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Transformer: A General Framework from Machine Translation to Others

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Abstract: Machine translation is an important and challenging task that aims at automatically translating natural language sentences from one language into another. Recently, Transformer-based neural machine translation (NMT) has achieved great breakthroughs and has become a new mainstream method in both methodology and applications. In this article, we conduct an overview of Transformer-based NMT and its extension to other tasks. Specifically, we first introduce the framework of Transformer, discuss the main challenges in NMT and list the representative methods for each challenge. Then, the public resources and toolkits in NMT are listed. Meanwhile, the extensions of Transformer in other tasks, including the other natural language processing tasks, computer vision tasks, audio tasks and multi-modal tasks, are briefly presented. Finally, possible future research directions are suggested.

Keywords: Neural machine translation, Transformer, document neural machine translation (NMT), multimodal NMT, low-resource NMT.

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1 Introduction

Machine translation (MT) aims at automatically translating natural language sentences using computers from one language into another. Since the first MT system was proposed, it has become one of the most important and challenging tasks in natural language processing (NLP) or even in the artificial intelligence community. With the effort of many researchers, MT has achieved remarkable progress in both methodology and applications.

With the rapid development of machine learning and the availability of large-scale parallel corpora, statistical machine translation (SMT) approaches[1, 2] appeared in the 1990s and have drawn much attention. Instead of designing the translation rules manually, SMT learns the language model and word or phrase mappings automatically from the parallel corpora. However, SMT represents the source and target sentences as symbolic and discrete tokens. Thus, the performance of SMT is far from satisfactory.

With the breakthrough of deep learning, many studies have incorporated deep neural networks into MT. Early studies are still based on the SMT framework, where deep neural networks are utilized to design new features or extract more accurate semantic representations[3]. In 2013 and 2014, end-to-end neural machine translation (NMT)[4–6] has emerged as a new paradigm and quickly replaced SMT as the mainstream approach. NMT adopts the distributed representation of sentences and utilizes a whole neural network to learn the mappings from source sentences to target sentences. In only a few years of development, the translation quality of NMT has significantly improved and exceeded that of SMT. In practice, many companies (such as Google, Microsoft and Baidu) have deployed their own online translation systems and provide users with increasingly high-quality translation services[7, 8].

From the perspective of NMT architectures, the early architectures are recurrent neural network (RNN) based NMT[4–6] and convolutional neural network (CNN)[9] based NMT models, which utilize the RNN and CNN to calculate the representation of source sentences and predict the target sentence. In 2017, a new framework, self-attention based NMT (Transformer), was proposed and sharply advanced the field of NMT[10]. At present, Transformer has become the dominant architecture for machine translation, surpassing convolutional and recurrent neural network based NMT in terms of both translation quality and training speed. Meanwhile, Transformer goes far beyond NMT and extends to other tasks, such as other natural language processing tasks, computer vision tasks, audio tasks and multimodal tasks.

In this article, we attempt to give a survey of Trans-

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former-based NMT, including the frameworks, the main challenges, the representative methods for each challenge and the available data and toolkits in NMT. We also briefly present the extensions of Transformer in other NLP tasks, including pre-training language models, text summarization, dialogue and knowledge graphs. Finally, possible future research directions are discussed.

The remainder of this survey is organized as follows. Section 2 introduces the encoder-decoder framework and Transformer. Section 3 lists the main challenges of NMT. Section 4 represents the representative approaches for each challenge. Section 5 shows the resources and toolkits in NMT. Section 6 briefly presents the applications of Transformer in other tasks. Section 7 introduces the current status of NMT. Section 8 suggests some potential research directions.

2 Neural machine translation

Since 2013, there have been various model architectures for NMT, such as recurrent neural network-based NMT (RNMT)[5, 6, 11], convolutional neural network-based model (ConS2S)[9, 12], and a self-attention neural network-based model (Transformer)[10]. At present, self-attention neural networks are the state-of-the-art and have been widely used. In this section, we mainly introduce the encoder-decoder framework and Transformer.

2.1 Encoder-decoder framework

Sequence-to-sequence learning with an encoder-decoder framework was first proposed by Sutskever et al.[5] and Bahdanau et al.[6]. The current NMT models still follow this encoder-decoder framework[10]. Fig. 1 shows the encoder-decoder framework. As the name suggests, the encoder transforms the source sentence $X = \{x_1, x_2, \cdots, x_m\}$ into hidden states $\boldsymbol{H} = (\boldsymbol{h}_1, \cdots, \boldsymbol{h}_i, \cdots, \boldsymbol{h}_m)$. The decoder generates the target translation $Y = \{y_1, y_2, \cdots, y_n\}$ from the hidden states $\boldsymbol{H}$. Generally, the current encoder-decoder framework consists of four basic components: the embedding layer, the encoder network, the decoder network, and the softmax layer.

Embedding layer. The embedding layer maps a discrete source sentence $X = (x_1, \cdots, x_i, \cdots, x_m)$ into continuous embeddings $\boldsymbol{X} = (\boldsymbol{x}_1, \cdots, \boldsymbol{x}_i, \cdots, \boldsymbol{x}_m)$, where $\boldsymbol{x}_i$ is embedding for the i-th token. Then, embeddings are fed into the encoder network.

Encoder network. It maps the source embeddings $\boldsymbol{X} = (\boldsymbol{x}_1, \cdots, \boldsymbol{x}_i, \cdots, \boldsymbol{x}_m)$ into source hidden states $\boldsymbol{H} = (\boldsymbol{h}_1, \cdots, \boldsymbol{h}_i, \cdots, \boldsymbol{h}_m)$. The encoder network can be implemented by a recurrent neural network[5, 6], convolutional neural network[9, 12] or self-attention-based neural network[10]. The encoder procedure can be represented by

$$\boldsymbol{H} = \text{Encoder}(\boldsymbol{X}). \tag{1}$$

Decoder network. The decoder network generates the target sentence $Y = \{y_1, y_2, \cdots, y_n\}$ word by word. Given already produced tokens $y_{<j} = \{y_1, y_2, \cdots, y_{j-1}\}$ at the j-th time step and the hidden states $\boldsymbol{H}$, the decoder obtains the target hidden states $\boldsymbol{Z} = (\boldsymbol{z}_1, \cdots, \boldsymbol{z}_{j-1})$ by

$$\boldsymbol{Z} = \text{Decoder}(y_{<j}, \boldsymbol{H}). \tag{2}$$

Similar to the encoder, the decoder network can also be implemented by a recurrent neural network, convolutional neural network or self-attention-based neural network.

Softmax layer. Finally the hidden states $\boldsymbol{Z} = (\boldsymbol{z}_1, \cdots, \boldsymbol{z}_{j-1})$ of the decoder network are fed into a softmax layer to predict each token at the jth time step. More specifically, a liner layer is first utilized to transform the hidden states $\boldsymbol{Z} = (\boldsymbol{z}_1, \cdots, \boldsymbol{z}_{j-1})$ into the score for each target token. Then, a softmax layer is utilized to obtain the predicted probability of j-th token $p(y_j|y_{<j}, X)$.

Given the parallel training dataset $D = \{(X, Y)\}$, where X denotes the source sentence and Y denotes the target sentence, the network parameters of the NMT θ can be optimized by maximizing the following log-likeli-

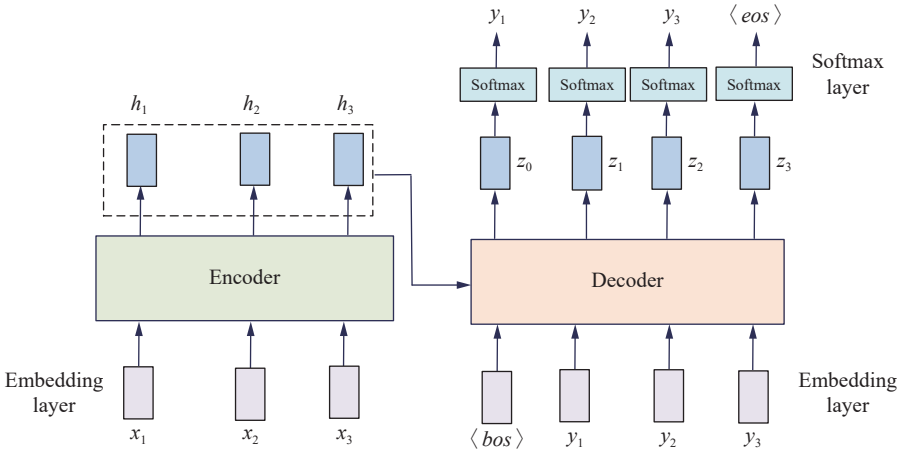


Fig. 1 Encoder-decoder framework, where encoder transforms the source sentence into hidden states and decoder generates target translation from the hidden states

hood objective function:

$$J(D,\theta) = \sum_{(X,Y)\in D} \log\ P(Y \mid X;\theta) = \sum_{(X,Y)\in D} \sum_{j=1}^{n} \log\ P(y_j \mid y_{<j}, X;\theta). \quad (3)$$

2.2 Transformer

Self-attention. Self-attention is the core component of Transformer, which can be seen as a mapping from queries Q, keys K and values V to an output. The output could attend to the information of different tokens and is computed as a weighted sum of the values V, in which the weight is determined by the queries Q and the keys K. More specifically, there are two important attention mechanisms in Transformer, i.e., scaled dot-product attention and multi-head attention. Fig. 2 shows the framework of these two attention mechanisms.

