

Semantic Communications: Principles and Challenges

(Invited Paper)

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Abstract

Semantic communication, regarded as the breakthrough beyond Shannon paradigm, aims at the successful transmission of semantic information conveyed by the source rather than the accurate reception of each single symbol or bit regardless of its meaning. This article provides an overview on semantic communications. After a brief review on Shannon information theory, we discuss semantic communications with theory, frameworks, and system design enabled by deep learning. Different from the symbol/bit error rate used for measuring the conventional communication systems, new performance metrics for semantic communications are also discussed. The article is concluded by several open questions.

Index Terms

Deep learning, semantic communication, semantic theory, task-oriented communication.

I. INTRODUCTION

Around 70 years ago, Dr. Weaver [1] categorized communications into three levels: transmission of symbols, semantic exchange, and effects of semantic exchange. The first level communications, transmission of symbols, have been well studied and delivered in conventional

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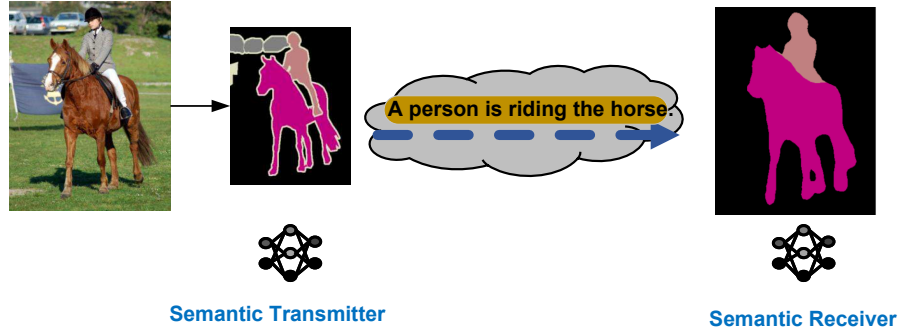


Fig. 1: The illustration of a semantic communication system for image recognition.

communication systems, which are approaching to Shannon capacity limit. However, in many situations, the ultimate goal of communications is to exchange semantic information, such as the natural language, while the communication medium, such as optical fiber, electromagnetic wave, and cable, can only transmit physical signals. Recently, semantic communication¹ has attracted extensive attention from industrial and academia [2], [3], which have been identified as a core challenge for the sixth generation (6G) of wireless networks.

In contrast to the Shannon paradigm, semantic communications only transmit necessary information relevant to the specific task at the receiver [1], which leads to a truly intelligent system with significant reduction in data traffic. Fig. 1 demonstrates the concept of semantic communications, where the transmission task is image recognition. Instead of transmitting bit sequences representing the whole image, a semantic transmitter extracts features relevant to recognize the object in the source image, i.e., horse riding in this example. The irrelevant information, such as image background, will be omitted to minimize the transmitted data without performance degradation. As a result, the demands on energy and wireless resources are reduced significantly, leading to a more sustainable communication network.

For many applications in the age of 6G and artificial intelligence (AI), the agent, such as smart terminals, robot, and smart surveillance, is able to understand the scene and executes the instruction automatically. Hence, the core of the task-oriented semantic communication is the deep semantic level fidelity rather than shallow bit-level accuracy. Such a semantic communication framework will be widely used in Industrial Internet, smart transportation, video conference, online education, augmented reality (AR), and virtual reality (VR), to name a few.

¹In this article, semantic communications refer to Level 2 and Level 3, also called task/goal-oriented communications.

Since the masterpiece from Shannon [1], the remarkable progress has been made in understanding the mathematical foundation of symbol transmission without considering semantics of the transmitted symbols or bits. Bar-Hillel and Carnap [4] revisited the missed semantic problem in Shannon’s work, and offered a preliminary definition of semantic information. Bao *et al.* [5] clarified the concepts of semantic noise and semantic channel. A semantic communication framework [6] was proposed to minimize semantic errors. These pioneering works are based on logical probability and are mainly designed for textual processing. Due to the lack of a general mathematical model to represent semantics, the development of semantic communications is still in its infancy after seven decades since it was first introduced.

Recent advancements on deep learning (DL) and its applications, such as natural language processing (NLP), speech recognition, and computer vision provide significant insights on developing semantic communications [3], [7]. Hwang [8] discussed intelligence transmission in the analysis and design of communication systems. Moreover, Chattopadhyay *et al.* [9] quantified semantic entropy and the complexity for semantic compression. Joint source-channel coding (JSCC) schemes [10], [11] were proposed to capture and transmit semantic features, in which the semantic receiver executes the corresponding actions directly rather than recovering the source messages. More recently, a series of semantic communication frameworks have been developed [12]–[15] for multimodal data transmission, which have attracted extensive attention.

So far, there have been several tutorials and surveys on semantic communications. Tong *et al.* [3] identified two semantic communication related critical challenges faced by AI and 6G, including its mathematical foundations and the system design. Kalfa [16] discussed semantic transformations of different sources for popular tasks in the field, and presented the semantic communication system design for different types of sources. Strinati *et al.* [17] indicated the role of semantic communications in 6G. Lan *et al.* [18] classified semantic communications into human-to-human (Level 2), human-to-machine (Level 2 and Level 3), and machine-to-machine (Level 3) communications. Various potential applications of semantic communications are presented. Furthermore, many researchers have dedicated to designing new frameworks [19]–[22] for semantic communications in the format of terse and forceful magazine articles. By summarizing the highly related works, they serve as a good start to step into the area.

In this article, we will provide a comprehensive overview on principles and challenges of semantic communications. We first review Shannon information theory and summarize the development of semantic theory. After clarifying the critical difference between conventional

and semantic communications, we introduce principles, frameworks, and performance metrics of semantic communications. Next, we present the developments of DL-enabled semantic communications for multimodal data transmission, including text, image, and audio. We conclude the article with research challenges to pave the pathway to semantic communications. This tutorial article tries to provide insights on answering the following common questions:

- *How to understand the semantic meaning of bit sequences?*
- *Where is the gain from in semantic communications?*
- *Is there a theoretic limitation for semantic communication systems?*

This article will present readers a clear picture of semantic communications. The rest of the article is structured as follows. Section II compares conventional and semantic communication systems and theories. Section III presents semantic communication system components, frameworks, and performance metrics. The recent advancements on DL-enabled semantic communication systems for transmitting multimodal data are discussed in Section IV. This article is concluded by open questions in Section V.

II. FROM INFORMATION THEORY TO SEMANTIC THEORY

In this section, we first discuss the critical difference between conventional and semantic communications. Then we briefly introduce information theory and semantic theory.

