module output. The decoder is similarly designed. In the simulation, the authors compare the performance of the attention-based DL JSCC scheme trained under the uniform distribution of SNR from 0 dB and 20 dB and five basic DL based JSCC schemes trained at the SNR of 1 dB, 4 dB, 7 dB, 13 dB, and 19 dB, respectively. As shown in the results, the peak signal-to-noise ratio (PSNR) curve of the proposed scheme can be seen as the upper envelope of the other PSNR curves of the baseline scheme trained at different SNRs, which demonstrate the higher robustness, versatility, and adaptability to the wide range of SNR of the attention-based approach. In addition, considering that images data have heavy spatial redundancy, the authors in [58] propose a resource-efficient SE model for image classification. They employ a masked autoencoder (MAE) with vision Transformer (ViT) architecture [159] in the encoding process, and adopt an asymmetric encoder-decoder architecture. The MAE can reconstruct an image from partial observations. Specifically, in the proposed architecture, a portion of the original image is masked and disregarded first. Then, the unmasked portion is embedded with the information about their position in the original image, which then goes to Transformer blocks to extract the image features [159]. As the encoder only needs to process the portion of unmasked patches, which significantly reduces the memory consumption. On the contrary, the input of the decoder is the full set of tokens consisting of encoded features of unmasked patches and the masked tokens, which is a shared and learned vector suggesting the presence of the patches that are to be predicted [58]. Moreover, different from the above end-to-end SE model, the decoder can be designed independently of the encoder, as the decoder is only used to perform the image reconstruction task, which allows for greater flexibility in the system design.

Inspired by the success of DL in NLP such as machine translation, the authors in [42] pioneer the implementation of SemCom for text transmission. They consider a simple system model, where a transmitter sends sentences to a receiver using the limited number of bits over an erasure channel. In the proposed scheme, the words are first represented by an embedding vector using GloVe [160], which is the pretrained lookup table available for extracting semantic information. Then, motivated by the success of the sequence-to-sequence learning framework in machine translation [151], [161], the long short-term memory (LSTM)-based encoder and decoder are employed, wherein the embedding vector of the previously estimated word is taken as the input for the next step and the beam search algorithm is used to find the most likely sequences of words [161], [162]. In this sense, the semantic information can be embedded into the sentence recovering. However, the word representation models like Glove or Word2Vec [163] only capture the relationship among words and fail to describe syntax information [43]. Therefore, the proposed method can only describe the probability of a certain word coming after another in a sentence, which makes it hard to deal with long sentences. In the face of the challenge, a newly proposed architecture called Transformer has attracted a great deal of attention, as it can extract both the semantic information and syntax from the whole sentences effectively [43].

The Transformer network is combined with multi-head attention mechanisms, which allows it to extract multiple characteristics of input sequences in parallel [132]. Therefore, compared with the recurrent neural network (RNN)-based architectures, such as LSTM, the Transformer network achieves lower computational complexity and more parallelizable computations while learning long-range dependencies in input sequence [132] [153]. Hence, in the recent works [43], [45], the Transformer networks replace the RNN networks, and the channel models are further extended to AWGN channels and fading channels. The Transformer-based SemCom shows its superiority in the low SNR region under the metrics of BLEU and sentence similarity. However, the Transformer is with fixed attention structure. In fact, in a sentence processing system, some words or phrases are more likely to cause semantic ambiguity than others owing to polysemy or noise interference [49]. With this in mind, the authors in [49] propose a flexible SE approach based on Universal Transformer (UT) [164], by introducing an adaptive circulation mechanism (ACM) in the Transformer to break the original fixed structure. Compared to the standard Transformer, UT is integrated with the Adaptive Computation Time (ACT) model [165], which is for dynamically modulating the number of computational steps needed to process each input symbol in the standard RNN based on a scalar halting probability predicted at each step. Such dynamic per-position halting mechanism allows UT-
based SE to give loop play to its own circulation mechanism and respond to different semantic information and varying physical channel through different cycles. During the simulation, the authors in [164] compare the performance in terms of BLEU of both the SemCom schemes, which employ the UT-based SE approach and classical Transformer-based SE approach, with the traditional source coding and channel coding cascaded schemes, which apply fixed-length coding (5-bit) for source coding and Turbo coding or Reed-Solomon coding for channel coding. For the both traditional schemes, the BLEU score keeps staying pretty low over a wide range of SNR, and is only significantly improved when the SNR is increased above 15 dB. In contrast, the both SemCom schemes achieve remarkably higher BLEU scores under a variety of changing channel conditions. Specifically, the trend in BLEU scores with SNR for both schemes is the same, but the UT-based algorithm consistently scores higher than the DD-based algorithm due to the adaptive circulation mechanism.

With the success of E2E SemCom focusing on images and text, the authors in [53] and [51] further investigate the SemCom for the audio signal. In [53], the authors design an audio SE based on a DL-based NLP model named Wav2Vec. The semantic encoder consists of two cascaded convolutional neural networks (CNNs), called feature extractor and feature aggregator, respectively [166]. The extractor is responsible for extracting the rough audio features from the raw audio vector, and the aggregator is responsible for combining the rough audio features into a higher-level latent variable that contains semantic relations among contextual audio features [166]. Accordingly, the semantic decoder is also based on Wav2Vec architecture, which is symmetrical to the encoder. However, in the simulation, the SE model is trained under AWGN channels with a fixed channel coefficient, which makes it challenging to guarantee decent performance under more complicated channel conditions. At the same time, similar to the evolution of text semantic encoder, the authors in [51], [52] further integrate the attention mechanism named SE-ResNet into SE, and the encoder and decoder are constructed by one or multiple sequentially connected SE-ResNet modules. The term “SE” in “SE-ResNet” represents a squeeze-and-excitation network, which is treated as an independent unit and employed to assign high values to the weights corresponding to the essential information during the training phase. In particular, the squeeze operation is to aggregates the 2D spatial dimension of each input feature, and the excitation operation is to learn and output the attention factor of each feature by capturing the inter-dependencies. Meanwhile, the residual network is adopted to alleviate the gradient vanishing issue due to the network depth. With the simulation, it can be shown that the proposed SE approach shows better performance under various fading channels and SNRs compared to the traditional methods. Later, the authors in [54] further focus on speech recognition tasks for the English language. In [54], the original speech sample sequence is converted into a spectrum before feeding into the transmitter. Moreover, they introduce a transcription of a single speech sample sequence, where each token represents a character in the alphabet or a word boundary. Based on the spectrum and transcription, they design the encoder and decoder. The semantic encoder is constructed by the CNN and the gated recurrent unit-based bidirectional RNN (BRNN) [167] modules. The CNN is utilized for data compression and the BRNN is utilized to extract the text-related semantic features before transmission. The channel encoding and decoding are performed by the dense layer, and the semantic decoding is responsible for decoding the recovered text-related semantic features into the text transcriptions. Considering the limited number of letters in the English alphabet, the semantic decoder is designed as a greedy decoder, wherein the maximum probability in all the steps is indexed and the corresponding token is employed to construct the final transcription.

In addition to the three representative data above, the authors in [60] take the visual question answering (VQA) task as an example and investigate a task-oriented SemCom system for multimodal data transmission. In a VQA task, some users transmit images while the others transmit texts to inquire about the information of the images. The answer is obtained at the receiver. In [60], they consider a simple communication scenario with an image transmitter, a text transmitter, and a receiver. Similar to the above works for image and text, the proposed image transmitter employs the ResNet-101 network [158] pre-trained on ImageNet [168] and the proposed text transmitter employs the Bi-LSTM network. Nevertheless, the design of the decoder is not well studied. Since the semantic information from both users is correlated, the decoder needs to merge the text and image semantic information as well as answer the vision questions. To address the issue, the authors adopt the memory, attention, and composition (MAC) neural network [169] to deal with the correlated data. Specifically, each MAC cell consists of three units. The control unit first generates a query based on the received text semantic information by an attention module, then the read unit receives the query and searches the corresponding key from image semantic information by another attention module [60]. Finally, the write unit integrates the information and outputs the predicted answers to the questions [60]. The effectiveness of the architecture is demonstrated by the simulation results. Furthermore, in [170], the authors unify the semantic encoding structure for both image transmitter and text transmitter based on Transformer. Meanwhile, they propose a new semantic decoder network which consists of two modules: the query module and the information fusion module. The query module adopts layer-wise Transformer, which consists of Transformer encoder layer and Transformer decoder layer. Different from classical Transformer, layer-wise Transformer in [170] takes the output tokens of each encoder layer as the input of each decoder layer, which can exploit
more keywords in the text information and the corresponding regions in the image information. The fusion module then fuses both information to get the answer. An instance of a simple VQA task can be found in Fig. 11.