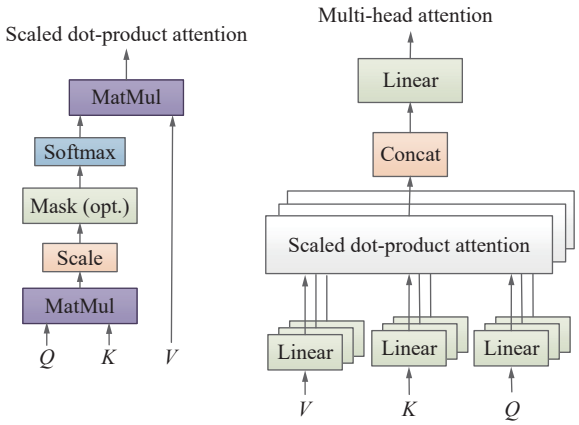


Fig. 2 The attention mechanisms in Transformer. Scaled dot-product attention (left) and multi-head attention (right) in Transformer[10].

1) Scaled dot-product attention: Given the queries Q, keys K (whose dimension is denoted by d_k) and values V, it first computes the dot products of the queries Q with all keys K, and divides the results by $\sqrt{d_k}$. Then a softmax function is utilized to obtain the weights. Finally, the attention output is calculated by multiplying the weights and the values. Formally, the procedure can be depicted as follows:

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^{\mathrm{T}}}{\sqrt{d_k}}\right)V. \quad (4)$$

2) Multi-head attention: Multi-head attention could make the model attend to the information from different representation subspaces of different tokens.

$$\text{MultiHead}(Q,K,V) = \text{Concat}(\text{head}_1,\cdots,\text{head}_h)W^O,$$
$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \quad (5)$$

where W_i^Q, W_i^H, W_i^V and W^O are learnable parameters. Given queries Q, keys K and values V, multi-head attention first projects Q, K and V for different heads with different linear projections W_i^Q, W_i^H, W_i^V. At each head, scaled dot-product attention is performed to obtain the attention output. Finally, the attention outputs of all heads are concatenated and then projected with W_i^O to the final outputs.

Model structure. As shown in Fig. 3, Transformer also consists of four basic components: the embedding layer, the encoder network, the decoder network, and the softmax layer.

1) Embedding layer: Similar to other NMT models, the embedding layer in Transformer also converts a source sentence $X = (x_0,\cdots,x_i,\cdots,x_m)$ into continuous embeddings $\boldsymbol{X} = (\boldsymbol{x}_0,\cdots,\boldsymbol{x}_i,\cdots,\boldsymbol{x}_m)$. After that, Transformer adds the positional embeddings to the input embeddings. They use sine and cosine functions to obtain the positional embeddings, which are then fed into the encoder layers.

2) Encoder network: The Transformer encoder consists of N identical layers. Each layer has two sub-layers. The first is a multi-head self-attention sub-layer, and the second is a feed-forward sub-layer. Then, residual connection and layer normalization are adopted to produce the final outputs. In the bottom multi-head self-attention sub-layer, the keys, values, and queries come from the positional embeddings. In the other multi-head self-attention sub-layers, all the keys, values, and queries come from the outputs of the previous layer of the encoder.

3) Decoder network: The decoder also consists of N identical layers. Different from the encoder layer, the decoder contains three sub-layers: The first is a masked multi-head self-attention sub-layer, and the second is a feed-forward sub-layer, and the third is encoder and decoder multi-head attention. Similar to the encoder, residual connections and layer normalization are also used to produce the outputs.

In the masked multi-head self-attention sub-layer, Transformer masks the subsequent embeddings to prevent the model from attending to subsequent tokens and ensures that at position j, the model can only utilize the information of the already produced outputs at positions less than j. In the encoder and decoder multi-head attention sub-layer, the queries are the output of previous decoder layer, and the memory keys and values come from the encoder. This allows the decoder to utilize the information from the source side.

4) Softmax layer: Similar to other NMT models, the outputs of the decoder are fed into a softmax layer to predict each token of the target sentence.

3 Main challenges and topics of NMT

NMT has made significant progress recently and has been widely utilized in many online MT systems[7, 8],

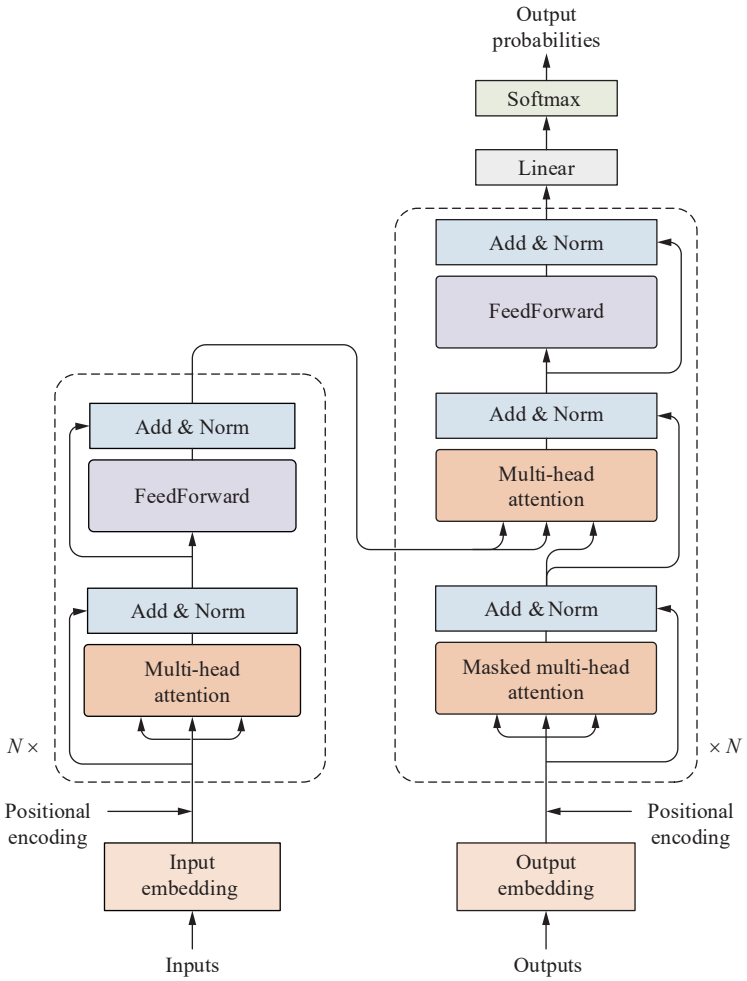


Fig. 3 Model structure of Transformer[10]

while the current NMT model still faces many challenges. In this section, we briefly introduce these challenges and topics of NMT.

Low-resource NMT. Current NMT models are data-driven methods and heavily rely on the quantity and quality of parallel training data. Only when the parallel training sentence pairs are frequent, can NMT learn the word and phrase translation pairs. Unfortunately, parallel training sentence pairs for NMT are expensive and hard to acquire in low-resource language pairs. Even in resource-rich language pairs, the training data are still inadequate in many domains, such as the medical domain, agricultural domain, and chemical domain. Therefore, improving the translation performance of low-resource NMT is a major challenge.

Document NMT. The current NMT usually takes sentences as the basic translation units. When fed an entire document, the current NMT models first split the document into sentences and then translate sentences in isolation without considering the cross-sentence dependencies. However, the absence of document context makes the model unable to deal with the document phenomena, such as deixis, lexical consistency, inflection, and omissions. Consequently, it is a major challenge for the NMT model to utilize document-level contextual information to improve translation quality over sentences in a document.

Multimodal NMT. Traditional NMT is a system whose input and output are both texts. However, human languages are not only about texts. Recently, there has been growing interest in multimodal machine translation, where the input contains other modalities, such as speech, image and video. Specifically, a typical MMT task is image-text translation, where the meaning of text may be ambiguous, and the help of images may be needed to determine the correct translation. Another major challenge is speech translation, which translates source language speech into target language text and has attracted much attention in recent years. The traditional speech translation system follows a pipeline framework, which contains an automatic speech recognition (ASR) module and a text machine translation module, leading to the problem of parameter redundancy, time delay, and error propagation. Thus it is a major challenge to build new neural architectures that can deal with multimodal inputs.

Beyond autoregressive decoding. The existing NMT model generates the target sentence token by token

from left to right, which is referred to left to right (L2R) autoregressive decoding. Although L2R autoregressive decoding is easy for the neural model to train and decode, it still contains the following two drawbacks: 1) Low parallelizability: It generates the i-th target token y_i only after all the previous target tokens ($y_{<i}$) have been predicted. 2) Limited context: The autoregressive manner predicts each output word only using previously generated outputs but cannot utilize the target-side future contexts $y_{>i}$. Thus it remains a challenge to build neural architectures that are beyond the current autoregressive decoding.

Prior knowledge integration. As we mentioned before, NMT is a data-driven method and it needs adequate parallel sentence pairs. In addition to the parallel sentence pairs, various prior knowledge (e.g., syntactic structure, bilingual lexicon and phrase, knowledge graphs) is also important for NMT. For example, incorporating an external bilingual lexicon could help the NMT model translate the low-frequency word. However, the current NMT network follows the encoder-decoder framework, which represents the tokens and semantics in distributed vectors. Prior knowledge is always represented by the discrete symbols, making it difficult to integrate prior knowledge into the current NMT framework. Accordingly, it remains a major challenge to integrate discrete symbol based knowledge into the distributed representation based NMT framework.