A. Difference between Conventional and Semantic Communications

Since research in semantic communications is still in its preliminary stage, there is no consistent definition of semantic communications yet. In Fig. 2, we compare the conventional and semantic communications. In a conventional communication system, the source is converted into bit sequences to process. At the receiver, the bit sequence representing the source is recovered accurately. In the conventional communication system, the bit/symbol transmission rate is bounded by Shannon capacity. Semantic communications transmit semantic meaning of the source. One of the critical difference is the introduction of semantic coding, which captures the semantic features, depending on tasks or actions to be executed at the receiver. Only those semantic features will be transmitted, which reduces the required communication resources significantly. Tasks at the receiver could be data reconstruction or some more intelligent tasks, such as image classification and language translation. Note that in semantic communications,

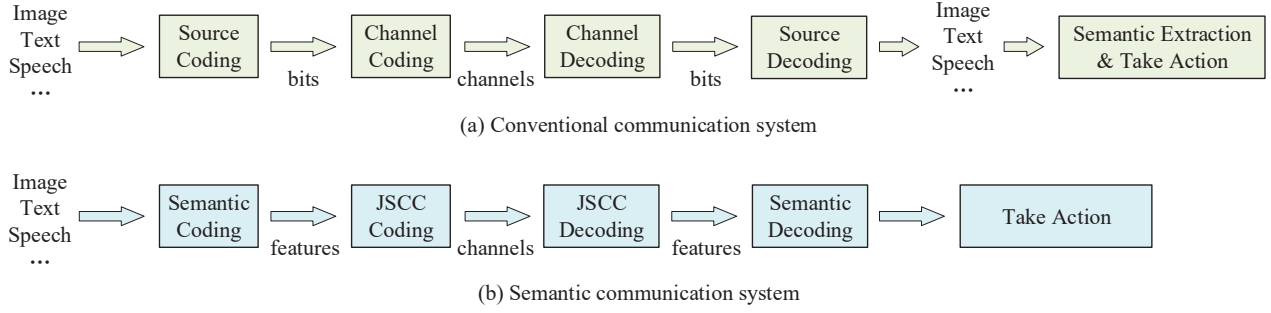


Fig. 2: Comparison of conventional and semantic communication systems.

data are not processed at the bit level, but the semantic level. Semantic communications could be described by semantic theory.

The following of this section starts from a brief review of information theory. We then present semantic theory developed in past decades though it is not well established yet.

B. Information Theory

In 1948, Shannon introduced the concept of information entropy [1], which exploits uncertainty to measure the information content in terms of bits.

Definition 1: Given the source, $X \in \{x_1, x_2, \dots, x_n\}$, with probabilities $\{p(x_i)\}_{i=1}^n$, the source entropy measures the average number of bits per symbol, which is defined as

$$H(X) = - \sum_{i=1}^n p(x_i) \log_2 p(x_i). \quad (1)$$

Theorem 1: For transmission over noisy channels, described by $p(y_j|x_i)$, channel capacity is given by

$$C = \max_{p(x)} I(X; Y), \quad (2)$$

where $I(X; Y) = H(X) - H(X|Y)$ is the mutual information between the input, X , and the output, Y , of the channel, and $H(X|Y) = - \sum_{j=1} p(y_j) \sum_{i=1} p(x_i|y_j) \log_2 p(x_i|y_j)$ is the conditional entropy of X for a given Y .

With the channel capacity, Shannon further developed the source-channel coding theorem.

Theorem 2: If x_i for $i = 1, \dots, n$, satisfies the asymptotic equipartition property (AEP) and $H(X) \leq C$, there exists a source-channel code with probability of error $p(\hat{x}_i \neq x_i) \rightarrow 0$. Conversely, there will be a positive probability of error if $H(X) > C$.

Conventional communication systems are based on Shannon's *separation theorem* including two stages: i) compress source data into its most efficient form; and ii) **map the sequence of source coding into channel coding.**

Theorem 1 provides an upper bound for distortion-less transmission. For a given distortion D^* , the minimum transmission information rate R can be described by the rate distortion theory below, also known as the lossy source coding theorem.

Theorem 3: For a given maximum average distortion D^* , the rate distortion function $R(D^*)$ is the lower bound of the transmission bit-rate [23]

$$R(D^*) = \min_{D \leq D^*} I(X; Y), \quad (3)$$

where $D = \sum_{x,y} p(x)p(y|x) d(x,y)$ is the distortion, $d(x,y)$ is the distortion metric with $d(x,y) = 0$ if $x = y$. As $R(D^*) = \min_{D \leq D^*} I(X; Y) \leq \min_{D=0} I(X; Y) = H(X)$, $R(D^*) \leq H(X)$.

Information theory is a rich subject nowadays and it is impossible to introduce it within a couple of pages. The above are only theorems and definitions that are highly related to the semantic theory in the subsequent discussions.

C. Semantic Theory

Entropy in Shannon information theory measures the information content by the uncertainty of the source. **However, how to measure the amount of semantic information, or the importance of information, for a specific transmission task is yet determined.**

Definition 2: Given a transmission task, V , the semantic information, Z , is the information relevant to V in the source, X .

The uncertainty in Z is less than that in X , which indicates the following relationship:

$$H(V) \leq H(Z) \leq H(X). \quad (4)$$

The semantic information, Z , is extracted from X , which can be regarded as the lossy compression of X . However, from the view of V , Z is the lossless compression of X since the task, V , could be fully served by it. With different tasks, the required semantic representation, Z , will be different.

With the transmission task, V , it is possible to measure the importance of information, say semantic information. For example, **for image classification tasks, the receiver is only interested in the objects in an image rather than the original image.** Therefore, the objects are considered

as essential information while the others are non-essential. Similarly, for text transmission, the receiver requires the meaning of text instead of the lossless text recovery.

1) **Semantic Entropy:** In the past decades, researchers have worked hard to find a way to quantify semantic entropy by following the path of information entropy developed by Shannon. However, it is still an active research area with huge space to investigate.

Based on logical probability, many different definitions of semantic entropy have been developed. Carnap and Bar-Hillel [4] measured the semantic information by the *degree of confirmation*, which is expressed as

$$H(\mathcal{H}, e) = -\log c(\mathcal{H}, e), \quad (5)$$

where $c(\mathcal{H}, e)$ is the degree of confirmation of hypothesis \mathcal{H} on the evidence, e . Bao *et al.* [5] defined semantic entropy of a message or sentence s as

$$H(s) = -\log_2(m(s)), \quad (6)$$

where the logical probability of s is given by

$$m(s) = \frac{p(\mathcal{W}_s)}{p(\mathcal{W})} = \frac{\sum_{w \in \mathcal{W}, |w|=s} p(w)}{\sum_{w \in \mathcal{W}} p(w)}. \quad (7)$$

Here, \mathcal{W} is the symbol set of a classical source, and $\mathcal{W}_s = \{w \in \mathcal{W} | |w| = s\}$ is the sets of models for s , i.e., the space in which s is true. Here, $p(w)$ is the probability of w . If there is no background available, $\sum_{w \in \mathcal{W}} p(w) = 1$. The conditional entropy with background knowledge is also defined by extending the above definition.

In fuzzy systems, semantic entropy is defined by introducing the concept of *matching degree* with the *membership degree* [24]. Membership degree is a concept in fuzzy set theory and is usually difficult to measure analytically. Therefore, it is defined manually by following expert intuition and experience. Liu *et al.* [24] defined ς as a semantic concept, which could be treated as the transmission task, and $\mu_\varsigma(X)$ as the membership degree for each $X \in \mathcal{X}$, where \mathcal{X} is the set of X . For the class, C_j , the matching degree, $D_j(\varsigma) = \frac{\sum_{X \in \mathcal{X}_{C_j}} \mu_\varsigma(X)}{\sum_{X \in \mathcal{X}} \mu_\varsigma(X)}$, characterizes the semantic entropy of X on the concept, ς . Note that the definition of matching degree shares similarity as that defined in (7). With the matching degree, semantic entropy on class C_j is defined as

$$H_{C_j}(\varsigma) = -D_j(\varsigma) \log_2 D_j(\varsigma). \quad (8)$$

The overall semantic entropy over \mathcal{X} could be obtained by summing up that of all classes. The basic properties of semantic entropy defined above are similar to those of information entropy. The difference is that the membership degree. It is related to the semantic concept or the transmission task, which characterizes the semantic information.