In conclusion, all of the above DL-based SemCom outperform those based on traditional communications for certain semantic metrics, especially in the low SNR regime. However, there are still some inherent limitations for DL-based SE architectures. Firstly, the loss function in the DL paradigm tends to be required to be differentiable for the back-propagation through transceivers [47]. In this sense, all the above studies still apply the commonly used loss functions in DL (i.e., cross entropy (CE) and mean square error (MSE)) to train neural networks, which leaves the existing works far from the desired SemCom. More significantly, in such end-to-end architectures, wherein the semantic and channel encoders and decoders need to be trained jointly, the SE and recovering are treated as a black box [131]. Due to the lack of interpretability for the available DL-based SE, the effectiveness of DL-based SE is hard to measure. In other words, all the above-mentioned architectures merely achieve semantic coding for a reliable and efficient transmission [47].

2) RL-based SE: Evidently, sophisticated semantic metrics utilized in the learning process can facilitate effective semantic learning and accurate SE. Meanwhile, many existing semantic metrics proposed in the field of NLP are non-differential. Fortunately, RL has been regarded as a promising paradigm to address the issues with user-defined, task-specific, and even non-differentiable task metrics in some other fields [171]–[173].

Considering the success of RL in sequence-generation tasks [174]–[176], the authors in [46], [47] make the first attempt to integrate RL into the end-to-end SemCom system for text transmission, where the encoder-decoder scheme can be viewed as the agent that interacts with an external “environment”, (i.e., sentences). In the general RL framework, the tasks required to be converted into a Markov decision process (MDP), which consists of five elements: state, action, policy, reward, and long-term return [173]. In their proposed encoding-decoding scheme, the LSTM is employed to provide the policy. Similar to the MDPs for other sequence-generation tasks, the state is defined as the recurrent state of the decoder and the previously generated words. In this sense, the transition between two adjacent states is determined by the next generated token. Intuitively, the action of the RL agent is to generate a new token, and thus the action space is the dictionary dimension. However, the determination of the reward function form is particularly tricky. Unlike most RL-based strategies with well-defined rewards at each time step, the rewards during decoding cannot be directly measured until at the end of a sentence. To overcome this challenge, several methods have been proposed. The first one is using Monte Carlo search to obtain the reward in each time step [176], [177]. The second one is training another neural network to estimate the reward or for an incomplete sequence [178]. However, the above methods are more time-consuming and resource-consuming and introduce the risk of divergence in a huge action and state space [46]. Moreover, quantifying the reward value in each time step may be inconsistent with ensuring the semantic meaning of the whole sentence. Thereby, in [46], the authors adopt a newly emerging approach named self-critical sequence training (SCST) [179]. The idea of SCST is to utilize the output of its own test-time inference algorithm to normalize the long-term rewards it experiences, rather than to focus on estimating the reward signal, or how the reward signal should be normalized [179], [180]. In [46], the mean return from a group of selected samples is used to normalize the rewards and treated as the baseline term in the objection function, which enables a stable and self-supervised training at the cost of nearly no extra computations. In the simulation, the proposed RL-based scheme is trained with the semantic similarity metric of CIDEr, and the performance is evaluated by BLEU scores from 1-gram to 4-gram. The size of gram means the length of the phrase considered in calculating the similarity between the reference and candidate sentences, which is detailed in Section V-B. By comparing the proposed scheme with the DL-based SemCom trained with cross-entropy loss, one can find that, with increasing size of the gram, the superiority of RL-based algorithms over traditional algorithms becomes more significant. This also demonstrates the capability of the proposed scheme to catch the underlying semantics, as the semantic meanings are generally expressed in longer phrases.

In [46], [47], the authors further discuss the generalization capability for non-sequence task with the example of image transmission. In their works, they propose a pixel-level recurrent decoding scheme, where the state of MDP is defined as the intermediate decoded image obtained by increasing or decreasing the pixel values with a small number. Moreover, as RL can be treated as an online paradigm, in addition to error-based metrics, some other metrics like AoI-based metrics and transmission delay can also be integrated into the reward, which is another promising advantage for RL-based SE methods [181]. Although such transformation from the decoding process to a recurrent procedure is feasible to implement in practice, it increases the decoding time at the same time.

Moreover, learning the optimal policy through interactions with the environment not only addresses the limitations on the differentiability of the semantic metrics, but also increases the training complexity. It is still a critical challenge to train such a complex model from scratch for high-dimensional tasks [47]. In the above works, the initial parameters are utilized the pre-trained model with stochastic gradient descent on the deterministic loss function. Simulation results show the effectiveness of RL-based SemCom for the non-differential semantic metric optimization by comparing it with the DL-based counterpart. However, for the more complicated language models like Transformer, how the RL-based system performs remains to be explored.

3) Knowledge base-assistant SE: Clearly, for a certain source, the semantic information may be distinct for different task [6]. Therefore, the SE is also task-dependent. Although the two SE methods above can be generalized to many tasks, they are only feasible for scenarios with fixed tasks. As the characteristics of the tasks have been embedded in the loss functions or long-term rewards, the above DL/RL-
based encoder and the decoder are unconscious of the specific goal of the task, and thus the above methods only touch the semantic level. In this sense, DL/RL-based SE for multi-task scenarios may introduce some irrelevant semantic information in transmission for a specific task. Otherwise, when the task changes, the system needs to be paused and retrained or replaced with well-trained model parameters trained for the new task, which not only wastes time and computing resources but also compromises system performance.

Considering the above issues, the authors in [61] propose a new SemCom architecture to achieve an efficient goal-related SE for the scenarios with changeable communication tasks. In the proposed architecture, the task block is considered as part of the system design, which enables the system to reach the effectiveness level [9]. In addition, the authors also integrate the knowledge base (KB) into both the encoder and the decoder for semantic extraction. A KB is a technology that has been widely used in automated AI systems to store the data with formal representation allowing for inference [182]–[184]. Specifically, for the SemCom system, the KB is employed to quantify the level of importance of semantic information for different goals of tasks and instruct the SE when the goal of task changes. Nonetheless, how to well establish and maintain such a KB still need in-depth investigations.

In general, a typical KB consists of a computational ontology, facts, rules, and constraints [9]. Particularly for the KB in the SemCom, it should be composed of source information, goals of the tasks, and the possible ways of reasoning that can be understood, recognized, and learned by all the communication participants [7], [61]. Following this, in [61], the authors first manage to establish the KB based on CNN for an image classification task and accomplish the KB-assisted SE. In their work, CNN is not merely used for image classification, but is also treated as the generator for semantic information. As the model parameters can identify the optimal form of feature maps that represent the original image (i.e., semantic information), the gradients of the CNN’s output with respect to feature maps are treated as the importance weights of the feature map to different classes [61]. Thereby, the KB is established by storing the importance weights of all feature maps for each class. Next, based on the KB, semantic encoding can be accomplished by refining the semantic information that is closely related to the specific task. On the other side, the semantic decoder employs fully-connected layers to select the class corresponding to the maximum value in the output vector. It is also worth noting that this architecture is still achieved in an end-to-end manner. The KBs in both the transmitter and receiver should be synchronized by a shared KB at an authoritative third party or a virtual KB. If the two KBs on the two sides mismatch, the semantic noise may be generated [38] which is discussed in detail in the next subsection.

Since KB-assisted SE focuses only on the goal-related semantic information, the KB-assisted SemCom with semantic compression rate (CR)\(^2\) of 98\% can still achieve more than 40\% classification accuracy gains compared with the conventional communications at 10 dB. However, it still has room for enhancement, such as the optimization of neural network structure and loss function [185]–[187]. Moreover, the proposed KB establishment method is hard to generalize so far, because most of the common AI techniques still lack explainability, which can be responsible for identifying the semantic information hidden in deep nets. Generally, it remains a particularly challenging issue to establish a general KB for capturing the diverse and complex relations between the semantic information and tasks for most scenarios.

4) Semantic-native SE: All the above three SE methods rely on well-trained neural networks based on a large amount of labeled data, which makes their works only feasible for communication systems with unvarying semantic information. Hence, they are powerless for scenarios where semantics vary over time, and such scenarios are more common in real life [131]. Specifically, in this sense, transforming “passive learning” into “active learning” is particularly imperative for SE in communication with varying semantics and context.

Indeed, there have been some primary research studies fitting the above idea called emergent communication [189], wherein the semantics and goal-oriented representations are not predefined and are required to be learned during the iterative communication between multiple intelligent agents [131], [189]. However, most of the works merely focus on some simple and specific AI tasks such as image-related referential games [64], where the accomplishment of SE may be spurious owing to the inscrutable patterns of the single transmitted objects [65].

In [131], the authors open up the black box of SE with the focus on a point-to-point communication scenario between two agents who can communicate in both directions. In analyzing the reliability (which is measured by the recognition accuracy in the considered scenario), they introduce the triangle of meanings [188] for human communication architectures in linguistics. As shown in Fig. 12, the vertices of the semantic triangle connect the three spaces of the observation of the input, concept (or meaning), and symbol (or representation) [131]. The edge from an input embedding to its concept is termed conceptualization, and the edge from the concept to its symbol is termed symbolization, while their opposite directions represent deconceptualization and desymbolization [131]. Based on this model, they propose two SemCom systems (indexed by System 1 and System 2, respectively). System 1 can be summarized by a multi-

\(^2\)The value of CR means the percentage of feature maps that are ignored.
triangular model with a shared input embedding. The conceptualization process can be interpreted as a stochastic soft decision or the likelihood of a decision in ML, which plays the similar role of unconscious pattern recognition to the ML in the aforementioned methods. In addition, the symbolization process is assumed to be predetermined among the agents. Due to the fact that rational speakers are self-aware of what they say, in System 2, the authors infuse contextual reasoning [190] process for each agent. In linguistics, contextual reasoning is often computationally described using the Rational Speech Act (RSA) model [191]–[193], which is rooted in the Gricean view of language use [194].