4 Representative approaches for each challenge

In this section, we mainly introduce the approaches for each challenge on the basis of Transformer. Meanwhile, we also represent the approaches on the basis of RNMT or ConS2S if these methods are very representative or model-agnostic.

4.1 Low-resource NMT

To improve the translation performance of low-resource NMT, there are several directions: 1) semi-supervised NMT, 2) unsupervised NMT, 3) multilingual NMT, and 4) pre-trained language models for NMT.

4.1.1 Semi-supervised NMT

Although parallel training data are difficult to acquire and expensive, monolingual training data are usually abundant and easy to obtain. As a result, it is important to boost the NMT models with monolingual data. Thus semi-supervised NMT methods have been proposed to incorporate the source and target monolingual data into NMT.

Incorporating target monolingual data. For target monolingual data, Sennrich et al.[13] proposed a back-translation (BT) method for NMT. They first trained a target-to-source NMT model using parallel training data and utilized this target-to-source NMT model to translate monolingual sentences and obtain synthetic parallel data. Then, they mixed the synthetic parallel data and original parallel data to learn the source-to-target NMT model. Due to its model agnostic and good performance, BT has been widely used, especially when only a small amount of parallel data is available[14]. Edunov et al.[15] investigated the BT method at a large scale, and their analysis results showed that sampling based data and noise beam search based synthetic data could produce better translation performance than argmax inference based synthetic data.

Incorporating source monolingual data. There are also some studies that explore source monolingual data to improve the translation quality of NMT. Zhang and Zong[16] proposed two different strategies to make full use of source monolingual data. The first is self-training, which is similar to the BT method and builds synthetic parallel data with a source-to-target translation model. The second is multi-task learning with a translation task and a source-side reordering task.

Incorporating both source and target monolingual data. Many researchers have tried to make full use of both source- and target-side monolingual data in NMT. Cheng et al.[17] presented a semi-supervised approach for NMT, whose main idea is to reconstruct the source and target monolingual corpora using an auto-encoder. He et al.[18] proposed a dual-learning approach for NMT. Their idea is inspired by the observation that machine translation tasks have a dual task, i.e., a primal task from source to target translation and a dual task from target to source translation. These two tasks could form a closed loop and help each other. Thus they propose a dual-learning algorithm to teach each other through a reinforcement learning process.

4.1.2 Unsupervised NMT

Unsupervised neural machine translation (UNMT)[19, 20] considers a more challenging scenario in which parallel sentence pairs are unavailable, and there are only massive source-side monolingual data and target-side monolingual data.

Early studies focused on the bilingual lexicon induction (BLI) task, which is a word-level translation task in unsupervised scenarios. BLI aims at inducing word translations with only monolingual corpora of two languages. At present BLI has become an important component for UNMT. Mikolov et al.[21] proposed a method to extend bilingual dictionaries based on large monolingual data. It learns a linear mapping to transform the source embeddings to target embeddings by minimizing the distance between the bilingual seeds. Subsequent studies totally eliminate the bilingual seed dictionary and learn the mapping function in a purely unsupervised way[22–24].

Motivated by BLI, various UNMT methods[19, 20] have been proposed to achieve the sentence-level translation. Artetxe et al.[19] proposed a UNMT with denoising and back-translation. Fig. 4 shows its architecture. For a sen-

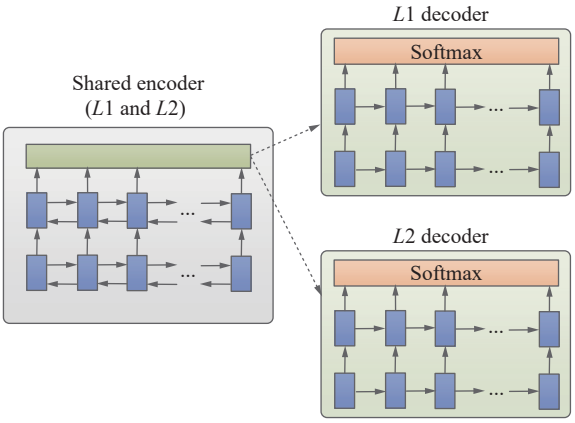


Fig. 4 Model structure of the UNMT in [19] with two steps: The denoising step reconstructs the sentence x from its noised version. The back-translation step translates the sentence x_{L1} to another language x_{L2}, and then inputs x_{L2} with the shared encoder and decoder for $L1$ to recover the original sentence x_{L1}.

tence x_{L1} in language $L1$, the proposed method contains two-steps to train the model:

1) Denoising step, which reconstructs the sentence from its noised version x'_{L1} with a shared encoder and decoder of language $L1$. The produce can be illustrated as follows:

$$x'_{L1} \rightarrow \text{Enc}_{\text{share}} \rightarrow \text{Dec}_{L1} \rightarrow x_{L1} \tag{6}$$

where $\text{Enc}_{\text{share}}$ is the shared encoder for $L1$ and $L2$. Dec_{L1} is the decoder for $L1$.

2) Back-translation step, which translates the sentence x_{L1} to another language x_{L2}, and then input x_{L2} with the shared encoder and decoder for $L1$ to recover the original sentence x_{L1} as follows:

$$\begin{aligned} &x_{L1} \rightarrow \text{Enc}_{\text{share}} \rightarrow \text{Dec}_{L2} \rightarrow x_{L2} \rightarrow \\ &\text{Enc}_{\text{share}} \rightarrow \text{Dec}_{L1} \rightarrow x_{L1}. \end{aligned} \tag{7}$$

For a sentence x_{L2} in language $L2$, the same two steps are conducted. By iterating above two-steps for $L1$ and $L2$, a UNMT model could be learned with only monolingual data.

In parallel, Lample et al.[20] also proposed a UNMT model, where the model starts with an unsupervised initial translation model via a word-by-word translation learned in an unsupervised way. Then, the model is trained by a reconstruction task and a back-translation task. Meanwhile, they also proposed a discriminator to improve the alignment of sentences in the source and the target languages.

Furthermore, Artetxe et al.[25] and Lample et al.[26] focused on the traditional SMT and proposed an unsupervised statistical machine translation (USMT), whose performance is comparable with that of UNMT. Since USMT and UNMT were proposed, several studies[27, 28] have tried to combine UNMT and USMT to improve unsupervised machine translation performance.

Recently, various methods have addressed the multilingual UNMT scenario, where there are some language pairs for auxiliary languages and monolingual for unsupervised languages, its goal is to learn the translation model for unsupervised languages with auxiliary parallel data[29–32].

4.1.3 Multilingual NMT

Standard NMT can only translate a source sentence into another target sentence. Although achieving promising results, it is inconvenient to train each separate NMT model for each language pair, especially when there is a demand to translate between hundreds of languages. Multilingual neural machine translation (MNMT)[33, 34] aim to build a unified NMT model to translate multiple languages. MNMT can not only improve the translation performance through knowledge transfer, but also facilitate model deployment. Fig. 5 shows the comparison of NMT (Fig. 5(a)), a completely shared MNMT[34] (Fig. 5(b)) and MNMT with language-independent and language-specific parameters (Fig. 5(c)).

Johnson et al.[34] proposed a simple but effective universal MNMT method. In this method, there is no need to change the network architecture. The only modification is that they introduce a special indicator at the beginning of the source sentence to indicate source and target language. For example, consider the following English-to-Italy sentence pair:

you probably saw it on the news. → forse lo avete visto sui notiziari.

It will be modified to:

$\langle 2it \rangle$ you probably saw it on the news. → forse lo avete visto sui notiziari.

Where $\langle 2it \rangle$ is an indicator to show that the target is Italy. After adding the tokens to multilingual training data, they train the MNMT model with all multilingual language pairs, where all source languages share the same encoder and all the target languages share the same decoder.

Due to its simplicity and low-resource language improvement, the universal MNMT has drawn much attention. Massively multilingual experimental results show that the completely shared model faces capacity bottlenecks for retaining the translation performance of each language[35]. Thus, various researchers have tried to balance the language-independent and the language-specific parameters in a whole model[36–38]. Bapna and Firat[38] proposed an adaptation approach for MNMT, which injects language specific adapter layers into a pre-trained MNMT model. These adapters could adapt the model to multiple individual language pairs simultaneously. Eriguchi et al.[39] proposed a two-stage training for MNMT that serves an arbitrary task-specific translation direction, which first pre-trains an MNMT model and then fine-tunes the model to the task-specific MNMT model.