The above definitions of semantic entropy assume that there exists a way to measure semantic information. All theorems are developed based on the assumption of available semantic representation without providing the specific approach to quantifying semantic information. A group of decent statisticians [9] is working on an active project to develop an information-theoretic framework for quantifying semantic information content in multimodal data, where semantic entropy is defined as the minimum number of semantic enquires about the source X , whose answers are sufficient to predict the transmission task, V . By doing so, the approach to finding semantic entropy becomes to find the minimal representation of X for serving the task, V . However, it is still under investigation and how to apply such a framework to practical scenarios is to be clarified.

2) Semantic Channel Capacity: In addition to (6), Bao *et al.* [5] further developed the following theorem for semantic channel capacity, which can be regarded as counterpart of *Theorem 1*.

Theorem 4: The semantic channel capacity of a discrete memoryless channel can be expressed as

$$C_s = \sup_{p(X|Z)} \left\{ I(X; V) - H(X|Z) + \overline{H_S(V)} \right\}, \quad (9)$$

where $I(X; V)$ is the mutual information, $H(X|Z)$ is the conditional probabilistic distribution of a semantic coding strategy, and $\overline{H_S(V)}$ is the average logical information of the received messages.

Note that higher $H(X|Z)$ means higher semantic ambiguity caused by the semantic coding while higher $H_S(V)$ leads to strong ability for the receiver to interpret received messages. The semantic channel capacity could be either higher or lower than the Shannon channel capacity $I(X; V)$, dependent on the semantic coding strategy and the receiver's ability to interpret received messages.

3) Semantic Rate Distortion and Information Bottleneck: Similar to (3), the rate distortion in semantic communication system is formulated as [25]

$$R(D_s, D_a) = \min I(Z; \hat{X}, \hat{Z}), \quad (10)$$

where D_s is the semantic distortion between source, X , and recovered information, \hat{X} , at the receiver, and D_a is the distortion between semantic representation, Z , and received semantic representation, \hat{Z} . Note that (10) considers the distortion caused by both semantic compression and channel noise.

Information bottleneck is an approach to finding the optimal tradeoff between compression and accuracy, which is to solve the following problem [26]

$$\min_{p(Z|X)} I(X; Z) - \beta I(V; Z), \quad (11)$$

where V is the desired semantic representation. As its extension, Sana *et al.* [27] designed a new loss function as

$$\mathcal{L} = \underbrace{I(Z; X)}_{\text{Compression}} - \underbrace{(1 + \alpha) I(Z; \hat{Z})}_{\text{Mutual information}} + \underbrace{\beta KL(X, \hat{Z})}_{\text{Inference}}, \quad (12)$$

where α and β are the parameters to adjust the weights of the mutual information term and the inference term. The compression term represents the average number of bits required for X . The inference term is the Kullback-Leibler (KL) divergence between the real posterior probability at the encoder, X , and the one captured by the decoder, \hat{Z} . Note that the upper bound of (12) is

$$\mathcal{L} = \mathcal{L}_{CE} - \alpha I(Z; \hat{Z}), \quad (13)$$

which is the loss function designed in [12] to be detailed in Section VI.

Though it is yet possible to quantify semantic communication systems as Shannon did for conventional communication systems, understanding the above concepts could provide us important insights, especially on the loss function design for DL-enabled semantic communications.

III. COMPONENTS, FRAMEWORKS, AND PERFORMANCE METRICS

As we can see from Section II, semantic theory is still in its infancy. But that does not prevent from developing practical semantic communication systems. This section introduces main components, developed frameworks, and performance metrics for semantic communication systems.

A. Semantic Communication System Components

As shown in Fig. 3, a semantic communication system includes semantic level and transmission level. The semantic level addresses semantic information processing to obtain semantic

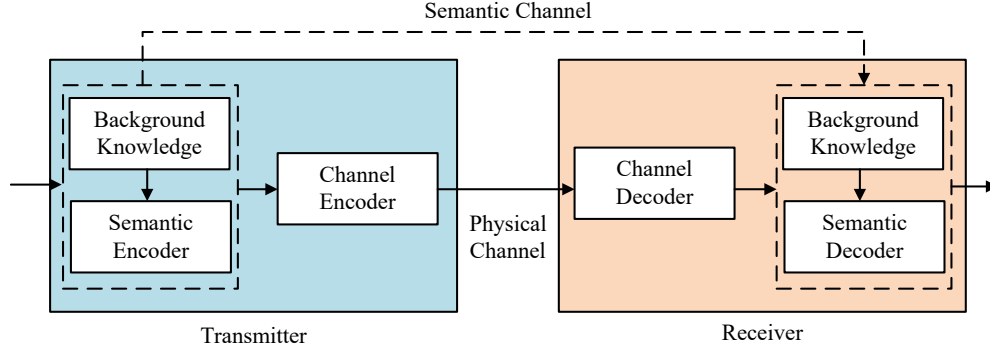


Fig. 3: The main components in a semantic communication system.

representation, which is performed by the semantic encoder and decoder. Here, the semantic information refers to that useful for serving the intelligent tasks at the receiver. The transmission level guarantees the successful reception of symbols at the receiver after going through the transmission medium, which are normally proceeded by the channel encoder and decoder. The semantic transmitter and receiver are equipped with certain **background knowledge** to facilitate semantic feature extraction, where the background knowledge could be different for various applications.

Note that there are two types of channels to deal with in semantic communication systems. The first type of channels are the physical channels, which introduce channel impairments, such as noise, fading, and inter-symbol interference, to the transmitted symbols. In the past, the majority efforts on wireless communications have been made to combat the physical channel impairments. **The second type of channels are the semantic channels**, which could be contaminated by semantic noise caused by misunderstanding, interpretation errors, or disturbance in the estimated information.

B. Semantic Noise

There are two types of semantic noise, which are generated by human. The first type of semantic noise refers **to semantic ambiguity, which mostly arises in the NLP area**. Slight changes to words in the sentence, such as synonym replacement and reverse alphabetical order randomly, may make the model misjudge the semantic meaning of the sentence [28]. This is because the DL-based method is more **vulnerable to adversarial attack** as shown in Fig. 4. A toxic detection system developed by Google can be deceived by adversarial examples [29]. A highly toxic

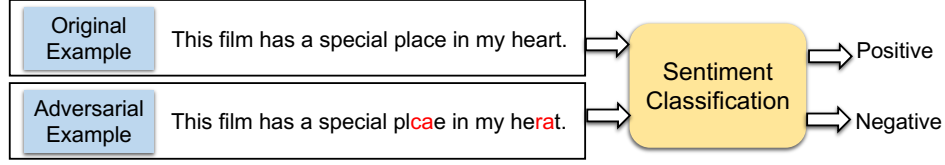


Fig. 4: An example of the first type of semantic noise.

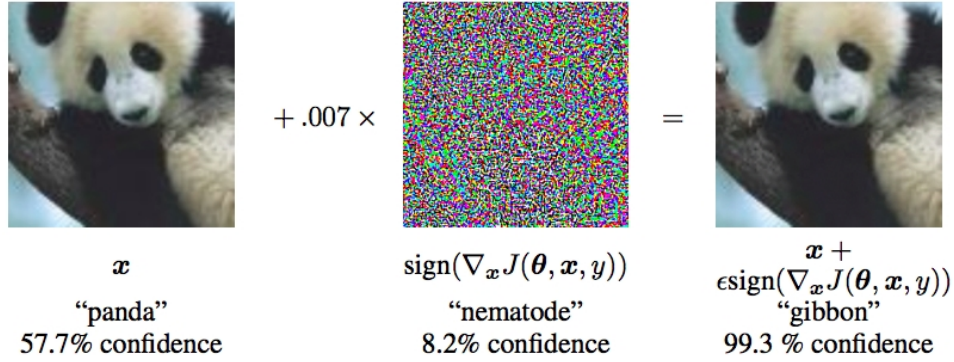


Fig. 5: An example of the adversarial example in image domain [30].

comment can achieve a low toxicity score by a subtle change, such as repeat a single word or add a period in the middle of the word.