In the proposed system, contextual reasoning is equivalent to communicating with a virtual agent that mimics and simulates its listener, which allows the agents to communicate effectively and efficiently based on reasoning. To demonstrate the significance of contextual reasoning, the authors abstract both the systems into stochastic models, and derive the bit-length of semantic representation in the two systems with Shannon coding. With the experimental results, it can be seen that the bit-length of semantic representation is significantly reduced with high reliability.

Undoubtedly, the semantic-native SemCom system is with a high degree of flexibility and adaptivity, which is more in tune with the vision of an intelligent and autonomous 6G network [195]. However, the above analysis is again only based on a toy model. It remains a huge challenge to put it into practice.

5) Some special SE: In addition to the four general SE methods above for semantic-oriented and goal-oriented communication systems, there are also some specialized methods for specific semantic-aware communication scenarios.

Distributed learning is a major class of applications for semantic-aware communications [68], [69], wherein the SE includes local model/gradient compression and participant selection. In [68], the authors study an FL scenario at the wireless network edge. In order to achieve better performance over the bandwidth-limited fading channel from the devices to the remote parameter server, they present two stochastic gradient descent (DSGD) schemes, namely digital DSGD (D-DSGD) and compressed analog DSGD (CA-DSGD), respectively. In the D-DSGD scheme, one device with the best channel states is selected at each iteration. The selected device firstly performs DSGD scheme [196], where both the current gradient estimate and the error accumulated from previous iterations are considered. Then, the scheme of compression for error compensated gradient vector [197] is performed, where it is first sparsified by setting the highest $n$ positive and the smallest $n$ negative entries to zero, where $n$ is less than half of the total number of parameters. According to the resultant sparse vector, the selected device computes the mean value of the positive and negative entries. If the mean value of the positive is larger than the negative entries, the selected device further sets all the negative entries of the sparse vector to zero and all the positive entries to the mean value of the positive entries, and vice versa. In contrast to the D-DSGD scheme, the CA-DSGD scheme focus on the average of the gradient vectors, which is more related to the goal of parameter server. It is developed from entry-wise scheduled analog DSGD (ESA-DSGD) [198], where each device sends its gradient estimate entirely with the simple truncated channel inverse scheme [199]. Considering the fact that the entries of the gradient vectors are not sent if the channel gain is below the threshold, the authors incorporate the error accumulation technique into the ESA-DSGD scheme to retain the accuracy of local gradients. Moreover, to reduce the transmission bandwidth, gradient sparsification, where the device sets all but $k$ elements with the highest magnitudes of entries to zero, is further integrated into the scheme and the time interval of interactions is reduced accordingly. However, it is worth noting that although the sparsified gradients with smaller $k$ at parameter server can be recovered in a more reliable manner with advanced noisy measurements, it provides a less accurate estimate of the actual average gradient. During the simulation, the authors compare the multiple DSGD schemes in multiple scenarios with IDD data distribution or non-IDD data distribution. From the simulation results, the CA-DSGD always has the best performance in terms of both accuracy and convergence speed. Although, due to the reduction in the similarity of the sparsity gradient patterns across devices, the CA-DSGD scheme converges slower in non-IID cases, the accuracy gap between the CA-DSGD scheme and the error-free shared link approach is still smaller than 0.05, while the gap between other schemes and the error-free shared link approach is around 0.2 or larger.

The authors in [69] further integrate semantic awareness into federated DRL with heterogeneous agents and different environments, wherein the agent requiring training is called the target agent and the agents that help the target agent with its training are called source agents. In their proposed scheme, they define a knowledge graph (KG) to record similarities among all the agents. Moreover, based on the KG, a subset of source agents with high similarity are selected to contribute to the training of the target agent. In order to capture the similarity between two agents, the authors jointly consider the inter-agent structural similarity and inter-agent structural similarity. The structural similarity is measured by the cosine similarity of the parameters of the policy networks of the two agents [200]. However, the lower structural similarity does not necessarily mean a negative collaboration. The semantic relatedness is utilized to measure the similarity of underlying learning tasks of the agents [100]. In the transfer knowledge domain, it can quantify the extent to which the transferred knowledge from a source agent can potentially help the target agent to find its optimal policy. In this sense, semantic relatedness is defined as the average return value received by the source agent from a target environment in a limited number of training episodes. However, since the average return value is obtained from limited training steps, the metric may be inaccurate, especially for a complex target environment with a large state space. Therefore, the combination of both the metrics with a weighted parameter can enhance the accuracy of similarity measurement. Besides, in order to align the DNN parameter dimensions of different agents, the principal component analysis (PCA) method or the zero-padding (ZP) method are employed for compression or expansion of the
source agents’ DNN parameters [201], respectively. With the simulation, the promising performance of the semantic-aware CDRL schemes [69] over bandwidth constrained wireless networks has been demonstrated by comparing with the uniform or random resource block allocation.

In addition to distributed learning, the authors in [70] focus on the remote monitoring scenario with wireless connectivity. Since the system dynamics are always non-linear and high-dimensional, the correction of distortions caused by wireless transmission is hard to achieve without a full understanding of the system dynamics. To this end, the authors combine Koopman autoencoder [202] and split learning (SL) to achieve the SE for the initial system state. In Koopman operator theory [203], a finite-dimensional non-linear system can be transformed into an infinite-dimensional linear system based on a Koopman operator (usually represented as a matrix) and its associated eigenfunctions. In particular, the Koopman operator helps to shift the viewpoint from the system state space to the observable space [70], [204], which can be regarded as a semantic representation and determined by the eigenfunctions of the Koopman operator. However, deriving the Koopman operator and corresponding eigenfunctions mathematically is also unattainable. Therefore, they resort to ML. In the proposed framework, they employ a tripartite autoencoder neural network architecture corresponding to the concatenated eigenfunction, the Koopman operator, and the inverse function of concatenated eigenfunction.

Besides the methods mentioned in [59], [68]–[70], there are other scenarios with straightforward semantic information, wherein the extraction of semantic information can be achieved during the optimization of system performance. For instance, in [63], the authors propose a video semantics based resource allocation for object detection tasks, wherein the SE is performed by determining the quantitative parameters, which characterizes the compression ratio of the video clips in high efficiency video coding [62]. Moreover, for the real-time remote tracking scenario in [115], the SE can be regarded as the sampling actions, which depends on the transition matrix of discrete-time Markov chain for the source’s states. Meanwhile, in [71], the authors study the problem of air-to-ground ultra-reliable and low-latency communication (URLLLC). In the proposed scheme, each agent locally constructs a star-topological graph, where the semantic information generated in agent interactions is encoded as the edge weight, which reflects the level of attention to the leaf agent when the internal agent takes its action. Furthermore, the semantic encoder employs the self-attention mechanism, which appears in the trainable form of a linear combination [153].

All in all, SE in communications is still in its infancy. The vast majority of SE methods rely entirely on ML. Due to the lack of mathematical quantifications of semantic information, treating a black box as the foundation of system design and optimization is not convincing enough to put it into practice.

B. Effective semantic metrics

Network performance measure’s choices have always been a nucleus concern in network design and optimization for generations. In the conventional communication system, due to the separation of transmission and data’s semantic information and effectiveness for achieving specific goals, the communication performance tends to be evaluated from different network layers through metrics such as BER, QoS, and QoE, respectively. Whereas, in SemCom, the interlayer coupling is enhanced to a great extent [40]. Hence, the new methods of evaluating communication performance in terms of semantics must be identified before the implementation of SemCom in practice. As mentioned in Section III-B, existing SemCom evaluations mainly focus on semantic error, AoI, and VoI. Next, we go into the details about the three basic metric types and the combined forms, as well as discuss the related remaining issues.

1) Error-based semantic metrics: As aforementioned, different from the metrics of BER and SER for the conventional communications, which are concerned with the accuracy of each bit and each symbol and treat all the bits and symbols equally important, the error-based metrics in the SemCom care about whether the meaning intended by the transmitter is equivalent to the meaning understood by its destination, i.e., semantic similarity [9]. Moreover, the available semantic metrics are all task-specific and there is not yet a general metric for different types of embedding [10]. Below we discuss the error-based semantic metrics in terms of specific applications.

At the moment, text transmission has received the most attention in the study of SemCom. Semantic similarity in text transmission usually refers to the exact degree of meaning conveyed by a whole sentence. To mathematically quantify the similarity, some researchers resort to some pioneering works in NLP, and apply the following metrics in the performance evaluation of their works.