Instead of designing language-specific parameters manually, some subsequent studies have attempted to

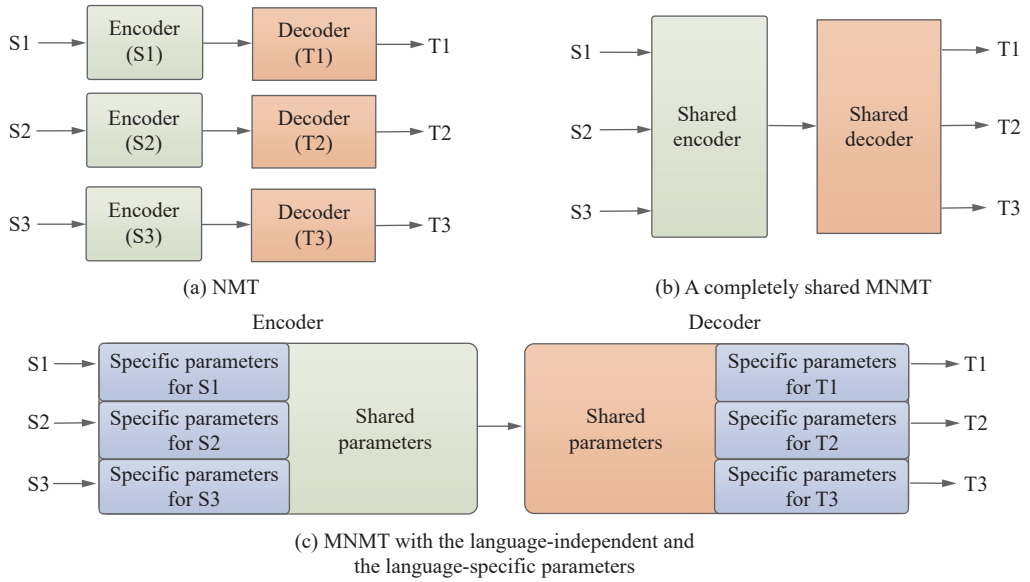


Fig. 5 Illustration of MNMT, where S1, S2 and S3 denote the three different source languages. Similarly, T1, T2 and T3 denote three different target languages. In standard NMT (a), we need to train each separate neural model for each language pair. In universal MNMT (b), all parameters are shared by all language pairs. In MNMT with language-independent and language-specific parameters (c), all parameters are divided into two parts: i) language-independent parameters to model the shared knowledge of all languages; ii) language-specific parameters to model the specific knowledge for each language.

search for a language-specific subspace of the whole model[40–42]. Lin et al.[41] proposed a method that dynamically learns language specific sub-network (LaSS) for MNMT, in which each sub-network shares partial parameters with some other languages while also retaining its language-specific parameters. Wang and Zhang[42] proposed a parameter differentiation based MNMT to make the model decide which parameters should be language-specific and which ones should be shared. Their model is initially completely shared by all languages, and then the model detects shared parameters that should be language-specific.

4.1.4 Pre-trained language models for NMT

Pre-trained language models (PTMs) are alternative ways to improve the translation performance of low-resource NMT. Recently, pre-training techniques have attracted much attention in natural language processing communities. The pre-trained models first learn the universal language representations through various pre-training tasks, and then fine-tuning methods are utilized to transfer the knowledge in pre-trained models to the downstream tasks. Qiu et al.[43] conducted a comprehensive overview of pre-trained language model for natural language processing.

Most of the early PTMs, such as ELMo[44] and BERT[45], achieve state-of-the-art performance in various language understanding tasks such as sentiment classification, natural language inference, and named entity recognition. Inspired by their success, many methods introduce these PTMs to NMT. Edunov et al.[46] incorporated the ELMo[44] into the NMT model by 1) inputting ELMo embeddings into the encoder and the decoder, and 2) finetuning the ELMo parameters with parallel sentence pairs. After that, the researchers attempted to enhance the NMT with BERT. Zhu et al.[47] proposed a BERT-fused translation model, in which it first utilizes the BERT to extract representations for a source sequence. Then, the representations are fused with each layer of the encoder and decoder in NMT via attention mechanisms. Similarly, Yang et al.[48] proposed three techniques (asymptotic distillation, dynamic switching, and rate-scheduled learning) to integrate BERT and NMT.

Considering that directly applying these BERT like pre-training methods on the natural language generation tasks, including machine translation tasks, is still inconvenient, thus some sequence-to-sequence pre-training methods have been proposed, such as MASS[49], T5[50] and BART[51].

MASS[49] (Fig. 6) adopts the encoder-decoder framework, where the encoder takes a sentence with a masked fragment as an input, and the decoder recovers the masked fragment. MASS can be utilized in various natural language generation tasks, such as NMT and text summarization. BART[51], a pre-trained model combining bidirectional and auto-regressive Transformers, is a denoising auto-encoder with sequence-to-sequence models. Specifically, BART is pre-trained in two stages: 1) corrupting the original text with a noise function, and 2) learning a reconstruction model to reconstruct the original text. Wang et al.[52] studied the impact of the jointly pre-trained decoder, and proposed an in-domain pre-training and input adaptation strategy to overcome the domain and objective discrepancies.

Different from the above pre-trained language models in a single language, the recent work attempts to build many cross-lingual or multilingual pre-trained models to make the model learn the cross-lingual or multilingual

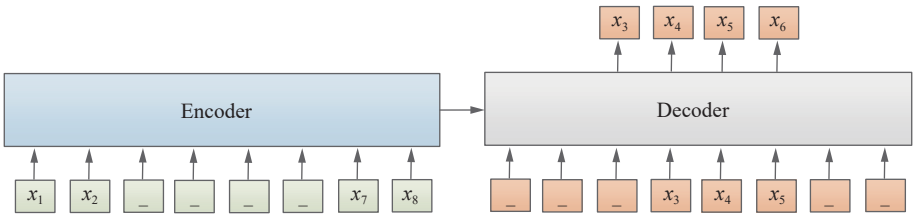


Fig. 6 Framework for MASS[49], which adopts the encoder-decoder framework, where the encoder takes a sentence with a masked fragment as input, and the decoder recovers the masked fragment. The token "_" denotes the mask symbol.

knowledge during the pre-training phase, such as mBERT[53], XLMs[54], mRASP[55], mT6[56], mBART[57] and CeMAT[58]. Take the mBART as an example. mBART[57] is a multilingual sequence-to-sequence denoising auto-encoder pre-training model, which extends BART[51] to many languages. The encoder takes the input texts with various noises, and the decoder recovers the original text. mBART is first pre-trained once for all available languages, then it can be fine-tuned by parallel sentence pairs for the NMT tasks.

4.2 Document NMT

Standard NMT methods usually focus on sentence-level translation. However, this sentence-level translation cannot address document-level translation. To utilize the cross-sentence context, many researchers propose document-level neural machine translation (DocNMT), which could improve the translation quality with the help of the context information in the document. As shown in Fig. 7, the current DocNMT can be roughly divided into two categories: DocNMT with source-side context[59–62] and DocNMT with target-side context[63–65].

DocNMT with source-side context. As the name suggests, given a source sentence, DocNMT with source-side context methods could utilize more source-side context to improve the translation quality. These methods can be divided into two kinds: 1) single encoder models and 2) multi-encoder models.

The representative single encoder model was proposed by Bawden et al.[59], where they first concatenated a source sentence with its source-side context and then input this long sequence into the neural model. Based on a single encoder model, Zhang et al.[62] studied the transfer of contextual information via multilingual transfer from document-rich languages to document-poor languages.

Different from the single encoder model, multi-encoder model[60, 61] encodes a source sentence and its contexts with different encoders. Voita et al.[60] proposed a context-aware DocNMT on the basis of Transformer. In the model, a source sentence and its contexts are first encoded independently. Then, an attention layer is used to obtain a context-aware semantic representation, which is utilized to produce the target sentence. Zhang et al.[61] extend the Transformer with a new context encoder and proposed a two-step training strategy to fully utilize document-level and sentence-level parallel training data. Lupo et al.[66] proposed a divide and rule pre-training approach to enhance the contextual training signal.

DocNMT with target-side context. In addition to the source-side context, researchers also utilize the target-side context to improve the DocNMT. These methods contain two different kinds of methods: 1) the context-cache model[63, 67] and 2) the two-pass decoder model[64, 65].

The context-cache model[63, 67] utilizes a cache to store the translation history, which is then used to improve the

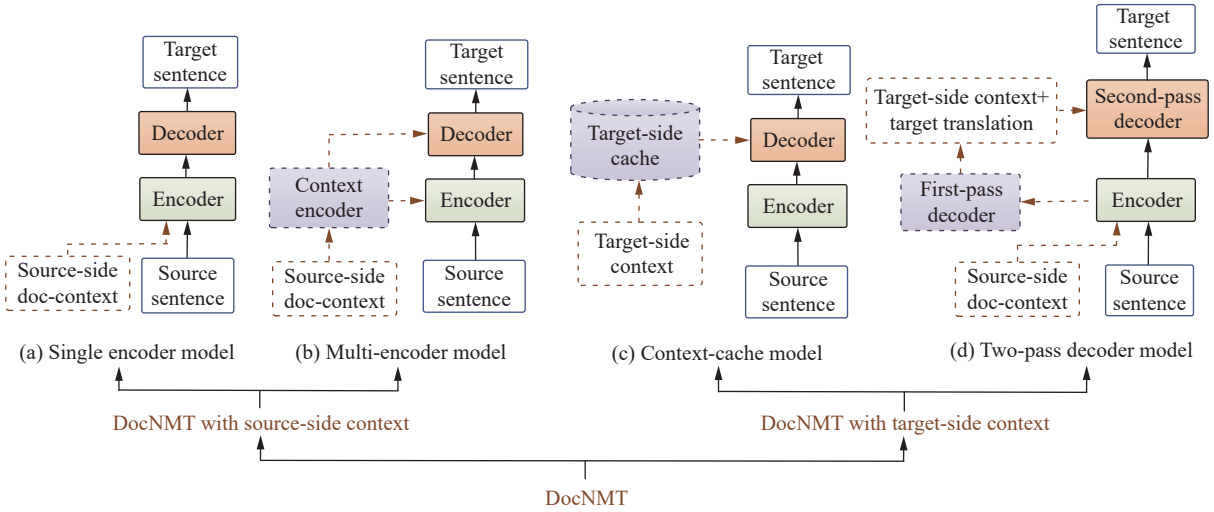


Fig. 7 Two categories of DocNMT: 1) DocNMT with source-side context and 2) DocNMT with target-side context.

translation performance. For example, Tu et al.[63] proposed an approach to augment NMT with a cache-like memory, which stores the target-side translation history.