The second type of semantic noise comes from the adversarial examples. Adversarial examples in the image domain are different from those in the text domain. Due to the discrete nature of text, it is impossible to add perturbation to text without being noticed by human. However, some modifications added to images are so subtle that human can hardly notice. An typical example of adversarial example in the image domain is shown in Fig. 5. We could see that the image with adversarial noise will mislead the DL models for classification but look the same as the original image if observed by human.

Some prior works have studied adversarial example generation. Goodfellow *et al.* [30] proposed a fast gradient sign method to generate perturbation by using the gradient of the loss function. Miyato *et al.* [31] developed a fast gradient method to generate adversarial examples. The role of adversarial examples for DL has two effects. First, it can be used to prevent machine learning system from attacks. Secondly, it is beneficial to improve the robustness of a DL-based system. Note that all the aforementioned adversarial examples are generated by human. To investigate whether there are adversarial samples in nature, a mobile phone camera is used to

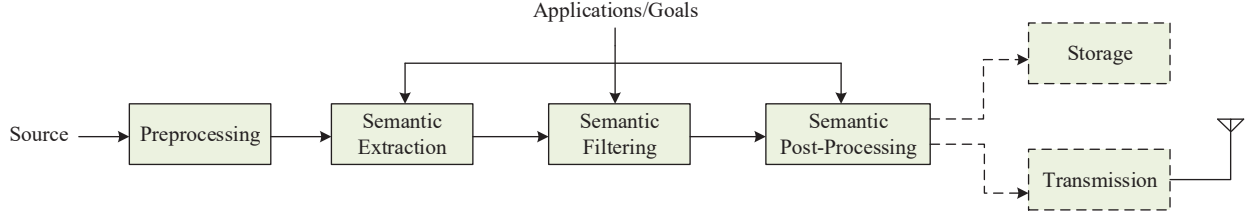


Fig. 6: The task-oriented semantic signal processing framework [16].

photograph adversarial samples [32], which have showed that images obtained by taking pictures of the adversarial samples will also be misclassified.

C. New Semantic Communication Frameworks

Based on the aforementioned components, various new structures have been developed for semantic communication systems and networks though most of them are still at the concept level. In the following, we discuss some of them.

1) **Task-Oriented Semantic System:** Similar to the general structure shown in Fig. 3, Kalfa *et al.* [16] proposed a semantic signal processing framework in Fig. 6, which can be tailored for specific tasks at the receiver easily. The proposed framework consists of pre-processing, semantic extraction, semantic filtering, semantic post-processing, and storage/transmission. In the pre-processing block, the input signal is transformed to an appropriate domain, in which the tasks can be performed efficiently. Afterwards, the block of semantic extraction identifies and classifies the components of a signal into a set of task-specific classes. After filtering the interested semantic information for specific tasks, the block of semantic post-processing schedules the transmission or storage according to the tasks at the receiver.

2) **Semantic Signal Processing:** An envisioned end-to-end architecture semantic communication framework was proposed in [22], [33]. As shown in Fig. 7, the major novelty of such a developed framework is the introduction of **semantic sampling that allows each smart device control its traffic via semantic-aware active sampling.** Particularly, samples are generated if the sampler is triggered for serving the task. The multiple access scheme is further developed based on obtained semantic information. Moreover, the developed communication system could extend up to either signal reconstruction or information exploitation for specific tasks, which is similar to that in [16].

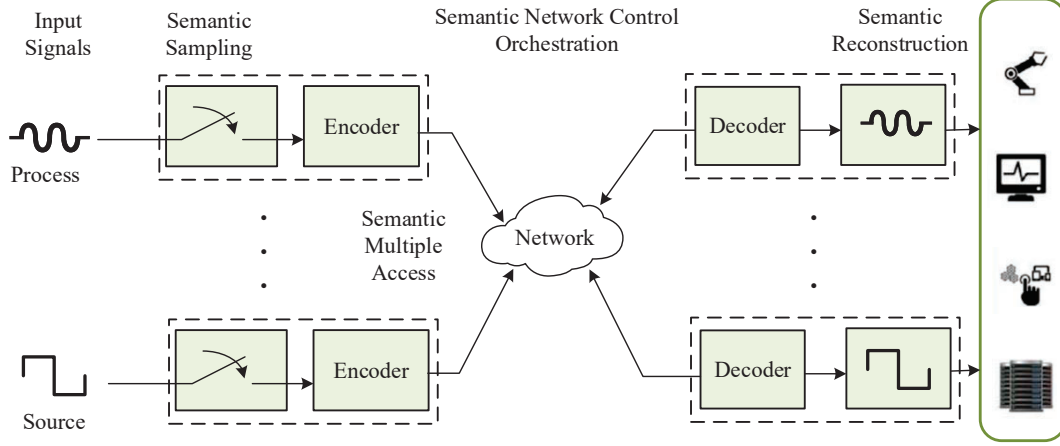


Fig. 7: From semantic sampling to semantic-aware user scheduling [33].

3) **System 1 and System 2 SNC:** A system 1 semantics-native communication (SNC) model was introduced in [34], where an entity of interest, e.g., abstract ideas, physical phenomena, or objects, is conceptualized and symbolized by a speaker as a semantic representation. These semantic coding operations are connected to the source-channel coding blocks of the classical Shannon communication model. Moreover, inspired by the advances of System 2 that enables reasoning, planning and handling exceptions, a System 2 SNC has been further proposed, which incorporates System 2 semantic coding to infuse reasoning into System 1 semantic coding. Compared to System 1 SNC that conveys all the semantics associated with the entity of interest, System 2 SNC significantly reduces the communication cost by sending only the most effective semantics to its interlocutors.

4) **Semantic OSI Model:** As shown in Fig. 8, Lan *et al.* [18] introduced a new model, which is built on the conventional Open System Interconnection (OSI) model by adding an extra semantic layer as a sub-layer of the application layer. It allows the semantic layer to interface with sensors or actuators and to access algorithms and data for specific tasks. In the semantic layer, the main purpose is to perform semantic coding, which transmit semantic encoded data to lower layers. Moreover, the radio-access layer aims at improving the system transmission performance, which transmits control signals to the semantic layer over a control channel. Those control signals are exploited by the semantic layer to remove semantic noise for semantic symbol error correction or to control computing at the application layer.

Similarly, Zhang *et al.* [20] proposed a new semantic system model with different layers as a

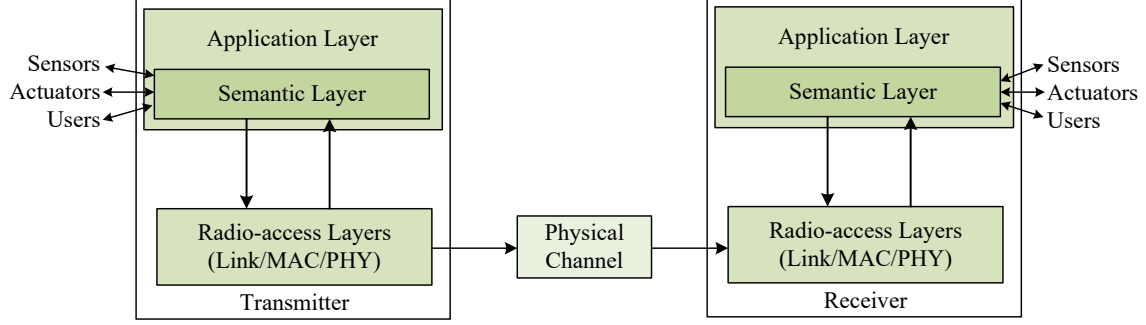


Fig. 8: The novel layered architecture of semantic communication system [18].

comprehensive system to replace the existing OSI model. In particular, the concept of *semantic base* (Seb) has been proposed as the unit of semantic information. However, how to quantify Seb is still to be investigated.