- Bilingual evaluation understudy (BLEU): Initially, BLEU is a method for automatic evaluation for machine translation [205], which is in line with what semantic measurement needs to do in the SemCom system. BLEU is used to compare n-grams of the candidate with the n-grams of the reference translation and count the number of matches, where n-grams represents the size of a word group. For example, for sentence “cat is on mat.” 1-gram: “cat,” “is,” “on” and “mat.” 2-grams: “cat is,” “is on” and “on mat”. It is first introduced into SemCom in [43], where the n-grams precision score denoted by $p_n$ depends on the difference between the minimum frequency of one element in the n-th grams. In this sense, the BLEU for the whole sentence is calculated as the product of the sum of the precision scores for the grams of all sizes and a brevity penalty (BP). The BP is determined by the length of the candidate (recovered) and reference (transmitted) sentences. The longer the candidate sentence is compared to the reference sentence, the lower the BLEU score is. Moreover, to make the ranking behavior more noticeable, BLEU is commonly used in its expression in the log domain.

- Consensus based Image Description Evaluation (CIDEr): CIDEr is proposed as an automatic consensus metric of image description quality in [206], which is originally
Sentence similarity: Sentence similarity is calculated as the cosine similarity of the semantic features extracted bidirectional encoder representations from transformers (BERT) [43]. BERT is a fine-tuned word representation model, which employs a huge pre-trained model including billions of parameters used for extracting the semantic information.

The semantic information considered in this metric is viewed from a sentence level owing to the sensitivity of BERT to polysemy. The pre-trained BERT model introduces much resource consumption in the training process and makes it hard to generalize in other tasks.

used to measure the similarity of a generated sentence against a set of ground truth sentences written by humans. Hence, it can also be used as a semantic metric for text transmission [46]. Similar to BLEU, the similarity between two sentences is calculated based on the set of n-grams presented in it. The difference is that, in CIDEr, not just one reference sentence is considered, but a set of reference sentences. When calculating sentence similarity, it takes into account the similarity between the candidate sentences and all semantically similar sentences in the reference set.

- Sentence similarity: Sentence similarity is a new metric initialized in [43] and [44] for SemCom based on bidirectional encoder representations from Transformers (BERT). BERT is a state-of-the-art fine-tuned word representation model [207], which employs a huge pre-trained model including billions of parameters used for extracting the semantic information. Fed by billions of sentences, the performance of semantic information extraction has been demonstrated in [207]. To this end, the sentence similarity is calculated directly based on the cosine similarity of the semantic features extracted by BERT.

It is to be noted that, although the BLEU and CIDEr have considered some of the linguistic laws, such as that semantically consistent words usually come together in a given corpus [46], they remain at the level of calculating the differences of words between two sentences and have no insight into the meaning of the whole sentence [44]. In this sense, the metric of sentence similarity is much closer to the desired SemCom paradigm, as the well-trained BERT model is sensitive to polysemy (e.g., the word “mouse” with a different meaning in biology and machine), which allows it to extract information in a sentence level.

On the other hand, the non-differentiability and high computing consumption of the three metrics hinder them from playing a role in the optimization of system optimization. Although both BLEU and sentence similarity have been proposed in [43], the training pipeline in the DL-based SemCom system still adopts CE loss. Moreover, for sentence similarity, the pre-trained BERT network embedding introduces much more resource consumption in the training process and makes it hard to generalize in other tasks. In other words, the BLEU and sentence similarity are just used to demonstrate the effectiveness of their proposed works compared to the traditional approaches. Later, the authors of [44] propose a semantic similarity detection method called Sim32, where the sentence similarity begins to be used to label whether estimated sentences are similar enough to express the semantic information in the training process. It is only in [47] and [46] that the metrics of BLEU and CIDEr begin to guide SE with help of RL, but at the cost of high computational complexity.

Similar to text data, the audio data is also very close to the human natural language. Thereby, for the SemCom for audio transmission, semantic similarity can be explained by the ease with which the receiver understands the decoded audio signal. Some similar works have been studied in the field of audio signal processing [208]–[210].

- Signal-to-distortion ration (SDR): SDR is originally de-
fined based on the usual definition of the SNR with a few modifications in [208]. In [52], it is introduced into SemCom as a performance metric, which is expressed by the $\mathcal{L}_2$ error between $s$ and $\hat{s}$. Compared to MSE, the ranking behavior of the difference between $s$ and $\hat{s}$ in SDR is more remarkable. Besides, the numerical precision of this measurement is lower for high-performance values than for low-performance ones, which is more intuitive for the design of the measurement method. However, this method does not go any further than MSE in terms of semantic awareness.

- Perceptual evaluation of speech quality (PESQ): PESQ is a specialized quality assessment model designed for speech use across a wider range of network conditions, which has been standardized as Recommendation ITU-T P.862. It is utilized in [51] and [52] to evaluate the performance. It combines the perceptual speech quality measure (PSQM) and perceptual analysis measurement system (PAMS) [209]. The basic PESQ diagram of PESQ is shown in Fig. 13. Different from the above metric which simply compares the difference between the two signals, PESQ assumes the short memory in human perception, which allows it more similar to the human behavior [51]. However, the method still only looks at the accuracy of the transmission instead of the semantic meaning.

In a nutshell, none of the above approaches evaluates the performance at the level of semantic understanding. In addition, only the MSE metric is used in DL for the SE in the existing works. The SemCom has only reached the semantic encoding level so far. A semantic measurement with semantic understanding like BERT and BLEU in the text transmission is still to be studied in the field of audio SemCom.

However, for the communication for visual data, there are no general semantic metrics which are analogous to human perception yet. The commonly-used metrics in the SemCom for visual data are still shallow functions [211], such as PSNR [57] and structural similarity index (SSIM) [212] employed in conventional communication systems. Moreover, compared to the text and audio data, the semantic similarity is more context-dependent, that is, it is hard to distinguish different “senses of similarity”: is a red circle more similar to a red square or a blue circle [211]? This imposes challenges to visual semantic metric design. Meanwhile, similar to text and audio data, the similarity judgment for visual data must also depend on a high-order structure [213]. To this end, DL-based feature capture can be considered as a potential way to assess the image semantic similarity [10]. In recent years, the internal activations of deep convolutional networks trained on a high-level image classification task have been considered to be often effective as a representational space for a much wider variety of tasks [211]. For instance, features from the Visual Geometry Group (VGG) architecture [214] have been used in other tasks like neural style transfer [215], and conditional image synthesis [216]. However, how to exploit this approach for SemCom performance evaluation needs to be further explored. In addition to image transmission which is only aimed at ensuring the fidelity of the visual data, there are also many emerging visual communications for specific tasks like object recognition and attribute classification, wherein the accuracy of task execution can directly characterize the effectiveness of SemCom.

2) Aol-based semantic metrics: In fact, taking age of information (AoI) into account in performance evaluation can be regarded as initial attempt in SemCom [67]. AoI is tailor-made for the monitoring systems, such as vehicular monitoring systems, industrial sensor networks, UAV path planning, and surveillance videos [217], wherein only the most recently generated state at the source is of interest to the destination. The age of a packet is defined as the difference between the current time and the timestamp of the packet [218], which captures how unfresh the data received by the monitor is. In the traditional content-blind communication paradigm, the systems just pursue to send updates as fast as possible and ensure the minimum transmission delay. Undoubtedly, this requires a lot of bandwidth resources. Moreover, if the delay-QoS cannot be guaranteed, the backlog of the packets in the communication system throttles the update and leads to a monitor having unnecessarily outdated status information. Fortunately, such issues can be addressed by the scheduling scheme based on AoI minimization. This is attributable to the fact that the fresh data can be given more importance and transmitted with priority during the scheduling process. Moreover, owing to the stochastic features of environments, an appropriate analysis of AoI can be chosen according to the specific system, such as time-average age and peak age, which are presented in detail in [217]. However, it should also be noted that there are still inherent flaws for AoI-based metrics, that is, they disregard the validity of the recovered data. For example, in some cases, the monitor is only concerned with the abnormal and abrupt states at sources [219]. Since AoI does not consider the value of current states for its monitor, some useless updates are transmitted to the monitor, which also results in a certain amount of resource waste.

3) Vol-based semantic metrics: Vol is also a newly introduced metric in communication systems, especially for networked control systems. Before that, the concept of Vol is well-known in information analysis wherein it is defined as the price that a decision maker is willing to pay for taking the information into account [220]. For conventional communications, Vol can be defined as a measure of uncertainty reduction from the information set of the source with a successful transmission [221]. Whereas, for the communications with specific tasks, the Vol needs to be redefined. In contrast to
AoI which just focuses on the timeless and ignores content. VoI is mainly utilized to measure the relevance of a piece of information to the communication tasks. Take a remote temperature control system [67] as an example. In that setting, the central controller is not concerned with the real-time temperature variation of the sources. The goal of the system is only to make sure the controller reacts swiftly to any abnormal temperature rise. In this sense, the data for the abnormal temperature should be assigned with high VoI. Moreover, in [61] wherein a task of image classification is studied, the VoI here is used to measure the importance of the extracted features to the accurate classification of the images. However, deriving the function of VoI is not an easy task for complex systems. Furthermore, the value of data is often determined not only by the content itself, but also by the communication context. Nevertheless, the aforementioned factors have not been well taken into account in existing VoI calculations.