Another line of DocNMT with target-side context is the two-pass decoder model. Voita et al.[64] introduced a two-pass DocNMT framework, where a source sentence is first translated with a context-agnostic model (first-pass), and the translation is then refined with the context of several previous sentences (second-pass). Furthermore, Voita et al.[65] proposed a repair approach for DocNMT, which could reduce the inconsistencies between sentence-level translations with only monolingual document-level data. Meanwhile, dynamic context methods[68] are proposed to select the useful document context for different DocNMT models.

4.3 Multimodal machine translation

The current NMT models mainly focus on the text translation scenario where both input and output are text sentences. However, in practice, there has been growing interest in multimodal machine translation (MMT), where the input contains other modalities, such as speech, images and videos. Here we mainly introduce the two tasks in MMT: 1) image-text translation and 2) speech translation.

4.3.1 Image-text translation

The setting of image-text translation (also named as image caption translation) is that the inputs of the translation model contain two modals: an image and its text description in source language. It needs to translate the description in the source language with the help of an image into the target language. Depending on the utilization of visual information, the current image-text translation methods can be categorized as 1) coarse-grained utilization and 2) fine-grained utilization.

Coarse-grained utilization methods[69–71] represent the image in the global semantics and then incorporate it by inputting it as an auxiliary or attending to relevant local regions. Huang et al.[69] enhanced the attention-based RNMT model by incorporating information in multiple modalities (image and text). They transform the visual features as one of the steps in the encoder, and then attend to both the text and the image during decoding. Calixto et al.[70] proposed a latent variable model to model the visual and textual features for image-text translation. Their model could utilize the visual and textual inputs during training but does not require images during testing. Ive et al.[71] proposed a translate-and-refine approach, where they generate the first draft only by the source text, and then improve the first draft with the target language and visual context.

Fine-grained utilization methods[72–74] aim at incorporating the entity-level or object-level visual context to improve the translation. Huang et al.[72] proposed an explicit entity-level cross-modal learning method to augment the entity representation, where a multi-task method is utilized to enhance entity representation and improve text translation. Wang and Xiong[73] presented an object-level visual context framework, that models the interaction between the visual and text modality by using the object-text similarity and object-source attention. Li et al.[74] proposed a selective attention multimodal Transformer and utilize vision Transformer to extract vision features.

4.3.2 Speech translation

Speech translation aim to translate a speech in the source language into text in the target language, which could facilitate the communication between two speakers of different languages. The traditional speech translation system follows a pipeline framework, which is composed of an ASR module and a text MT module. In the pipeline system, two modules are learned independently, leading to the problem of time delay and parameter redundancy. To overcome these problems, end-to-end speech translation[75–78], which directly translates from source language speech to target language texts, has attracted much attention in recent years. Thus here we focus on the end-to-end speech translation methods.

Generally, the current speech translation methods can be divided into the following two types: 1) incorporating the data of ASR and text translation, and 2) bringing the feature gap.

Incorporating the data of ASR and NMT. To train an end-to-end speech translation model, we need parallel data with audio signals and their corresponding target translations. Considering the low resources of training data for speech translation, many researchers have tried to incorporate the training data of ASR and NMT into speech translation tasks to improve the performance. Multi-task learning and data augmentation[75, 76, 79], pre-training[80–83] and knowledge distillation[84–87] are the three main directions.

Multi-task learning for speech translation could better optimize the parameters of end-to-end model with the auxiliary tasks, i.e., ASR tasks or NMT tasks[75, 76]. Data augmentation[79] tends to generate synthetic data for speech translation.

In the pre-training framework, the parameters are first pre-trained by the ASR training data or MT training data, and then the pre-trained parameters are utilized as a parameter initialization of the speech translation model[80–83]. Bansal et al.[80] proposed a pre-training method with ASR training data, which first pre-trains the parameters on a high-resource ASR task, and then fine-tunes the parameters with speech translation dataset. Wang et al.[81] proposed a tandem connectionist encoding network to reuse all subnets in pre-training, keep the roles of subnets in consistent, and pre-train the attention module. WavLM in [82] first learns universal speech representations using large-scale unlabelled speech data, and then adapts the representations to various speech processing tasks. Tang et al.[83] proposed a speech and text

joint pre-training to combine the pre-training method and multi-task method.

The third direction is knowledge distillation based methods[84–87]. Liu et al.[84] proposed a knowledge distillation based speech translation, where the speech translation is a student model, whose input is a speech. The machine translation model is a teacher model, whose input is a source text. By utilizing a knowledge distillation method, the speech translation model learns by not only the correct target texts, but also the output probabilities produced by the machine translation model. Inaguma et al.[85] proposed a bidirectional knowledge distillation method, in which they combine a source-to-target NMT model and a target-to-source NMT model to distill the knowledge from both forward and backward NMT models to the end-to-end speech translation model. Ren et al.[87] introduced two different knowledge distillation methods for speech translation: attention-level knowledge distillation and data-level knowledge distillation.

Bringing the feature gap. The traditional speech translation model utilizes the frame-level features as speech representations. The frame-level features create longer, sparser input sequences than their text equivalents[77, 88, 89]. This increases the memory usage and model parameters, and thereby impacts the translation quality. Accordingly, some studies have been proposed to bridge the gap between frame-level speech features and word-level text features. Salesky et al.[88] explored the phoneme-level speech representations for speech translation. They first utilized the alignment methods to generate phoneme labels, and then created phoneme-level feature representations from variable numbers of frames. Ye et al.[77] designed a contrastive learning method for speech translation to reduce the gap between the representations of speech and the corresponding transcription.

4.4 Beyond autoregressive decoding

As we introduce in Section 3, the existing NMT model generates the target sentence token by token from left-to-right in an autoregressive manner, which contains two drawbacks, i.e., low parallelizability and limited context. In recent years, many methods beyond autoregressive decoding have been proposed to overcome the drawbacks of autoregressive decoding. Generally, non-autoregressive Transformer (NAT)[90] and bidirectional decoding[91–93] are two main research lines, where NAT can generate all target words in parallel, and bidirectional decoding can simultaneously predict the target sentences from both left-to-right and right-to-left directions.

4.4.1 Non-autoregressive decoding

To speed up the generation and improve the parallelizability, Gu et al.[90] first proposed a NAT model to decode target tokens in parallel. Given a source sentence x and target sentence y, NAT calculates the probability $p(y \mid x; \theta)$ as follows:

$$p(y \mid x; \theta) = p_l(T \mid x; \theta) \prod_{i=1}^{T} p(y_i \mid x; \theta) \tag{8}$$

where $p_l(T \mid x; \theta)$ determines the length of target sentence T given x. To achieve this, NAT proposes a fertility predictor, where it first predicts the fertility $\Theta(x_j)$ (the number of target words that should be translated) for each source word x_j. Then the total length is calculated by $T = \sum \Theta(x_j)$. Finally, NAT copies the source tokens based on predicted fertilities and generates the target sentence in parallel. Meanwhile Gu et al.[90] also proposed a knowledge distillation method to transfer the knowledge from autoregressive Transformer (AT) models to NAT models. The idea of knowledge distillation has been widely adopted in many studies[94, 95]. Ding et al.[96] proposed a monolingual knowledge distillation model, that leverages monolingual data to perform knowledge distillation, and trains the NAT model with distilled monolingual data. Shao et al.[97] proposed a diverse distillation with reference selection for NAT.

Although the remarkable efficiency has been achieved by NAT, it still suffers from quality degradation compared to the AT models. Thus, many methods have been proposed to improve the translation of NAT[98–101]. Wang et al.[98] proposed a semi-autoregressive Transformer-model (SAT), which keeps the AT global while conducts NAT locally. Gu et al.[100] proposed a Levenshtein Transformer, which is a partially autoregressive model with the insertion and deletion operations.