D. Performance Metrics

In the conventional communication systems, bit-error rate (BER) and symbol-error rate (SER) are usually adopted as the performance metrics. However, they are not applicable to measure semantic communication systems any more as the focus of communications is shifted from accurate symbol transmission to effective semantic information exchange. At the moment, a general metric is still missing for semantic communications. In the following of this section, We will discuss metrics for different sources, including text, image, and speech, in the literature.

1) **Text Semantic Similarity:** Word-error rate (WER) is used to measure the semantic text transmission [10], [35], which is not applicable for semantic text transmission as two sentences with different words may share high semantic similarity. The bilingual evaluation understudy (BLEU) score is a commonly used metric to measure the quality of text after machine translation [36], which has been exploited to measure semantic communication systems for text transmission [12], [14]. The BLEU score between the transmitted sentence s and the received sentence \hat{s} is calculated by

$$\log \text{BLEU} = \min \left(1 - \frac{l_{\hat{s}}}{l_s}, 0 \right) + \sum_{n=1}^N u_n \log P_n, \quad (14)$$

where l_s and $l_{\hat{s}}$ are the length of s and \hat{s} , respectively, u_n defines the weights of the n -grams, and P_n is the n -grams score defined as

$$P_n = \frac{\sum_k \min(C_k(\hat{s}), C_k(s))}{\sum_k \min(C_k(\hat{s}))}, \quad (15)$$

where $C_k(\cdot)$ is the frequency count function for the k -th element in the n -th gram. BLEU score counts the difference of n -grams between two sentences, where n -grams refer to the number of words in a word group for comparison. For example, for sentence “This is a dog”, the word groups are “this”, “is”, “a” and “dog” for 1-gram. For 2-grams, the word groups include “this is”, “is a” and “a dog”. The same rule applies for the rest.

The range of BLEU score falls between 0 and 1. The higher the score, the higher similarity between the two sentences. However, few human translations will attain the score of 1 since sentences with different expressions or words may refer to the same meaning. For example, sentences “my bicycle was stolen” and “my bike was stolen” share same meaning but the BLEU score is not 1 since they are different when compared word by word.

To characterize such a feature, **sentence similarity** [12] was proposed as a new metric to measure the semantic similarity level of two sentences, which is expressed as

$$\tau(\hat{s}, s) = \frac{B_{\Phi}(s) \cdot B_{\Phi}(\hat{s})^T}{\|B_{\Phi}(s)\| \|B_{\Phi}(\hat{s})\|}, \quad (16)$$

where B_{Φ} is the BERT model [37] to map a sentence to its semantic vector space, which is a pre-trained model with billions of sentences. **Instead of comparing two sentences directly, we compare their semantic vectors obtained by the BERT model.** Sentence similarity ranges from 0 to 1. The higher the value, the higher similarity between the two sentences.

To achieve the tradeoff between the transmission accuracy and the number of symbols used for each message, a metric [27] has been designed as

$$\gamma = \frac{1}{N} \times (1 - \psi(s, \hat{s})), \quad (17)$$

where N is the number of symbols per message and $\psi(s, \hat{s})$ is the semantic error between s and \hat{s} . Note that $\psi(s, \hat{s})$ could be in various formats, such as BLEU score and mean-squared error (MSE), which is dependent on the transmission task at the receiver.

Moreover, some other metrics have also been introduced recently, i.e., average bit consumption per sentence measures the system from a communication perspective [35].

2) **Image Semantic Similarity:** The similarity of two images, A and B , is measured as

$$\eta(f(A), f(B)) = \|f(A) - f(B)\|_2^2, \quad (18)$$

where $f(\cdot)$ is the image embedding function mapping an image to a point in the Euclidean space. The image embedding function $f(\cdot)$ is the essential part for finding the image semantic similarity. Note that the commonly used metrics, such as peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM), are shallow functions and fail to count many nuances of human perception. Moreover, traditional image similarity metrics are build on the top of hand designed features, such as Gabor filter and scale-invariant feature transform (SIFT). Their performance is heavily limited by the representation power of features.

Image semantic similarity metric depends on the high-order image structure, which is usually context dependent. DL-based image similarity metrics could achieve promising results, as the convolutional neural network (CNN) encodes high invariance and captures image semantics. It is discovered that deep CNNs trained on a high-level image classification task are often remarkably useful as a representational space. For example, we can measure the distance of two images in VGG feature space as the perceptual loss for image regression problems [38]. They define two perceptual loss functions based on a VGG network, ϕ . The feature reconstruction loss encourages the two images with similar feature representations computed by ϕ . Let $\phi_i(x)$ be the activation function of the l th layer, which is of shape L . The feature reconstruction loss is calculated by

$$\mathcal{L}_{\text{feature}}^{\phi, l}(A, B) = \frac{1}{L} \|\phi(A) - \phi(B)\|_2^2. \quad (19)$$

The style reconstruction loss penalizes differences in colors, textures, and common patterns. It is the difference between the Gram matrices, G_l^ϕ , of the two images given by

$$\mathcal{L}_{\text{style}}^{\phi, l}(A, B) = \|G_l^\phi(A) - G_l^\phi(B)\|_F^2. \quad (20)$$

The effectiveness of deep features in similarity measuring is not restrict to VGG architecture. Richard *et al.* [39] evaluated deep features across different architectures and tasks, which showed significant performance gain compared to all previous metrics and coincided with human perception. Furthermore, a deep ranking model proposed in [40] characterizes the image similarity relationship within a set of triplets: a query image, a positive image, and a negative image. The image similarity relationship is characterized by the relative similarity ordering in triplets. Moreover, metrics, including adversarial loss [41], inception score (IS), and Fréchet inception distance (FID) [42], have also been proposed to measure the similarity between images generated

from generative adversarial networks (GAN) and natural images, from a image distribution perspective.

Visual semantic embedding is another way to assess the image semantic similarity [43]. As mentioned earlier, the concepts from different images can be extracted and compared. The visual translation embedding (VTransE) network [44] maps the visual features of objects and predication into a low-dimensional semantic space. Therefore, the semantic similarity can be measured. The relationship detection model in [45] learns a module to map features from the vision and semantic modalities into a shared space, where the matched feature pairs should be discriminative against those unmatched ones and maintaining close distances to semantically similar ones. As a result, the model can represent semantic similarity of images well at the relationship level. Semantic embedding has been widely used in scene graph generation (SGG), image captioning, and image retrieval. Hence, it is with great potential to be exploited in semantic communication systems.

3) Speech Quality Measurement: Perceptual evaluation of speech distortion (PESQ) [46] is a common metric for the quality of speech signals under various conditions, such as background noise, analog filtering, and variable delay, which has been adopted for performance metric in speech semantic communication systems [13]. The range of PESQ is between -0.5 and 4.5. PESQ is one of the standard metrics as suggested by the International Telecommunication Union (ITU-T) recommendation P.862 [47]. Particularly, it consists of the perceptual speech quality measure and perceptual analysis measurement system.