4) Combined semantic metrics: As aforementioned, the above three types of semantic metrics only focus on one attribute of the information conveyed by the recovered data. To address this limitation, burgeoning research efforts have been investigating new semantic metrics that combine multiple attributes to varying degrees [92]. The authors in [67] integrate AoI into error-based metrics, and propose a new metric named age of incorrect information (AoII). AoII characterizes the impact of the prolongation of one inaccurate state on semantic recovering. Compared to both error-based and AoI-based metrics above, AoII is incorporated with more meaningful semantics by jointly considering the content and timeliness. Specifically, AoII considers not only the repercussions of a transient state on the overall communication goal, but also the repercussions of the states lasting for different duration. For instance, the repercussions of a long burst of error are far more severe than an instantaneous burst of error for video transmission [222]. The comparison of the AoI and AoII is shown in Fig. 14. Meanwhile, the authors in [223] integrate Vol into the AoI-based metrics by considering a pull-based system and propose a new metric called age of information at query (QAoI), which reflects the freshness of the instants when the receiver actually needs the data [92]. In a pull-based system, the information is effective at the receiver only at certain query instants. In this sense, the communication is expected to be query-driven, that is, the transmitter knows the query instants and optimizes the transmissions with respect to the timing of the query process.

Hence, the query-driven QAoI-based on scheduling scheme is more efficient and effective for such a system than the query-blind AoI-based one to achieve sending just before the query instants. As shown in Fig. 15, the QAoI-based scheme is more likely to provide updates that are fresh when a query arrives, although its average AoI may be worse than the AoI-based scheme [223].

As stated in Section III-B, most of metrics applying to semantic-oriented and goal-oriented communications can fall into the above types. However, as for semantic-aware communications, the semantic metrics are more flexible and diversified. Since the semantic information in these areas is not the concern of the system or the receiver, the semantic metrics are always determined by the motivation of SE or the impact of SE on the performance. Taking the parameter compression for distributed learning [68] as an example, the metric can be interpreted as the compression ratio or impact on the performance and the convergence rate. In another example, in order to avoid inter-UAV collisions [71], the semantic measures can be designed according to the symmetry between the attention of two agents. In general, the more relevant the role of semantic evaluation in system optimization, the more significant SE is for system optimization.

All in all, compared to studies on SE, research on semantic measurement for SemCom is relatively scarce. Most of semantic metrics are in complex form, which makes it hard to play a role in the optimization of the scheduling scheme and resource allocation. Moreover, multimodal data fusion has been regarded as a trend of future communication scenarios. However, a general semantic metric is still underexplored. Furthermore, most of the available semantic metrics merely focus on the evaluation of communication performance like BER, SER, and delay in the conventional communications. How to quantify the amount of semantic information and the resource to be consumed like throughput and bandwidth are still pending [10].
C. Semantic noise management

After discussing the methods for semantic measurement, we first start this subsection by showing the reasons behind semantic ambiguity, which are summarized into two main points. One inherent reason, which has been widely considered in the existing works, is the stochastic noise and interference in the wireless channel, which cause syntactic errors and thus affect the semantics inference [42], [44], [47]. However, it is worth mentioning that, in general, an error at the syntactic layer does not necessarily induce an error at the semantic layer. If with an effective SE method, the decoder is expected to correct a number of syntactic errors and recover the right semantic meaning exploiting the rules of the language subsuming the exchange of information [9]. This is the superiority of SemCom over conventional communication. However, in some cases, semantic ambiguity may occur as well even in the absence of syntactic errors, and it is due to the second reason, semantic noise [93]. In the rest of this subsection, we discuss the challenges of semantic noise management in SemCom with reference to the role of noise and interference in wireless communications, and the challenges of wireless communication in SemCom be discussed in the next section.

1) Robust SemCom against semantic noise: As mentioned before, semantic noise is mainly caused by the mismatch between the knowledge libraries of the transmitter and receiver [224]. In the vast majority of the existing works, researchers often assume that the transmitter and receiver share the same invariant knowledge set [43], or that the knowledge libraries of both communicating parties keep consistent through a virtual shared knowledge libraries [61]. However, in fact, the background knowledge of each transceiver may evolve individually and the data can even be maliciously attacked during download and transmission. In this sense, such an assumption does not hold in practice. Moreover, in some special cases, the privacy of user data is also an obstacle to achieving background knowledge matching. With this in mind, some researchers have made a few preliminary explorations for communication scenarios with semantic interference [48], [58], [225].

The authors in [225] consider a simple communication scenario for word transmission. Taking into account the different background knowledge of the receiver, the authors label the receivers into two types: adversarial and helpful. To find the optimal transmission policies with the minimum end-to-end average semantic error, they formulate the SemCom problem as a two-player non-cooperative Bayesian game [226]. One player (indexed by Player 1) acts as the receiver, which belongs to one of the two mentioned types. The other player (indexed by Player 2) serves as both the encoder and decoder. The action set of Player 1 represents the probability distribution for a receiver to interpret a word into other words if it is received accurately. That is, it characterizes the impact of the background knowledge of the receiver on the decoding process. The action set of Player 2 consists of all the pairs of the mapping in both the encoding and decoding processes. Moreover, they characterize the structure of the strategies at equilibrium and propose an iterative algorithm to find the favorable strategies for both players. However, the above approach is only applicable to the word transmission where the total number of words is small.

In [58], the authors focus on robust SemCom for images classification. They consider a scenario where the source image dataset suffers a malicious attacker, i.e., a semantic noise is added to each image. For semantic extraction, MAE with Transformer blocks is employed (the details can be found in Section V-A). Since MAE randomly masks partial patches of the image during the encoding process, the impact of semantic noise added in the patches of the image can be eliminated to some extent [58]. Moreover, they propose a codebook for encoded feature representation, which consists of multiple discrete basis vectors trained together with the encoder and decoder parameters. Based on the well-trained codebook, the continuous encoded features output by the encoding neural networks are mapped into the discrete indices of basis vectors by a nearest neighbour search [58]. Hence, the distortion caused by semantic noise can be corrected with a high probability during discrete representation at the transmitter, which greatly enhances the robustness of the communication. In addition, the authors employ the adversarial training, which can be formulated as solving a min-max optimization problem by executing two steps iteratively. One is to obtain the optimal semantic noise for images which maximizes the loss function with the fixed trainable parameters. The other is to update the trainable parameters by stochastic gradient descent based on the dataset with noise-added images. Meanwhile, to further improve the robustness, a trainable parameter of weight perturbation can be introduced into the loss function and find a better solution for the whole min-max optimization. With the simulation, the proposed MAE scheme can achieve an accuracy of 0.6 or greater over the SNR range from -6 dB to 10 dB. Whereas, the classification accuracy of the traditional scheme (JPEG + LDPC) is close to zero with SNR ranging from -6 dB to 6 dB. Only when the SNR reaches 18 dB does the traditional scheme achieve comparable performance to that of MAE scheme with an SNR of -6 dB.

In addition, inspired by the traditional relay node, which can help establish the communication between a source and a destination [227], the authors in [48] propose a new semantic forward (SF) protocol in the relay node to solve the mismatch of background knowledge of the communication parties. The key idea of SF is that the relay node can perform the semantic decoding for the received signal based on the background knowledge between the source node and itself, and then it can recode the signal based on another background knowledge between the source node and the relay node. In fact, their work fails to provide a solution on how to reduce semantic noise or how to recover semantic information from the received messages with semantic noise more accurately. However, their work can offer a potential solution to situations where the communicating parties are unwilling to share BK due to privacy preservation, by introducing an authoritative third party (e.g., edge intelligence in 6G) as a coordinator.

2) Privacy SemCom based on semantic noise: Despite the negative impact of semantic noise on the semantic recovering at the target receiver, it is also possible to use such a mismatch
in background knowledge to construct a privacy-preserving SemCom channel between two communicating parties [38]. Specifically, the knowledge background is only shared between the two communicating parties and evolves as they interact with each other. Thereby, the eavesdropper is hard to get a view of the knowledge background of the transmitter. In an ideal situation, even if the eavesdropping link is established successfully in the physical layer, the eavesdropper is unable to recover what is actually communicated. Nonetheless, in practice, the eavesdropper is likely to acquire a similar background knowledge to the transmitter. Therefore, the existing SE methods that rely solely on background knowledge are not sufficient to achieve privacy preservation at the semantic level. Considering the success of artificial noise in wireless secure transmissions [228], [229], enhancing semantic noise via the sophisticated-designed background knowledge may be a potential approach to enable secure semantic communication. However, to the best of our knowledge, there have been no relevant studies in the literature.

VI. COMMUNICATION-RELATED CHALLENGES AND TECHNIQUES FOR 6G SEMCOM

The focus of discussion in this section shifts from semantic-related to communication-related challenges and techniques. While conventional and SemCom systems use different methods to encode and decode information, they both face the same communication constraints, such as unpredictable channel conditions, limited transmission, and processing resources. However, unlike prior works in conventional communication systems, the solutions in SemCom are required to address new challenges in modern communication systems. In the following, we discuss the challenges and techniques in performance analysis, resource allocation, and networks.