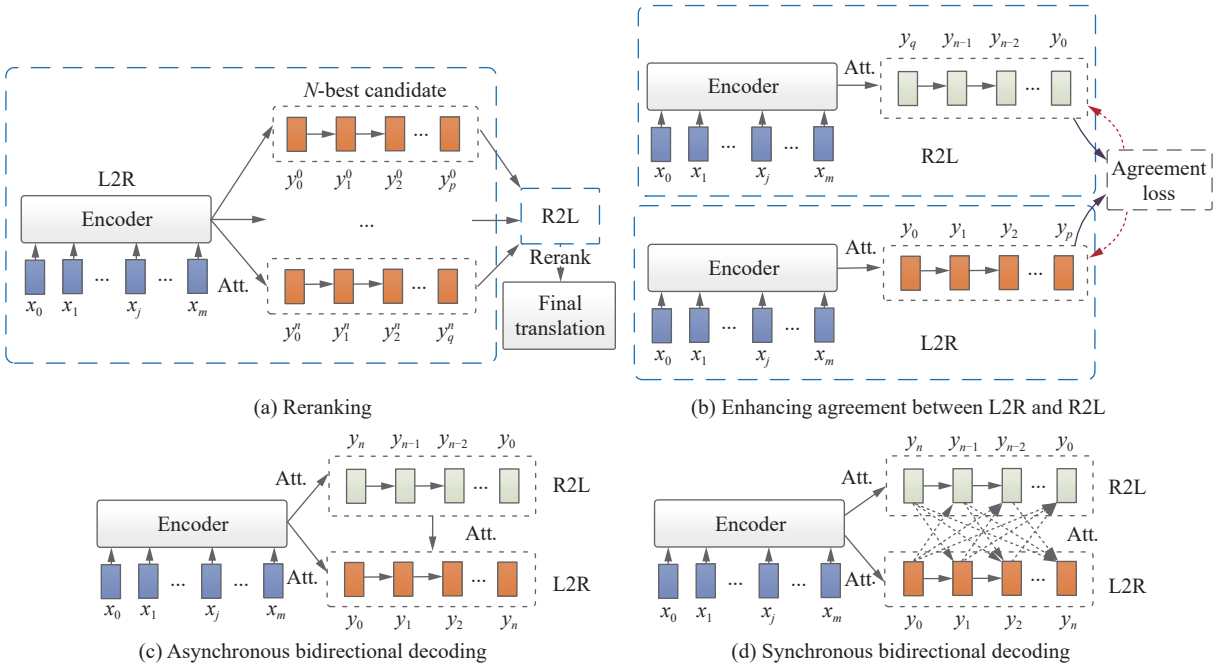
There are also some studies to improve NAT with multi-pass iterative refinement. Lee et al.[102] proposed a conditional NAT with iterative refinement, which is designed based on latent variable models and denoising autoencoders. Zeng et al.[103] proposed a plugin algorithm, called as aligned constrained training, to handle low-frequency constraints in NAT.

4.4.2 Bidirectional decoding

Some methods are proposed to combine the merits of L2R decoding and R2L decoding. As shown in Fig. 8, these methods can be divided into four categories: 1) reranking, 2) enhancing agreement between L2R and R2L, 3) asynchronous bidirectional decoding, and 4) synchronous bidirectional decoding.

The first common studies to combine L2R and R2L models are reranking[104, 105]. Reranking techniques have been widely applied in SMT systems. In regard to NMT, the L2R model first generates n-best target candidates. Then, the R2L score is utilized to select the best candidate as the final translation.

Another branch of bidirectional decoding is enhancing agreement between L2R and R2L[8, 106, 107]. Intuitively, the translation results from L2R and R2L decoding should be the same. Thus, agreement information is utilized to encourage the neural model to produce better translations.



(a) Reranking (b) Enhancing agreement between L2R and R2L

(c) Asynchronous bidirectional decoding (d) Synchronous bidirectional decoding

Fig. 8 Four different kinds of methods to achieve bidirectional decoding

Subsequent studies[91, 108] proposed an asynchronous bidirectional decoding to combine the L2R and R2L models. Specifically, Zhang et al.[91] added an R2L (or backwards) decoder into the standard NMT model. Fig. 8(c) shows the framework, which mainly contains three components: 1) an encoder, which encodes the source sentence into the hidden states; 2) an R2L decoder, which translates target translation in the R2L manner; and 3) an L2R decoder, which produces the final translation using L2R decoding with source-side hidden states and R2L hidden states.

Different from asynchronous bidirectional decoding, Zhou et al.[92] proposed a synchronous bidirectional decoding for NMT, which could predict final outputs using L2R and R2L decoding simultaneously and interactively. Fig. 8(d) shows the framework, where the L2R decoding could generate each token y_i not only depends on previously generated tokens (i.e. $y_1, y_2, \cdots, y_{i-1}$), but also relies on previously predetermined target tokens (i.e., y_n, $y_{n-1}, \cdots, y_{n-i+1}$) of R2L decoding. Meanwhile, R2L decoding also generates each target token in the same way. Furthermore, Zhou et al.[109] extended synchronous bidirectional decoding by producing target sentences from both sides (L2R and R2L) to the middle, which significantly speeds up decoding time and also improves the generation quality.

4.5 Prior knowledge integration

In addition to parallel sentence pairs, prior knowledge is also an important resource for NMT. According to the different types of knowledge, these studies can be divided into three types: 1) bilingual lexicons, 2) phrase tables and terminologies, and 3) knowledge graphs.

Bilingual lexicons in NMT. Some experimental results[110, 111] show that the current NMT model has problems in handling low-frequency words. To improve the translation accuracy of low-frequency words, many researchers tend to incorporate bilingual lexicons into NMT[110–113][1]. Zhang et al.[112] proposed to a posterior regularization method to integrate prior knowledge into NMT. They represented the prior knowledge, including bilingual dictionary, phrase table, coverage penalty and length ratio, in a log-linear model to guide the learning of NMT model. Arthur et al.[110] focused on low-frequency words and proposed a method to incorporate discrete bilingual lexicons into NMT. Feng et al.[111] proposed a memory-enhanced NMT, where each memory element stores a source-target pair, and memory is utilized by the attention layer to improve the neural model.

Phrase table and terminologies in NMT. The current NMT generates the target sentence word-by-word, making it difficult for the neural model to translate phrases or terminologies with multi-words. To better deal with phrases or terminologies, some researchers tend to utilize the phrase table[116–119] and terminologies[120, 121] in NMT. Wang et al.[116] proposed a method to integrate a phrase memory from the SMT model into the NMT model. Specifically, the SMT model dynamically generates phrase memory. Then, the decoder selects a phrase from the

[1] Another solution to overcome the problem of low-frequency and out-of-vocabulary words is to decompose these words into smaller granularities, such as hybrid word-character[114], sub-word[115] or word piece[7]. At present, sub-word methods[115] have been widely used to address the low-frequency words and open vocabulary problem.

memory or a word from the neural model with a balancer. Dahlmann et al.[117] proposed a hybrid search that extends NMT beam search with phrase-based models. During the beam search, their method inserts phrasal translations into NMT, and then the various scores from the SMT and NMT are utilized in a log-linear model to decide the final translation. Xu et al.[119] proposed attentive phrase representations for NMT, where it first generates phrase representations from the corresponding token representations, and then incorporates the phrase representations into Transformer to capture long-distance relationships.

Knowledge graphs in NMT. Knowledge graphs (KGs) contains lots of structured facts on entities. The current KG is always organized with triples (h, r, t), where h and t indicate head and tail entities, and r denotes their relation. To utilize these KGs and enhance the entity translation in KGs, many studies incorporate KGs into NMT[122–124]. Zhao et al.[122] proposed a KG enhanced NMT method. It first induces the translation results of new entities via entity alignment. Then, it generates pseudo parallel sentence pairs with the induced entity pairs. Finally, the NMT model is jointly learned with the original and pseudo parallel sentence pairs. DEEP[124] is a denoising entity pretraining method to leverage monolingual data and a knowledge base to improve named entity translation accuracy. Meanwhile, to further improve the translation quality of entities, it also utilizes the multi-task learning to fine-tune a pre-trained NMT model on both entity-augmented monolingual data and parallel data.

Table 1 summarizes the mentioned challenges in NMT and the corresponding partial representative methods. There are still many topics which are involved in NMT while not mentioned in this article, such as robustness, interpretability, and enhancing the current training objectives.

5 Resources and tools

Thanks to the open research environment in the NMT community, there are many open resources and toolkits, which significantly improve development. Table 2 lists the available and useful corpora for different machine translation tasks.

Text parallel data. There are several widely used text parallel data for machine translation tasks. The Conference on Machine Translation (WMT)[2] conducts different shared translation tasks and releases the corresponding parallel data in each year. In addition, the *International Conference on Spoken Language Translation* (IWSLT)[3] is also an annual scientific conference, that organized many evaluation campaigns and published a large amount of parallel data. The *China Conference on Machine Translation* (CCMT)[4], organized by the Chinese Information Processing Society of China, also conducts machine translation evaluations each year. The evaluations in CCMT mainly focus on Chinese-centric translation tasks (such as Chinese-to-English, Mongolian-to-Chinese, Tibetan-to-Chinese, etc.) in different domains (such as daily conversation translation, government document translation, news translation, etc.). All evaluation participants in CCMT could acquire the corresponding parallel data for free.

We can also find the parallel data from the LDC[5] and Europarl[6]. Meanwhile, a widely used project is OPUS[7], which is a growing collection of parallel texts from the web.

Image-text translation data. Compared to text parallel data, the image-text translation data are quite rare. The most widely used is the Multi30k dataset[127], which extends the Flickr30K dataset (the original descriptions are English) with German translations and German descriptions.

Speech translation data. The widely used end-to-end datasets for speech translation are Fisher and Callhome[131], TED[84][8], Augmented LibriSpeech[128] and MuST-C[129].

Document translation data. The parallel document-level data mainly include TED[130], News-Commentary[9] and Europarl[126].

There are also many open-source toolkits for the research and development of NMT systems. Table 3 provides some broadly used toolkits, including the programming language and the framework. In addition, there are some other survey papers on NMT[132–134].

6 Extensions to other tasks

Although Transformer was originally proposed for NMT, it now goes far beyond MT and extends to more tasks. Many studies apply Transformer to different tasks and achieve state-of-the-art performance. In this section, we briefly introduce the application of Transformer in other tasks, including NLP tasks (such as pre-trained language models, summarization, knowledge graphs, dialogue), the computer vision tasks (image classification, image generation), audio tasks (automatic speech recognition and speech synthesis) and multi-modal tasks.