To assess the quality of synthesized speech signals, unconditional Fréchet deep speech distance (FDSD) and unconditional kernel deep speech distance (KDSD) in [48] are taken as two quantitative metrics, which have been adopted in the speech semantic communication system design [49]. The lower the values of FDSD and KDSD, the higher similarity between the real and synthesized signals.

For the original speech samples, $\mathbf{D} \in \mathfrak{R}^{K \times L}$, and the synthesized ones, $\hat{\mathbf{D}} \in \mathfrak{R}^{\hat{K} \times L}$, the FDSD is defined as

$$\Gamma^2 = \|\boldsymbol{\mu}_{\mathbf{D}} - \boldsymbol{\mu}_{\hat{\mathbf{D}}}\|^2 + \text{Tr} \left[\boldsymbol{\Sigma}_{\mathbf{D}} + \boldsymbol{\Sigma}_{\hat{\mathbf{D}}} - (\boldsymbol{\Sigma}_{\mathbf{D}} \boldsymbol{\Sigma}_{\hat{\mathbf{D}}})^{\frac{1}{2}} \right], \quad (21)$$

where $\boldsymbol{\mu}_{\mathbf{D}}$ and $\boldsymbol{\mu}_{\hat{\mathbf{D}}}$ represent the averages of \mathbf{D} and $\hat{\mathbf{D}}$, respectively, while $\boldsymbol{\Sigma}_{\mathbf{D}}$ and $\boldsymbol{\Sigma}_{\hat{\mathbf{D}}}$ denote their covariance matrices.

KDSD [48] is given by

$$\begin{aligned} \Delta^2 = & \frac{1}{K(K-1)} \sum_{\substack{1 \leq i, j \leq K \\ i \neq j}} q(D_i, \hat{D}_j) \\ & + \frac{1}{\hat{K}(\hat{K}-1)} \sum_{\substack{1 \leq i, j \leq \hat{K} \\ i \neq j}} q(D_i, \hat{D}_j) + \sum_{i=1}^K \sum_{j=1}^{\hat{K}} q(D_i, \hat{D}_j), \end{aligned} \quad (22)$$

where $q(\cdot)$ is the kernel function.

IV. DEEP SEMANTIC COMMUNICATIONS FOR MULTIMODAL DATA

Though semantic theory has been investigated for decades, the lack of a general mathematical tool limits its applications. Thanks to the advancements of DL, some interesting works have been developed for semantic communications in recent years. This section presents the latest work on the deep semantic communication system design for text, image, speech, and multimodal data.

A. Text Processing

The advancement on NLP enables text coding to consider the semantic meaning of text, which motivates us to re-design the transceiver for achieving successful semantic information transmission. For the system shown in Fig. 3, neural networks are used to represent the transmitter and receiver in DL-enabled semantic communications. The core of DL-enabled semantic communication is to design **semantic coding**, which can understand and extract semantic information. Those semantic features are then compressed. Moreover, the **channel decoder** is trained to combat the channel impairment. Another core is to design **a proper loss function** to minimize semantic errors and channel impairments. If the system is designed for serving a specific task at the receiver, the loss function should be adjusted accordingly to capture features relevant to the task.

For erasure channels, Farsad *et al.* [10] developed a long short-term memory (LSTM) enabled **JSCC for text transmission**. The cross entropy is adopted as the loss function and WER is used for performance metric. It shows the great potential of DL-enabled JSCC compared to the conventional communication system. Though the concept of semantic communication was not mentioned in [10], it inspires subsequent research greatly.

Afterwards, Xie *et al.* [12] developed a Transformer based joint semantic-channel coding for an end-to-end semantic communication system, named DeepSC. In such an end-to-end system, the block structure of the conventional communication system has been merged [7]. Particularly,

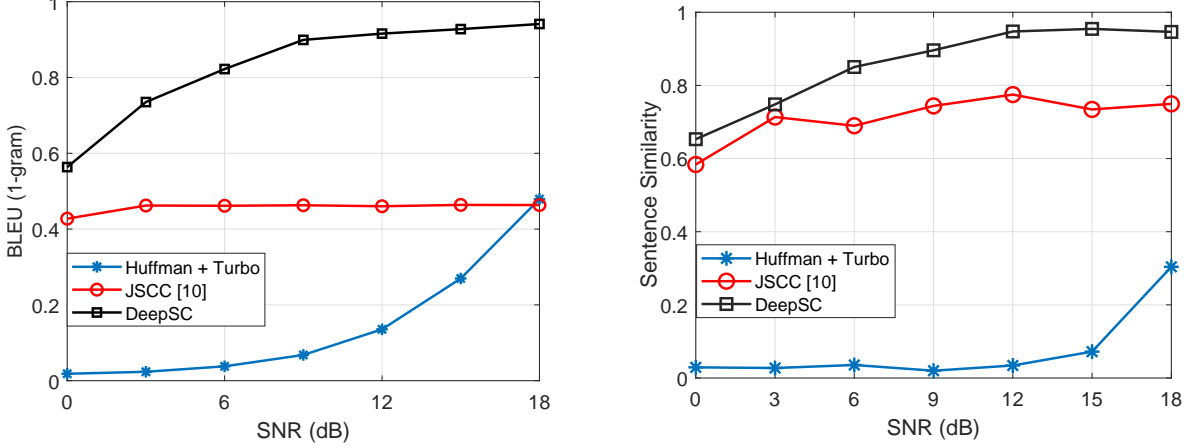


Fig. 9: BLEU score comparison of DeepSC and traditional methods under Rayleigh fading channels, with 8 symbols used for each word. [12].

a new loss function given by (13) was provided, which counts the cross entropy for better understanding texts and the mutual information for higher data rates [12]. By designing such semantic coding and channel coding layers, DeepSC is capable of extracting semantic features and guaranteeing their accurate transmission. It has been verified that DeepSC outperforms typical communication systems significantly, especially when channel conditions are poor. For instance, the BLEU score in Fig. 9 is improved by 800% compared to the conventional method with Huffman coding and Turbo codes when $\text{SNR} = 9$ dB. When measured by sentence similarity defined in (13), we could also see the significant performance gap between DeepSC and the conventional method. Note that when $\text{SNR} = 12$ dB, the BLEU score is less than 0.2, which makes the received sentence almost impossible to read by human beings. It could be reflected by the sentence similarity which is almost 0 with $\text{SNR} = 12$ dB.

Moreover, Table I provides an snapshot of the received sentences after they pass through Rayleigh fading channels, of which the traditional methods exist more or less spelling mistakes. Note that the performance metrics, such as BLEU score and sentence similarity, cannot be used as the loss function in DeepSC as it will cause gradient disappearance for the transceiver training.

Since then, several variants of DeepSC have been developed. Particularly, Jiang *et al.* [35] combines semantic coding with Reed Solomon coding and hybrid automatic repeat request for improving the reliability of text semantic transmission. A similarity detection network was proposed to detect meaning errors. Moreover, Sana *et al.* [27] defined a new loss function (12) to

TABLE I: An comparison of received sentences with DeepSC and benchmarks when transmitted over Rayleigh fading channels, SNR=18 dB, and 8 symbols used for each word. [12].

Transmitted sentence	it is an important step towards equal rights for all passengers.
DeepSC	it is an important step towards equal rights for all passengers.
JSCC [10]	it is an essential way towards our principles for democracy.
Huffman + Turbo	rt is a imeomant step tomdrt equal rights for atp passurerrs.

capture the effect of semantic distortion, which can dynamically trade semantic compression loss with semantic fidelity. Note that (12) is upper bounded by (13), but it is hard to use (12) as the loss function for the neural network training. Another contribution from [27] is the introduction of adaptive number of symbols used for each word for further performance gain in terms of the metric defined in (17). The performance gain becomes obvious when the maximum number of symbols for each word is large, but it also increases the size of data to be transmitted. To make the trained model affordable for capacity-limited IoT devices, Xie *et al.* [14] developed a lite model of DeepSC by pruning and quantizing the trained DeepSC models, which could achieve 40x compression ratio without performance degradation.