A. Performance analysis

In conventional communication systems, source coding encodes the data into a sequence of symbols with optimized length, and channel coding adds redundant symbols to the sequence to detect and recover the data corruption during the wireless transmission. With the help of performance analysis methods, we can further obtain insights related to the wireless environment and coding mechanism, which guides us to better design systems. In the SemCom systems, the source and channel coding can be connected more tightly with the help of AI. Jointly designing and training source and channel coding are shown to benefit data transmission in the DL-based communication systems [42]. However, the use of methods that cannot currently be interpreted by the explicit mathematical expressions limit the use of performance analysis. SemCom system designers have to consider how to make connections between the complex and changing wireless environment and sophisticated SemCom mechanisms, so as to obtain insights to guide the system design. Thus, we discuss the impact of the channel model, SNR, and error reduction mechanism on the SemCom performance.

1) Varying channel models: In conventional wireless communications, several classical channel models are commonly used in the performance analysis, e.g., Rician, Rayleigh, and Gaussian channel models. Moreover, to unify system performance with various channel environments, generalized fading distributions are proposed, e.g., \( \alpha - \mu \) [230], Fisher-Snedecor \( \mathcal{F} \) [231], FTR fading models [232]. These channel models have various parameters to represent the different conditions of the wireless environment, such as the strength of the shadow effect and the multi-path effect. In SemCom systems that have an end-to-end structure, modeling the channel layer is a challenging task. Most of the existing works model the channel layer in two ways: fixed channel layers with the fading models used in conventional wireless communications, and generative channel layers with the neural network, e.g., GAN.

Fixed channel layer modeling scheme: In the fixed channel layer modeling scheme, the channel layer is modeled as a fixed fading model that is used throughout the training process. For example, the erasure channel is used in [42] to model the dropping of data packets. The input of the erasure channel is a binarized bit vector from the encoder. Every element in the bit vector can be \(-1\) or \(1\), and the dropped element will become 0 at the output of the erasure channel. A drop probability is determined before the training. Eventually, the elements of the output vector after the erasure channel are in \(\{-1, 0, 1\}\). This process is similar to the dropout technique used to prevent the over-fitting problem in deep neural networks. Hence a dropout layer can be used to represent the erasure channel of the communication systems. For input that is not quantized or binarized, communication channels such as additive white Gaussian noise (AWGN), Rayleigh channels, and Rician channels are considered. Recent research works in SemCom for text [43], speech signals [51] and multimodal data [60] consider the channel layer as AWGN, Rayleigh channels, and Rician channels, for the training process. However, the performance evaluation is done with the same channel conditions in the training, without considering the fact that the changes in the wireless environment can lead to the change of the suitable channel model. Another drawback of using a fixed channel layer modeling scheme is that, if the SemCom model is trained under a certain fading channel, it is impractical to retrain the model for each possible channel condition and load all these models to the transmitter and the receiver. Although the trained model has shown some robustness, e.g., the authors in [51] tested the model trained with Rician channels under AWGN and Rayleigh channels while achieving MSE loss less than \(1 \times 10^{-4}\), we cannot explain the upper-bound of the robustness, and are not sure whether the model will fail when the environment changes. Instead of training with fixed channel layers, the generative channel layer modeling scheme is used to capture the dynamic behavior of the channel states.

Generative channel layer modeling scheme: The typical generative network adopted in existing works is generative adversarial net (GAN) [233]. There are two main components in GAN, i.e., a generator and a discriminator. The generator aims to generate data samples that are as similar to real data samples as possible. The discriminator will be given real and generated data randomly and it will output a label to
indicate whether the given data is real or generated. During the training process, the objective loss function helps the generator to generate more realistic data and the discriminator to output more accurate labels. To generate category-specific data, the conditional GAN [233] is proposed where the extra context information is provided to the GAN to obtain samples of the given context. In [234], a conditional GAN is used to model the channel conditions. The conditional GAN is provided with both the pilot information and encoded signal from the transmitter and asked to generate an output signal that is similar to the real data. To evaluate the performance of the proposed conditional GAN in real channel conditions, the trained model is tested with the WINNER II channels [235]. It is shown that the conditional GAN model outperforms the baseline system in terms of BER and BLER, especially when the SNR is over 10 dB. Although the Generative channel layer modeling scheme improves the adaptability of the training model to the wireless environment, more training overhead is required than the fixed channel layer modeling scheme. This motivates us to think about the tradeoff between the performance and resource overhead.

Overall, fixed channel layers and generative channel layers provide wireless channel modeling during the training of the SemCom systems. The choice of different schemes has an impact on the performance of SemCom. One possible solution is to combine the advantages of both schemes. For example, a two-phase training strategy is proposed in [147] to adapt to the real channels. In Phase I, the model is trained with a suitable channel model to obtain model parameters with reasonable accuracy. In Phase II, the receiver is fine-tuned over the actual channel. The fine-tuned autoencoder constantly achieves lower BLER than the autoencoder without fine-tuning. However, how to choose the optimal training solution in different wireless environments is still an open question.

2) Uncertain SNR: After discussing the effects of the channel environment on the SemCom performance, here we consider the impact of SNR uncertainty on the trained SemCom model. Note that the influence of the wireless environment is mainly from the channel model selection, due to the effects of shadowing or scattering. The SNR uncertainty is from the effect of noise and interference, as well as the variation in transmit power, e.g., when adaptive transmit power schemes are used. Since the fixed SNR approach is typically adopted in the training of SemCom models, e.g., for text [43], speech signals [51] and multi-modal data [60], we need to consider whether the change in SNR will have a negative impact on performance.

Several works tested the robustness of the trained model to SNR. In [51], the model is trained with a fixed SNR of 8 dB, and is then evaluated under SNR from 0 dB to 20 dB. It is found that the model has a higher MSE loss in the lower SNR region in the test under AWGN channels, Rayleigh channels, and Rician channels. However, it is still uncertain whether a model trained at a fixed SNR value can always be applied to a wide range of SNRs. Furthermore, while the SemCom constantly achieves higher performance than the conventional communication systems, both of them suffer a poorer performance in the lower SNR region. Because low SNR environments are common in the cellular edge, shopping malls, or suburban areas, we need to consider the performance of SemCom when the SNR is low and the accuracy of the decoded signal is reduced.

To solve the aforementioned problems by making the model robust to different SNR regions, especially to the low SNR regime, the authors in [236] proposed an SNR adaptive mechanism. In the proposed model, the SNR is estimated by a pilot signal at the receiver. The estimated SNR value is then extended to an SNR map that has the same size as the channel output feature map. Both the SNR and channel output feature maps pass through a CNN layer before they are added together. The result of the element-wise addition is used as the input of a denoising module. A few transposed convolution layers are used to reconstruct the original image. It is found that, compared to the model that is trained with fixed SNR, the model trained with the proposed SNR adaptive mechanism has a smaller gap of PSNR between the high SNR region and low SNR region. By considering the SNR information in the decoding process, the proposed model shows higher adaptability to the SNR.

Instead of adding the SNR values to the channel features, another method to enhance the robustness of the SemCom model is to scale the channel features according to different SNR values [57]. The training method proposed in [57] adopts channel-wise soft attention, where each channel feature is multiplied by a scaling factor. To obtain the scaling factors, the SNR value is concatenated with the context information vector extracted from the input image and fed into two fully connected layers. Each element in the output vector is a scaling factor of a feature channel. It is shown that, with the help of the soft attention mechanism, the model can achieve a higher PSNR compared to baseline models which use basic deep learning networks without the attention module. In particular, the model with the soft attention mechanism can achieve more than 35 dB PSNR when the SNR is high.

However, both of these solutions are designed to solve specific communication problems. For the generalized SemCom system, the question of how to ensure that the trained semantic model can adapt to the variable SNR is still waiting for a better answer. The boundaries of the generalization capability of semantic models need to be further investigated.

3) Error reduction mechanism: To accommodate the changing wireless environment and the uncertainty of SNR, many mechanisms have been designed to improve SemCom performance. Now we focus on the error correction mechanism [237] that can further increase the probability that semantic information is correctly transmitted.

In conventional communication systems, the error of transmission could be reduced by using several error correction algorithms. In SemCom, the error correction mechanism should also be carefully designed to minimize the transmission errors of semantic information. For example, in [44], hybrid automatic repeat request (HARQ) is used to reduce the transmission error of semantic text transmission. With the help of HARQ, a re-transmission will be requested if the received code block has uncorrectable error. The authors in [44] first develop models with semantic encoder from [43] and Reed Solomon
We will discuss the methods of resource allocation in terms of satisfaction, clarity, and fluency [241], [242]. In the following, we specifically discuss the QoS aims to optimize transmission rate, delay, and outage probability. The design of a resource allocation scheme, the QoS and the QoE values the importance of the information behind the bit flow. This motivates us to develop the new resource allocation frameworks for the novel SemCom systems. Typically, in the design of a resource allocation scheme, the QoS and the QoE should be taken into consideration to build an efficient system. Specifically, the QoS aims to optimize transmission rate, delay, and throughput [239], [240], and the QoE focuses on user satisfaction, clarity, and fluency [241], [242]. In the following, we will discuss the methods of resource allocation in terms of bandwidth and energy in SemCom.