[2] WMT was held 10 times as a workshop from 2006 to 2015. Since 2016, it is was held as a conference in Berlin, Germany. The latest WMT 2022 can be found in https://www.statmt.org/wmt22/index.html.

[3] https://iwslt.org/

[4] The latest CCMT 2022 can be found in http://sc.cipsc.org.cn/mt/conference/2022/

[5] https://www.ldc.upenn.edu/

[6] https://www.statmt.org/europarl/

[7] https://opus.nlpl.eu/

[8] http://www.nlpr.ia.ac.cn/cip/dataset.htm.

[9] https://www.casmacat.eu/corpus/news-commentary.html

Table 1 Challenges in NMT and partial representative methods

Challenges	Main directions	Description	Methods
Low-resource NMT	Semi-supervised NMT	Improving NMT with source and target monolingual data	Using source data[16]
			Using target data[13]
			Using both source and target data[17, 18]
	Unsupervised NMT	Building a NMT model with only massive source and target monolingual data	Unsupervised NMT[19, 20]
			Unsupervised SMT[25, 26]
			Combining UNMT and USMT[27, 28]
			Multilingual UNMT[29, 30]
	Multilingual NMT	Building a unified NMT model to translate multiple languages	Parameters completely shared[34]
			Balance the language-independent and language-specific model[40–42]
	Pre-training for NMT	Enhancing NMT with pre-trained language models	Utilizing ELMo[46] and BERT[47, 48]
			Sequence-to-sequence pre-training[49, 51]
			Multilingual and cross-lingual pre-training[53–55]
Document NMT	DocNMT	Enhancing NMT with document context	DocNMT with source-side context[59–62]
			DocNMT with target-side context[63, 64]
Multi-modal NMT	Image-text NMT	Translating a source sentence and an image into the target	Coarse-grained utilization[69–71]
			Fine-grained utilization[72–74]
	Speech translation	Translating a speech in source language into a text in target language	Incorporating the data of ASR and NMT[80–85]
			Bringing the feature gap[77, 88, 89]
Beyond autoregressive decoding	Non-autoregressive decoding	Generating all target words in parallel	NAT[90]
			Semi-NAT[98]
			NAT with multi-pass iterative refinement[99, 102]
	Bidirectional decoding	Combining the left-to-right and right-to-left decoding	Reranking[104, 105]
			Enhancing agreement[8, 106, 107]
			Asynchronous bidirectional decoding[91]
			Synchronous bidirectional decoding[92]
Prior knowledge integration	Knowledge enhanced NMT	Enhancing NMT with various symbolic knowledge	Bilingual lexicons[110, 111]
			Phrase tables[116–119] and terminologies[120, 121]
			Knowledge graphs[122-124]

6.1 Extensions to other NLP tasks

Transformer for pre-trained language models. A recent huge breakthrough in NLP is pre-trained language models, which are first pre-trained on a large corpus and then utilized in different downstream NLP tasks to avoid learning a model from scratch[135]. Currently, Transformer has become the mainstream architecture for pre-trained language models in three different ways:

1) Transformer encoder: Many pre-trained language models for the natural language understanding tasks use the Transformer encoder as their architectures. The most repressive model is BERT[45], which utilizes masked language modelling and next sentence prediction as the pre-training objective. Furthermore, many BERT-like models have been proposed on the basis of BERT, such as RoBERTa[136] and SpanBERT[137].

2) Transformer decoder: Meanwhile, some studies utilize the Transformer decoder as the backbone architectures. For example, the generative pre-trained Transformer (GPT)[138] and its subsequent versions (GPT-2[139] and GPT-3[140]) pre-trained the language models in a zero-shot setting with the Transformer decoder.

3) Transformer encoder-decoder: There are also some pre-trained language models with the standard Transformer encoder-decoder architecture, such as MASS[49], T5[50] and BART[51], which have been introduced in Section 4.1.4.

Transformer for summarization. Text summarization is an important NLP task to generate natural lan-

Table 2 Some available resources for NMT

Types	Corpus name	Main language pairs
Text parallel data	WMT	*
	IWSLT	*
	CCMT	*
	LDC	*
	Europarl[125]	*
	OPUS[126]	*
Image-text translation data	Multi30K[127]	En ⇒ De
Speech translation data	Augmented LibriSpeech[128]	
	TED[84]	En ⇒ De/Fr/Zh/Ja
	MuST-C[129]	En ⇒ 14 languages[10]
	Fisher and callhome	En ⇒ Es
Document translation data	TED[130]	*
	News-commentary	*
	Europarl[125]	*

guage summaries that compress the information in a longer text. The current summarization also follows the encoder-decoder framework. Different NMT, the encoder-decoder framework in text summarization encodes a document and then generates summary with the decoder. Inspired by the remarkable progress of Transformers in NMT, many methods also apply the Transformers to text summarization tasks. Liu et al.[141] considered Wikipedia as a multi-document summarization where the inputs are topics and documents, and the target is the Wikipedia text. They utilize Transformer decoder to achieve this goal. Recently, many approaches have applied the Transformer-based pre-trained language model to summarization, such as BART[51] and PRIMERA[142]. PRIMERA[142] uses the gap sentence generation objective with an entity pyramid, in which the model masks salient sentences then it generates these important sentences.

Transformer for knowledge graph learning. Knowledge graphs contain much structured human knowledge and have drawn great research attention in NLP and knowledge mining[143]. Transformer is also widely utilized in recent advances of knowledge graph research. Here, we introduce the application of Transformer in knowledge representation learning. Knowledge representation learning (KRL) aims at mapping entities and relations into low-dimensional vectors while capturing their semantic meanings. The Transformer in KRL is helpful in compositional representation models or contextualized representation model. In compositional representation models, entity embeddings are composed of token embeddings. Saxena et al.[144] treated knowledge link prediction as sequence-to-sequence tasks and then train a Transformer to learn the knowledge representation and compositional functions. Other models utilize the Transformer to get the contextualized knowledge representation. CoLAKE[145] dynamically represents an entity with the knowledge context and language context and jointly learns knowledge and language representation in a unified representation space.

Transformer for dialogue. Dialogue systems are a popular topic in NLP and are widely used in daily life. Dialogue systems contain two kinds of research lines: task-oriented dialogue systems, which serve as assistants to solve specific tasks, and open-domain dialogue systems, which communicate with human without task restrictions. Transformers are widely utilized in both task-oriented dialogue systems and open-domain dialogue systems. Henderson et al.[146] proposed a response selection model for task-oriented dialogue with the Transformer framework, which first pretrains the response selection model with general-domain corpora and then fine-tunes the pretrained model with the target dialogue domain. Zhang et al.[147] proposed a dialogue generative pre-trained Transformer, which is trained on large-scale dialogue pairs and sessions from Reddit. Ma et al.[148] focused on the multimodal task-oriented dialog systems and propose a unified Transformer semantic representation framework, where a Transformer encoder is used to project all the multimodal features into a unified semantic space and a hierarchical Transformer response decoder is utilized to generate target text responses.

Transformer for question answering. Textual question answering (QA) aim to provide precise answers to questions from users in natural language. Specifically, textual QA is studied under two task settings based on contextual information, i.e., machine reading comprehension (MRC) and open-domain QA (OpenQA). Specifically, MRC tends to make machines answer a question given specified context passages. In contrast, OpenQA tries to answer a given question without any specified context. It requires the model to first search for the relevant documents as the context. Bao et al.[149] analysed matching components and Transformer encoding for MRC. Recently, Transformer-based pre-trained languages models have also been widely utilized in MRC and have achieved remarkable progress[150]. For OpenQA task, instead of extracting answer spans, researchers utilize Transformer to generate the answers. Masque[151] utilizes the Transformer and multi-source abstractive summarization to learn the multi-style answers for OpenQA. Transformer-XH[152] boosts Transformer with structured text data for complex reasoning OpenQA. Similar to the other tasks, some OpenQA systems[153] also borrow Trans-

[10] Arabic, Chinese, Czech, Dutch, French, German, Italian, Persian, Portuguese, Romanian, Russian, Spanish, Turkish, Vietnamese

Table 3 Some broadly used open-source NMT toolkits

Toolkits	Language	Framework	URL
OpenNMT	Python	Pytorch	https://opennmt.net/
Fairseq	Python	Pytorch	https://github.com/facebookresearch/fairseq
Tensor2tensor	Python	Tensorflow	https://github.com/tensorflow/tensor2tensor
Sockeye	Python	Pytorch/MXNet	https://github.com/awslabs/sockeye
Marian	C++	*	https://marian-nmt.github.io/
THUMT	Python	PyTorch/TensorFlow	https://github.com/THUNLP-MT/THUMT
Hugging face	Python	PyTorch/TensorFlow	https://github.com/huggingface/transformers

former based pre-trained language models to generate more natural and precise answers.

6.2 Extensions to computer vision

Inspired by the success of Transformer in the field of NLP, researchers have applied Transformer to computer vision (CV) tasks to replace traditional CNNs[154–156]. Here, we briefly introduce the application of Transformer for image classification and image generation.