B. Image Processing

In this part, we first introduce different approaches of image semantic extraction. DL-based image compression and semantic communications for image transmission are then discussed.

1) Non-Structural Image Semantic Representation: The representation of pixel-level images usually lacks of high-level semantic information. Classical machine learning methods utilize hand-crafted features for image representation. Later on, sparse coding [50] was introduced to represent image patches as a combination of overcomplete basis elements, also known as a codebook. However, the representation power of shallow features is usually limited.

After the breakthrough of convolutional neural networks (CNN), powerful deep features become available. In a CNN, each layer generates a successively higher-level abstraction of the input data, named a feature map, to keep essential yet unique information. By employing a very deep hierarchy of layers, modern CNNs achieve superior performance in image semantic representation and content understanding. Although these approaches have achieved advanced performance in visual feature extraction, there is still a gap between visual features and semantics.

To narrow the gap, some researchers focus on extracting image utilizing context information. The deep semantic feature matching approach proposed in [51] incorporates convolutional feature pyramids and activation guided feature selection. Promising results have been obtained in estimating correspondences across different instances and scenes of the same semantic category. Huang [52] proposed the image and sentence matching approach by utilizing the image global context to learn the semantic concept, such as objects, properties, and actions. The description of image regions is generated in [53], where the visual-semantic alignment model infers the alignment between segments of sentences and the region of the image described by those text segments. Shi *et al.* [54] proposed a semantic representation for person re-identification, where semantic attributes include the color and category of clothes as well as different parts of the body.

Some researchers tried to extract concise representation for image semantics, such as semantic segmentation map, sketch, object skeleton, and facial landmark. These semantic labels describe the layout of those objects. For instance, each pixel in semantic segmentation is labeled with the class of its enclosing object or region. Object skeleton describes the symmetry axis, which is widely used in object recognition/detection. Facial landmarks are used to localize and represent salient regions of the face, i.e., eyes and nose, which are applied to various tasks, such as face alignment, head pose estimation, and face swapping, to name a few.

2) Structural Image Semantic Representation: The efforts of structural image semantic representation have been concentrated on using graph-based machine learning techniques to reduce semantic gap between the low-level image features and the profusion of high-level human perception to images. With the power of graph representation, the solution space is reduced, which results in faster optimization convergence and higher accuracy in the representation learning. Graph based methods have demonstrated effective performance in image segmentation, annotation, and retrieval. In this way, the gap between image vision content and the semantic tags can be bridged.

Scene graph has been regarded as a typical representation of the semantic graph, which is a data structure to describe objects and their relationship in a real scene. A complete scene graph could represent the detailed semantics of scenes, which can be used to encode 2D/3D images/videos into semantic features. Scene graph is a new content for scene description, which has been widely adopted in inference tasks, such as question answering, image retrieval, and image captioning.

SGG is developed to build a more complete scene graph. Particularly, VTransE places objects in a low-dimension relation space where the relationship can be modeled as a simple translation vector ($subject + predicate = object$) [44]. Note that elements of visual scenes have strong structural regularity [55]. Based on this, some structural repetitions in scene graphs can be examined. The architecture of stacked motif network divides SGG into the stage predicting bounding boxes, object labels, and relationships. Moreover, causal-TDE is based on causal inference other than the conventional likelihood. In [56], a causal graph for SGG was proposed to remove the effect from the undesired bias by counterfactual causality.

3) Deep Learning based Image Compression: Traditional image compression projects an image into its sparse domain and reconstructs the image under the guidance of pixel level accuracy. They suffer from blocky and ringing artifact in low bit rate and the reconstructed image is not visually pleasant. It is the frontier that machine learning based image compression methods transform the traditional pixel reconstruction into semantic reconstruction. Content understanding is considered as the core of the next generation image coding.

Deep autoencoder encodes the image into a low dimensional latent code thus achieves high efficient compression. Various end-to-end deep autoencoder based image compression architectures were proposed in [57]–[59]. To deal with the non-differential rounding based quantization, differentiable alternatives have been proposed for the quantization and entropy rate estimation. Based on the fact that local information content of an image is spatially variant, a content-aware bit rate allocation method was proposed in [60].

Moreover, GAN is used to produce visually pleasing reconstruction for very low bit rates. The pioneer work [61] introduced GAN to compression and proposed a real-time adaptive image compression method. By utilizing an autoencoder feature pyramid to downsample an image and a generator to reconstruct it, the compressor typically produces files 2.5 times smaller than the typical image compression method, such as JPEG. Agustsson *et al.* [62] introduced the GAN based extreme learned image compression, which obtains visually pleasing results at an extremely low bit rate. Furthermore, if a semantic label map is available, the non-essential regions in the decoded image can be fully synthesized. Wu *et al.* [63] proposed a GAN-based tunable image compression system, in which the important map is learned to guide the bit allocation.

4) Semantic Communications for Images: Fig. 10 illustrates the structure for image semantic communications. The semantic encoder extracts the low-dimensional semantic information, in the form of visual-semantic embedding, semantic label, or semantic graph. Machine learning

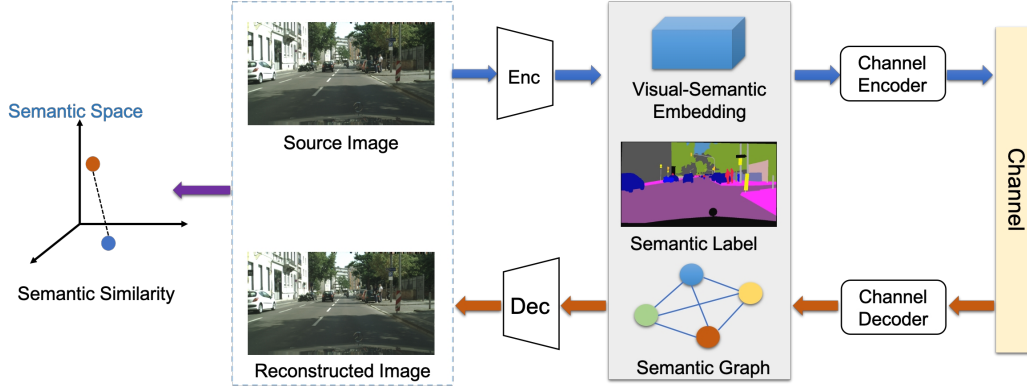


Fig. 10: A semantic communication framework for image transmission.

techniques are adopted to design an efficient semantic encoder. The successive stage is the channel encoder, which can be jointly trained with the semantic encoder.

Kurka *et al.* proposed DeepJSCC [64], [65] for adaptive-bandwidth wireless transmission of images. It exploits the channel output feedback signal and outperforms separation-based schemes. DeepJSCC performs well in the low SNR and small bandwidth regimes with slight degradation. At the receiver, the semantic decoder usually adopts the GAN based architecture to map semantic information into its vision space. Such an under-determined image reconstruction training task is optimized using the criterion of semantic similarity.