**B. Resource allocation**

Several resources, such as bandwidth and transmit power, are required for data transmission. On the one hand, resource allocation frameworks in conventional communication systems aim to minimize metrics such as the bit error rate, packet error rate, and outage probability, on the other hand, the SemCom values the importance of the information behind the bit flow. This motivates us to develop the new resource allocation frameworks for the novel SemCom systems. Typically, in the design of a resource allocation scheme, the QoS and the QoE should be taken into consideration to build an efficient system. Specifically, the QoS aims to optimize transmission rate, delay, and throughput [239], [240], and the QoE focuses on user satisfaction, clarity, and fluency [241], [242]. In the following, we will discuss the methods of resource allocation in terms of bandwidth and energy in SemCom.

1) **Bandwidth resource:** Because the bandwidth resources are precious for any communication system, an effective bandwidth allocation is necessary for achieving SemCom to improve the overall performance of the system. Unlike the allocation of bandwidth resources in conventional communications, the uneven distribution of semantic information should be taken into account in SemCom, i.e., more bandwidth should be allocated to data/agents that have more semantic information.

One possible solution is to jointly perform the bandwidth allocation during the training process. In [69], a CDRL algorithm is designed, where multiple agents can coordinate over a wireless network to share their policies and collaboratively learn the best policy for the respective tasks. However, due to the limited bandwidth, agents that require training (target agents) can only collaborate with limited amount agents (source agents). Therefore, the metrics used to identify the most helpful agents are important for effective resource allocation. Building on previous works that consider the structural similarity of the agent model, the authors in [69] include the semantic relatedness between the agents to construct a KG to aid the task selection of agents. The inter-agent semantic relatedness is defined as the return value of the target agent after a fixed number of training steps under the source agent’s policy. After jointly optimizing the training loss and wireless bandwidth allocation, a KG is obtained, in which the values of the edges between the agents capture the structural and semantic relatedness between the connected agents. The KG is then used by the base station to select the most relevant agents for collaboration during the optimization. Simulation results show that the system performance can be improved by 83%, compared to the baseline method that does not consider the semantic relatedness between the agents. However, the issue of combining dynamic allocation of bandwidth to semantic content transmission has not been fully studied. In some SemCom systems that do not require training, the bandwidth allocation schemes need to be designed to allocate more bandwidth for more important transmitted content to ensure information quality.

2) **Energy Resource:** In addition to the allocation of bandwidth resources, the allocation of energy resources is also an important issue. For the growing number of IoTs with energy harvesting capabilities, it is important to determine the importance of information with the help of semantics. Allocating more energy to transmit data containing richer semantic information ensures the efficient use of energy. In addition, semantic metrics can be used to determine the quality of the collected energy, which can help build an efficient network market.

Based on the sentence similarity metric proposed in [43], a semantic based valuation function is used in [50] for energy harvesting IoT devices to derive the value of harvested energy. In the proposed system model, there are IoT devices that adopt SemCom systems and a hybrid access point (HAP) that transmits energy to nearby IoT devices. The IoT devices operate by harvesting energy from the HAP [243], [244] to transmit text data to the HAP. However, the HAP is considered to serve only one user at a specific time. To obtain the wireless energy, the IoT devices will submit their bids and the HAP will decide the winner and payment. A truthful auction mechanism is proposed so that the IoT devices will bid according to their true valuation of the energy. Instead of using the performance metrics of the conventional communications, a valuation function based on the BLEU score and the similarity score is used by the IoT devices to obtain their bid values.

However, at present, the application of semantic metrics in the energy resource allocation is still in the early stage. Many SemCom networks that require energy-harvesting devices to work have not been studied, e.g., a UAV-aided network working with simultaneous wireless information and power transfer protocol.

**C. SemCom networks**

For the SemCom network, the wireless communication layer will have a greater impact on the system performance than that of the end-to-end communication. Because many heterogeneous devices work in one SemCom network, the differences in equipment hardware and wireless environments can bring challenges to the system construction.

1) **Different device capacities:** To enable SemCom systems, most of the discussed approaches involve installing encoders and decoders into the transmitters and receivers respectively. While the DL-based auto-encoder systems can help to extract meaningful information from raw data effectively, the cost of
implementation is not cheap. Particularly more computational power and communication resources are required for the training process. Research shows that scaling up deep neural networks with correct techniques almost always leads to better performance [158], [207]. However, scaling up the model increases the storage requirement to store a higher number of the model parameters. In reality, communication devices have limited computational power, communication resources, and storage capacity. Especially in SemCom networks, it is unrealistic to assume that all devices have sufficient capacity. Therefore, in SemCom networks developing effective methods to balance the performance and cost requirements for heterogeneous devices is one of the important challenges.

To make the model proposed in [43] more affordable to devices in SemCom network with limited computing capability, the authors in [45] experimented with model compression to reduce the size of the model. A joint pruning-quantization scheme [45] is proposed to compress the model effectively with the idea of model pruning [245]. In the proposed method, less significant model weights are zeroed out, and the model weights that are larger than a pruning threshold remain. To determine the pruning threshold, the model weights are first sorted in the ascending order by the weight values, and then the pruning threshold is selected such that the outcome of pruning satisfies a pre-defined sparsity ratio between 0 and 1. The sparsity ratio indicates the desired ratio of zeros of the model weights. The pruned model is then fine-tuned to recover the performance of the model. The size of the model is further reduced by network quantization that converts the model weights from 32-bit float point to \( m \)-bits integer, \( m < 32 \). A calibration process is needed to prevent overflows at the activation layer. In particular, an exponential moving average (EMA) is introduced to dampen the effect of outliers in the output of activation. Similar to model pruning, the model is fine-tuned after the quantization. Remarkably, the compressed model can achieve a similar BLEU score to the uncompressed model after model pruning with a sparsity ratio of 60% and 8-bit integer quantization. However, the performance loss due to further compression of the semantic model needs to be systematically investigated. We need to consider the capacity of different devices in the network and performance requirements.

2) \textit{Intelligently Connected IoT Networks:} For SemCom networks containing multiple smart devices, we need to design the network according to different wireless link environments of different devices. One solution is to consider the wireless links as intelligent agents in the training process.

The authors in [63] propose a resource allocation algorithm for semantic video transmission in spectrum multiplexing scenarios in vehicular networks. In the proposed algorithm [63], semantic understanding accuracy of the video transmission is optimized by a multi-agent deep Q-network. In the network, vehicle-to-infrastructure (V2I) links and vehicle-to-vehicle (V2V) links are the agents. Based on the observations about the environment states, such as channel gains and interference power under the resource blocks, the agents choose to reuse spectrum resource blocks. Then, the agents receive the reward based on the V2I average object detection accuracy and V2V average transmission rate. Simulation results show that under the same spectrum and transmit power, the proposed network constantly achieves higher accuracy of video semantic understanding than the QoS and QoE based resource allocation framework, with as high as 70% improvement for the density of correctly detected objects.

However, when the channel model is not available, the feedback links are absent for supervised learning. To solve this problem, the authors in [145] propose a meta-learning approach for the receiver to adapt to the unknown new channel condition. Meta-learning which means “learning to learn” refers to learning the adaptation module in the receiver [145]. The meta-learning method first trains the adaptation rule during the training phase. In particular, during the meta-training phase, the receiver will be meta-trained to update the decoder parameters based on the output of the physical channel. During the testing phase, the receiver will self-optimize the model parameters using the trained adaptation rule. Simulation results show that the model with meta-training can achieve a lower BLER than the model with conventional training, when more than one pilot frame is sent by the transmitter during the testing phase.

3) \textit{Coding and decoding scheme:} The coding and decoding scheme needs to be improved based on the various channel conditions of different users in the SemCom network. Unlike the two-phase training strategy which fine-tunes the model with supervised data, the authors in [47] propose a self-supervised mechanism in consideration of the varying channel states. In particular, a message is allowed to be encoded and decoded multiple times until a stopping criterion is fulfilled. For every cycle of encoding/decoding, the encoded/decoded information will be evaluated by a confidence mechanism to determine its semantic confidence. If the encoded/decoded information reaches a pre-defined confidence threshold, the encoder/decoder will release the information for the next process. Another stopping criterion is when the cycle length of encoding/decoding reaches a pre-defined maximum cycle length. With the distillation and confidence mechanisms, the encoder and decoder can fine-tune the encoded and decoded information in a self-supervised way, regardless of the channels.

Moreover, in a multi-user scenario, the fluctuation in resources, such as available spectrum and transmit power, can have a non-negligible impact on the SemCom performance [246]. To this end, the variable-length semantic encoding, which is comparable to scalable video coding [247] and multiple description coding [248] in conventional communication, urgently needs to be investigated to cope with the dynamic SemCom network.