Transformer for image classification. Early studies incorporated the self-attention strategy on the basis of CNN-based architectures. Later, vision Transformer (ViT)[154], a pure architecture Transformer-based architecture, was proposed for image classification task. ViT first splits an image into a sequence of patches, which are treated as tokens in NLP. Then, patch embeddings are fed into a standard Transformer encoder and the hidden states are calculated. Similar to BERT, a special token "`class`" is added into the input sequence, and its corresponding hidden states are utilized to perform image classification. Following the paradigm of ViT, many ViT variants have been proposed, such as Transformer iN Transformer (TNT)[157], Swin Transformer[155], T2T-ViT[158], and CSWin Transformer[159].

Transformer for image generation. Transformers are also widely utilized in image generation task. Transgenerative adversarial networks (TransGAN)[160] presents a pure Transformer-based GAN architecture, where a memory-friendly Transformer-based generator with multiple stages could gradually increase the feature map resolution and a multi-scale Transformer-based discriminator could capture the semantic contexts and low-level textures simultaneously. Esser et al.[161] proposed a taming Transformer for image generation, where they use CNNs to learn a codebook of context-rich visual parts and utilize Transformers to model their composition within high-resolution images.

6.3 Extensions to audio tasks

Since Transformer has shown its great advantage in NLP and CV tasks, now it has also been extended to many audio-related tasks, such as audio classification[162], speech recognition[163, 164], and speech synthesis[165–167]. Here, we briefly introduce the Transformer for speech recognition and speech synthesis.

Transformer for speech recognition. Automatic speech recognition (ASR) can also be treated as a sequence-to-sequence task where the input is a speech sequence, and the output is its transcribed text sequence. Dong et al.[163] introduced the Transformer into speech recognition and proposed a speech-Transformer model. Tian et al.[164] proposed a synchronous transformer (Sync-Transformer) for online speech recognition. Sync-Transformer combines the Transformer and self-attention transducer. The self-attention in the Sync-Transformer encoder could make the node attend only its left context. Then its decoder starts to predict tokens immediately after a chunk of the state sequence is produced by the encoder.

Transformer for speech synthesis. Speech synthesis, or text-to-speech, aims at synthesizing natural speech given text and is a hot research topic. Li et al.[165] proposed a Transformer-based speech synthesis model, where the self-attention mechanism is introduced to replace the traditional RNNs in the encoder and decoder. Some subsequent studies are proposed to enhance the robustness of the Transformer-based speech synthesis model. Meanwhile, the Transformer-based pre-trained language model is also widely utilized in speech synthesis to enhance text representation[166, 167].

6.4 Extensions to multi-modal tasks

Due to its flexible and expansible architecture, Transformer has also been applied in many multi-modal scenarios. Here, we briefly introduce the application of Transformer for visual question answering and multi-modal pre-training.

Transformer for visual question answering. Visual question answering (VQA) aims at generating answers given a question in natural language and a corresponding image. Recently, VQA has attracted much attention and Transformers also play an important role in this task. Hu et al.[168] proposed a multi-modal Transformer for VQA, where they represent the semantic embeddings of different modalities into a common space and self-at-

tention is applied to model inter- and intra-modality context. Meanwhile, LaTr[169] is a layout-aware Transformer for scene-text VQA and consists of three building blocks: A Transformer-based language block which is pre-trained on only text, a layout-aware denoising pre-training block, and a ViT block to extract the visual features.

Transformer for multi-modal pre-training. Inspired by success of Transformer-based pre-trained language models (e.g., BERT), researchers have proposed various Transformer-based multi-modal pre-training models, such as SpeechBERT[170] to model audio and text, VisualBERT[171] and VL-BERT[172] to model vision and text, VideoBERT[173] to model the video and text. CLIP[174] is a contrastive language-image pre-training model, that takes natural language as a supervision to learn image representations. CLIP jointly trains an image encoder and a text encoder by utilizing a contrastive objective to predict the correct pairings of (image, text) in the training set. UniT[175] is a multi-modal multi-task pre-training model across different domains via a unified Transformer. UniT jointly learns 7 different visual and textual tasks including object detection, visual entailment, visual question answering, and natural language understanding tasks. Experimental results show that UniT could improve the performance of several multi-modal tasks.

In conclusion, Transformer has demonstrated its architectural superiority to model various NLP, CV and audio tasks. Furthermore, Transformer has shown its potential for building a general-purpose model to handle a vast number of multi-modal applications.

7 Current status and analysis

NMTs, especially the Transformer-based NMT, have proven their power for MT tasks. However, we should be soberly aware that NMT is still far from satisfactory. In this section, we briefly introduce the current status of NMT.

For formal texts in high-resource language pairs, the current NMT can produce high-quality translation results. It must be admitted that tremendous progress has been made by the Transformer-based NMT model. In the date-rich language pairs (such as Chinese-English and German-English), the translation quality of the formal written text (such as news, reports or daily conversations) by NMT models is quite high. Even the experimental results from Hassan et al.[8] in the WMT 2017 news Translation task from Chinese to English show that "the Translation quality is at human parity when compared to professional human translations". Due to its low cost, high efficiency, and high translation quality, NMT could basically meet the translation demands and has been widely used.

Low-resource translation is still far from satisfactory. Although many methods have been proposed for low-resource NMT, the quality of low-resource translation is still lower than that of high-resource translation. As a data-driven method, Transformer still heavily relies on parallel training data. For the low-resource translation, NMT is only helpful when the users just want to acquire the topic or general gist of the input sentences or documents.

Some language phenomena are still not well addressed. It is an important issue for an NMT model to deal with many special language phenomena, such as unseen words, entities and terminologies, abbreviations, idioms, omissions, and ambiguity. More seriously, language is dynamic and new language phenomena appear almost every day. However, the current NMT models still learn the translation knowledge from parallel training data and cannot handle these phenomena well. These problems occur widely and severely harm the translation quality of NMT.

The utilized information in multi-modal NMT is limited. Take the speech translation as an example. The current speech translation only incorporates speech signals. In face-to-face communication scenarios, in addition to the speech signals, some paralinguistic features, such as tone of voice, posture and gesture, are also important for the neural model to recognize the intention, desire and mood of speakers, while such paralinguistic features are not taken into consideration.

The improvement of pre-trained languages model for the NMT task is not that significant. Although many pre-training language models for NMT have been proposed to improve the translation quality, the improvement of the translation task is significantly less than that of other NLP tasks, such as text classifications, question answering, and named entity recognition. Potential evidence is that in the WMT 2021 Biomedical Translation Shared Task[176], in all eight participating teams, only two teams utilize the pre-trained language models. In contrast, the leaderboards of the general language understanding evaluation (GLUE) benchmark[11] and superGLUE[12] are almost various pre-training languages models.

Overall, Transformer-based NMT has brought the quality of NMT up to a new stage. For high-resource NMT with formal texts, the translation quality of the current NMT model can basically meet the translation demands for daily use. While in many scenarios, such as new language phenomena, multi-modal translation and low-resource translation, current Transformer-based NMT models still have a long way to go.

8 Future research directions

As we mentioned above, many NMT approaches have been proposed and have achieved remarkable progress,

[11] https://gluebenchmark.com/leaderboard

[12] https://super.gluebenchmark.com/leaderboard

while many challenges remain. In this section, we list some potential and important research directions.

Robust NMT. In addition to the formal written texts (such as news and reports), in practice, the NMT model faces various informal texts with different noises, such as speech noises from the ASR model, noisy web-crawled corpora or limited exposure to training data. Although many methods have been proposed to improve the robustness of NMT, there remains a huge gap between the translation quality with clean input and the real noise inputs. In addition, the current NMT models are also vulnerable to adversarial attacks, which are also a serious problem in commercial systems. Therefore, it remains a major challenge to design more robust NMT models to deal with informal texts with real noise inputs and adversarial attacks.

NMT with broader background knowledge. In many cases, only source sentences or speech cannot support the NMT model to produce the desired translation result. Meanwhile, some language phenomena, such as terminologies, abbreviations, idioms, and omissions, are still not well addressed. To overcome these problems, a potential solution is to combine broader background knowledge, which includes not only the mentioned syntactic structures, bilingual lexicons, phrase tables and terminologies, and knowledge graphs but also commonsense knowledge, local culture, history, etc. The knowledge is hard to learn from parallel sentence pairs. Accordingly, it remains a major challenge to represent and incorporate broader background knowledge into NMT.

Designing better pre-trained language models for low-resource NMT. Recently, the emergence of pre-trained language models has brought the NLP community to a new era. Although many methods are proposed to utilize the pre-trained language models for NMT, the improvement of the translation task is not as great as that of other natural language understanding tasks. Thus, designing better pre-trained language models or multilingual pre-trained language models for low-resource NMTs is an important future research direction.

Incorporating more information for multi-modal NMT scenarios. For speech translation, despite of large improvements, the end-to-end framework currently cannot perform on par with the cascaded method in many cases. Meanwhile, paralinguistic features, such as tone of voice, posture and gesture, also need to be taken into consideration. The current image-text translation only addresses the translation of image captions. In addition, scene image text translation is another important scenario, but it has attracted little attention. Scene image text refers to text in natural scenes, captured in its native environment, such as the scanned document, signboards and product packaging. Thus scene image text translation remains a major challenge due to complex backgrounds, various fonts, and imperfect imaging conditions.

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Declarations of Conflict of interest

The authors declared that they have no conflicts of interest to this work.

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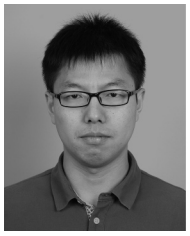

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