More works have been designed for serving certain vision tasks, named task-oriented semantic communications. Particularly, Lee *et al.* [66] designed a joint transmission-classification system for images, in which the receiver outputs image classification results directly. It has been verified that such a joint design achieved higher classification accuracy than performing image recovery and classification separately. Kang *et al.* [67] proposed a scheme for joint image transmission and scene classification. The deep reinforcement learning was exploited to identify the most essential semantic features for serving the transmission task so that to achieve the best tradeoff between the classification accuracy and the transmission cost. Jankowski *et al.* [68] considered image based re-identification for persons or cars as the communication task, where two schemes were proposed to improve the retrieval accuracy. For the image/video transmission, task-oriented semantic communications lower the network traffic significantly. However, as the system is trained for a specific task, the trained model should be updated or even re-trained if the transmission task changes.

C. Speech and Multimodal Data Processing

1) **Semantic Communications for Speech:** Semantic communication systems have also been designed for speech transmission [49], [69]. Weng *et al.* [13] proposed an extension of DeepSC for speech signals, named DeepSC-S. Particularly, joint semantic-channel coding could deal with source distortion and channel effect. In this work, the bit-to-symbol transformation is not involved. MSE is adopted as the loss function to minimize the difference between the recovered speech signals and the input ones. In addition, signal-to-distortion ratio (SDR) and PESQ are adopted as two performance metrics to the quality of recovered speech signals. Tong *et al.* [69] extended it into a multi-user case and implemented federated learning to collaboratively train the CNN based encoder and decoder over multiple local devices and the server. MSE is also used as the loss function and performance metric, which hardly reflects the amount of semantic information reserved at the receiver.

Inspired by the unprecedented demands of intelligent tasks, DeepSC-ST [49] utilized recurrent neural networks (RNNs) to extract the text-related semantic information from the speech signals at the transmitter and to recover the text sequence at the receiver for speech synthesis. Inspired by the related works in speech recognition, connectionist temporal classification (CTC) [70] is adopted as the loss function, where character-error-rate (CER) and WER are adopted as two performance metrics to measure the accuracy of the recognized text information. The aforementioned FDSD and KDSD are exploited to measure the similarity between the real and synthesized speech signals.

2) **Semantic Communications for Multimodal Data:** Multimodal data processing has been considered as a more critical task as shown in Fig. 11. For tasks, such as AR/VR and human sensing care system, the generated multimodal data are correlated in the context. By introducing new degrees of freedom, multimodal data improves performance of the intelligent tasks [71].

Semantic communications are promising to support multimodal data transmission. Xie *et al.* [15] developed MU-DeepSC for the visual question answering task, where text based questions about images are transmitted by one user and the enquiry images are transmitted from another user. Cross entropy is adopted as the loss function while the task related metric, i.e., answer accuracy rate, is used to measure the performance of MU-DeepSC. Different from all the aforementioned works for the point-to-point transmission, MU-DeepSC is designed for serving multi-user transmission. As an extension of DeepSC, A Transformer based framework [72] has

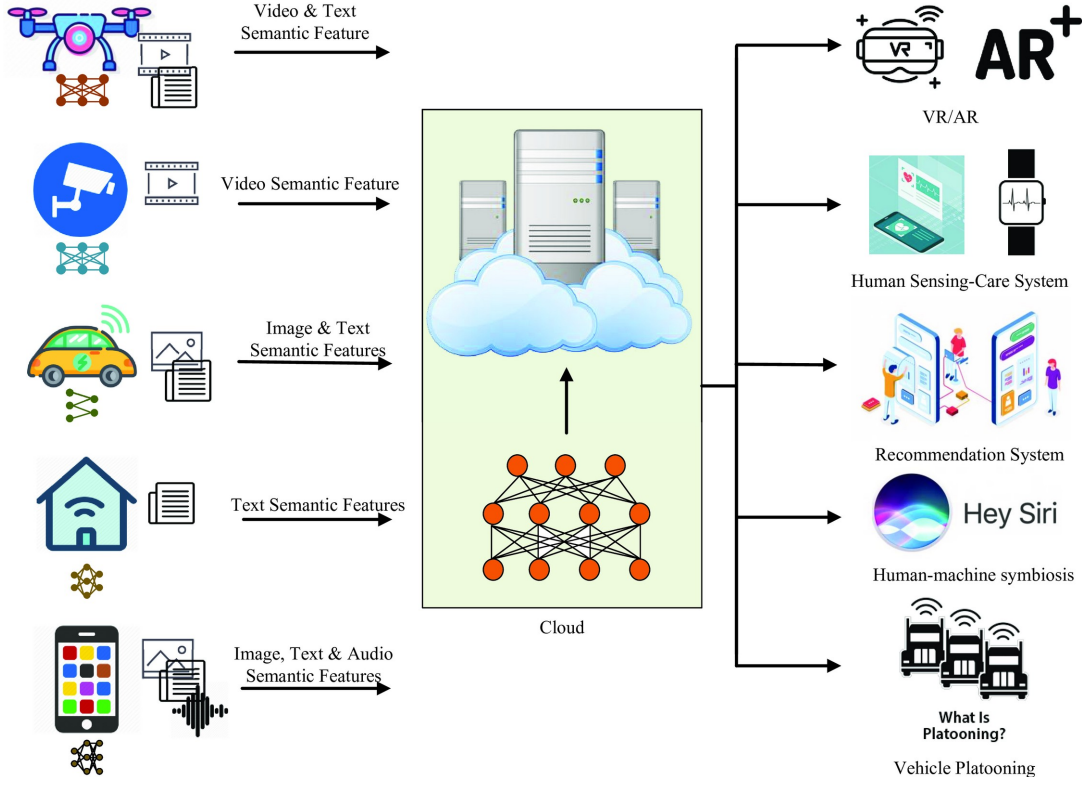


Fig. 11: The illustration of semantic communication applications.

been developed as a unique structure for serving different tasks. Various tasks have been tested in [72] to show its superiority.

V. RESEARCH CHALLENGES AND CONCLUSIONS

We can now conclude that the semantic communication is a breakthrough of the conventional communication. However, its general structure and many related issues are not clear yet, which motivates us to investigate more in this area. To pave the way to semantic communications, the following open questions should be answered:

- 1) **Semantic theory:** Though some researchers have tackled semantic theory in past decades, most of them are based on logical probability with limited application scenarios, which follows the framework of conventional information theory. It is still questionable whether we could follow the similar path to quantify semantic communications by semantic entropy, semantic channel capacity, semantic level rate-distortion theory, and the relationship between inference accuracy and transmission rate.

- 2) **Semantic transceiver:** Semantics provide concise and effective representations, thus making the semantic communication an efficient system in terms of bandwidth saving and subsequent task processing. However, a general semantic level JSCC for different sources are not available yet. Moreover, it is significant to design a semantic noise robust communication system, incorporating machine learning techniques like adversarial training. Furthermore, proper loss functions without causing gradient disappearance are expected.
- 3) **Resource allocation in semantic-aware network:** In semantic-aware networks, it is essential to rethink the resource allocation for semantic interference control. In contrast to the resource allocation in the conventional communications, which focuses on engineering issues, i.e., improving bit transmission rate, semantic-aware resource allocation aims to address both engineering and semantic issues. The objective of semantic-aware resource allocation is to improve communication efficiency in semantic domain. However, this issue still faces following challenges:
 - *How to evaluate the semantic communication efficiency, i.e., semantic transmission rate or semantic spectral efficiency?*
 - *How to formulate a general resource allocation problem for difference task-oriented semantic systems to optimize the resource allocation policy to maximize the semantic communication efficiency?*
- 4) **Performance metrics:** Though several new performance metrics have been explored in semantic communication systems as aforementioned, it is expected to learn more appropriate evaluation metrics for semantic communications, for instance, the metric to evaluate the amount of semantic information that have been preserved or missed. Moreover, a general performance metric, such as SER or BER for conventional communication systems, is expected to measure different semantic communication systems.

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