\textbf{VII. FUTURE DIRECTIONS}

In the previous sections, we review the potential SemCom applications in 6G and the state-of-the-art techniques applied in SemCom. In addition to the remaining issues discussed in Section V and Section VI, several other SemCom-related directions can be explored further in terms of system effectiveness, sustainability, and trustworthiness.
Interpretability and explainability of SE: The communication environment is always experiencing a variety of uncertainties, such as unexpected changes in the network environment or completely new source information. The black box nature makes the SE model unpredictable for the output corresponding to uncertain inputs in practice, which restricts the SE model’s social acceptance and practicality, as well as leaves little basis to use as a guide for SE model optimization. Meanwhile, the available SE models are with little or no understanding of how and why the internal states in the hidden layers and the features contribute to a given example to produce a decision or outcome [249], which fails to give valuable insights into the design of SemCom systems and the semantic information transmission. Therefore, the issues related to interpretability and explainability of SE have to be addressed. As defined in [250], interpretability is used to measure the degree to which a human can consistently predict the model’s decisions. Gaining an insight into how and why the SE model arrives at a particular decision or outcome not only builds confidence in the model to deal with unknown situations, thereby reducing the risk of uncertainty, but also helps to understand the overall strengths and weaknesses of the models and guides improvements to the model [251]. In contrast to interpretability, the study of explainable AI focuses on the hidden states in DNN and aims to open up the black box. For example, the contribution of each input semantic feature to the accuracy of the semantic inference can be quantified by analyzing the gradient information of the semantic decoder. Based on this, the radio resource allocation at the sender can be achieved with a more flexible and fine-grained implementation, such as allocating the crucial semantic feature higher transmitting power to ensure its transmission reliability and the accuracy of the semantic inference.

Tradeoff between SE accuracy and communication overhead: Most of the existing works focus on how to perform accurate SE to save radio resources and enhance communication performance, while ignoring the extra communication overhead for SE. In fact, SE model training and updating require significant additional resources. For example, the training of accurate semantic extraction models relies on a complete KB with both senders and receivers, which requires, first of all, adequate storage resources. In addition, as the communication context evolves, each user’s local KB is constantly being updated individually. In this sense, ensuring that updates to the local database of all communicating participants can be shared in real time is extremely challenging, especially for the case with a large number of participating users who are geographically distant, which can cause significant communication overhead. Moreover, in an ideal case, retraining or fine-tuning of the SE model needs to be done promptly after the KB update. However, this is unrealistic for practical systems with limited computational resources. Therefore, making a favorable trade-off between SE accuracy and communication overhead is essential for the implementation of SemCom. For example, we can utilize edge intelligence to train the SE model based on the shared KB of local senders and receivers stored in the MEC server of the local area first. Then, with the help of the distributed learning paradigms, such as federated learning, a generalized SE model can be obtained by aggregating multiple well-trained SE models for different geographical areas. In this way, storage resources scattered around the edge can be efficiently utilized to reduce storage pressure on end devices or the central cloud, and the communication overhead caused by sharing data over long distances can be greatly reduced. However, the reasonable division of geographical areas and the strategic deployment of edge servers are still to be explored. Moreover, the aggregation period and the participants selected in each round are also the essential issues that can be optimized in making a tradeoff between SE accuracy and communication overhead.

Combination of SemCom and semantic caching: In traditional communications, the implementation of data caching on the router, MEC server, base station, etc., has already shown to be of great benefit in avoiding unnecessary delay and network overhead for [252]. By joint optimizing caching and communication, with a 1% increase in cache hits, the perceived latency is reduced by 35% [253]. However, traditional caching in terms of raw data is no longer ideally suitable for SemCom systems, as the frequent and repetitive semantic extraction of the raw data results in redundancy and inefficiency of the system. Meanwhile, the data volume of semantic information extracted is much smaller compared to the raw data. In this sense, semantic caching strategies that fit with SemCom cannot only enhance system efficiency, but also save memory resources. However, there are new issues raised for semantic caching. For example, different from the traditional data caching, such as that mainly focusing on the hit rate of the data content, semantic caching is more concerned with whether the semantic information in the cache can be accurately inferred by the requester. Since there may be multiple semantic information for the same data content, which ones to cache demands more prior knowledge, such as the popularity of the specific semantic information. Moreover, as the context of SemCom is constantly changing, the lifetime of semantic information is more difficult to determine. To this end, it also requires new estimate refreshing algorithms for semantic caching.

Reasoning in implicit SemCom: The majority of previous SemCom research focused on transferring explicit semantic information, such as the labels of things that can be directly identified from the source signals, e.g., images, voices, and texts. However, communication between users is not only limited to explicit information, but also contains rich implicit information that is difficult to express, recognize, or recover. For an example in [254], a kid sends her father a voice message asking, “What is a Tweety?” The major semantic part of this message, “Tweety”, might be interpreted in several ways, such as a smartphone app, a canary bird, or a character from a cartoon television program. Therefore, to deduce the message’s exact meaning, the receiver must be able to infer the implicit information from the transmitter’s context and background. Thus, it is unrealistic to assume that the destination user has a well-defined analytical expression, such as a reward function or utility function, which is directly optimized to maximize its understanding of the semantic meaning. A few works have considered this point and tried to propose solutions. A genera-
tive adversarial imitation learning-based reasoning mechanism learning (GAML) is designed in [254] for the destination user to learn and imitate the reasoning process of the source user to obtain the implicit semantic meaning. It is shown that GAML can achieve significant error correction performance and offer 20% of accuracy improvement over genetic algorithm (GA)-based reasoning solution. In another work [255], the authors develop a novel inference function-based approach that can infer hidden information such as incomplete entities and relations that cannot be directly observed from the message, where the solution achieves 76% and 48% of accuracy in recovering missing information when using additive and linear inference functions, respectively. However, both solutions in [254], [255] add additional inference overhead, and there is still room for further performance enhancement. Moreover, because explicit semantic information is typically dominant, the communication resources should be allocated proportionally between explicit and implicit semantic information, which inspires us to further design the joint optimization algorithms.

**Artificial intelligence in SemCom channel management:** In SemCom, AI is more often deployed on the transmitter and receiver for coding and decoding to serve upper layer applications. However, in the 6G wireless communication that has a higher data rate and more frequent handover, channel modeling becomes more and more complex than the traditional stochastic or deterministic approaches [256]. This prompted us to think about whether AI could be brought down to the SemCom channel layer to help model, estimate, and change channel conditions. Unlike simply applying AI to the end-to-end SemCom model training, the development of new intelligent materials gives AI more freedom in wireless channels [257]. It is believed that the radio environment in the future generation of wireless communication networks will become controllable and intelligent by leveraging the emerging technologies of reconfigurable metasurface (RMS) and AI [258]. RMS can effectively control the wavefront, e.g., the phase, amplitude, frequency, and even polarization, of the impinging signals. Through the use of AI-enable programmable intelligent materials, SemCom networks can further surpass the limits predicted by the classical Shannon theory by jointly optimizing the transmitter, the receiver, and the environment.

**Tradeoff between SemCom performance and security:** Data security and privacy issues are always significant topics in the field of wireless communications [16]. Due to the fact that SemCom requires only partial data to be transmitted and the decoding of semantic information relies on the receiver’s background knowledge, it has also been regarded as a potential method for secure communications [38]. In addition, the security of the data can be further enhanced by encrypting the extracted semantic information. However, this also leads us to consider the tradeoff between computational resource overhead and data security. One possible solution is to use the physical layer security technologies. Considering the success of covert communication [259], we can make the data eavesdropper unsure whether the SemCom is ongoing by introduced interference to the physical layer for secure wireless transmission. However, although the computational resources for encrypting the data are reduced, we need to keep the transmitting power not too high to ensure the covertness of the communication. In addition, the interference signals have a negative impact on the transmission of semantic information, which brings a trade-off between the covertness and signal quality.

**SemCom for emerging applications and the future Internet:** The advent of 6G will signal a shift in emphasis away from smartphone oriented communications towards the Internet of Everything [260]. With a new focus on realizing the future Internet, such as the Metaverse, there comes along a new set of challenges as well. For example, users will be accessing the Metaverse not just with smartphones, but also with HMD. Unfortunately, today’s HMDs tend to overheat quickly and mobile HMDs have their battery levels depleted too quickly to enable prolonged use. As such, SemCom will be instrumental towards enabling ubiquitous and scalable access to emerging applications and the future Internet. Moreover, the SemCom architectures will have to be reconfigured to optimize user metrics based on the user needs of such emerging applications, e.g., minimizing the breaks-in-presence [261] experienced by users when utilizing HMDs.

**VIII. Conclusion**

In this paper, we have provided a comprehensive survey of SemCom for 6G. First, we have highlighted the mutually reinforcing properties of 6G and SemCom. Then, we have introduced the development from classical SemCom related theory and modern AI-enabled SemCom. Next, focusing on modern SemCom, we have outlined the system models for semantic-oriented communication and goal-oriented communications, and three types of semantic metrics in SemCom. Meanwhile, we have presented the potential applications for SemCom in the 6G network and discussed the challenges and techniques related to semantics and communication, respectively. Moreover, we highlight some future directions.

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