

# Large-scale Multi-Modal Pre-trained Models: A Comprehensive Survey

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## Abstract

With the urgent demand for generalized deep models, many pre-trained big models are proposed, such as BERT, ViT, GPT, etc. Inspired by the success of these models in single domains (like computer vision and natural language processing), the multi-modal pre-trained big models have also drawn more and more attention in recent years. In this work, we give a comprehensive survey of these models and hope this paper could provide new insights and helps fresh researchers to track the most cutting-edge works. Specifically, we firstly introduce the background of multi-modal pre-training by reviewing the conventional deep learning, pre-training works in natural language process, computer vision, and speech. Then, we introduce the task definition, key challenges, and advantages of multi-modal pre-training models (MM-PTMs), and discuss the MM-PTMs with a focus on data, objectives, network architectures, and knowledge enhanced pre-training. After that, we introduce the downstream tasks used for the validation of large-scale MM-PTMs, including generative, classification, and regression tasks. We also give visualization and analysis of the model parameters and results on representative downstream tasks. Finally, we point out possible research directions for this topic that may benefit future works. In addition, we maintain a continuously updated paper list for large-scale pre-trained multi-modal big models: [https://github.com/wangxiao5791509/MultiModal\\_BigModels\\_Survey](https://github.com/wangxiao5791509/MultiModal_BigModels_Survey).

**Keywords:** Multi-modal, Pre-trained Model, Information Fusion, Representation Learning, Deep Learning

## 1 Introduction

Along with the breakthroughs of recognition performance of AlexNet [1] on the ImageNet competition [2], the artificial intelligence have developed greatly. Many representative deep neural networks are proposed, such as VGG [3], ResNet [4], Inception [5], LSTM [6]. The researchers usually collect and annotate some samples for their task, and train their models based on pre-trained backbones on large-scale datasets (such as ImageNet [2] for

computer vision, Glove [7] and Skip-thought vectors [8] for natural language processing). Many tasks can be solved well in such an end-to-end manner compared with traditional handcrafted features, such as object detection, segmentation, and recognition. However, the generalization ability of obtained deep model is still limited. Collecting and annotating a larger dataset can address these issues to some extent, but this procedure is expensive and tedious.

To address this issue, Ashish et al. propose the Transformer network [9] which achieves new SOTA (State-Of-The-Art) performance on machine translation task. After that, the self-supervised pre-training on large-scale corpus, then, fine-tuning on downstream tasks attracts more and more researchers’ attention. Many pre-trained big models are proposed by following such paradigm, such as BERT [10], GPT [11, 12], T5 [13], XLNet [14] which also trigger new research highlights of pre-training in CV community. More and more large-scale NLP and CV models demonstrate the powerful effect by pretrain-and-finetuning paradigm, including ViT [15] and Swin-Transformer [16].

Although the progress brings new impetus to the development of artificial intelligence, however, the issues caused by the defect of single modality are still hard to solve. Researchers attempt to incorporate more modalities to bridge the data gap for deep models. Many multi-modality fusion based tasks are also explored in a traditional deep learning manner, such as RGB, Depth, Natural Language, Point Cloud, Audio, Event stream, etc. Many large-scale pre-trained multi-modal models [17–23] are proposed which set new SOTA on downstream tasks one after another, as shown in Fig. 1. In this paper, we give a comprehensive review of these works which target to help the new researchers who are interested in this area to understand the history and latest developments quickly.

**Organization of our review.** In this paper, we firstly review the background of multi-modal pre-training technique in Section 2, from the traditional deep learning paradigm to pre-training in single modality tasks, including natural language processing, computer vision, and automatic speech processing. Then, we focus on MM-PTMs and describe the task definition, key challenges, and benefits, in Section 3.1 and 3.2. The key components are also reviewed in the following sub-sections, including large-scale data, network architectures, optimization objectives, and knowledge-enhanced pre-training. To validate the effectiveness of pre-trained models, many downstream tasks are used for quantitative assessment. In Section 4, we provide detailed reviews on the task definition and evaluation metrics of these tasks. In Section 5, we review the model parameters and hardware for training and also report

the experimental results of several representative downstream tasks. Finally, in Section 6, we conclude this survey and propose multiple research directions needed to be studied. The architecture of this survey is visualized in Fig. 2.

### Difference from existing reviews.

Although there are already two surveys [24, 25] proposed for MM-PTMs, the difference between our survey and existing ones can be summarized as follows:

- **Scope:** Existing multi-modal surveys [24, 25] focus on vision-language only, however, the multi-modal information problem is a wider research topic. This paper is more comprehensive than the aforementioned reviews by introducing more modalities, such as audio, video, table, etc.
- **Timeliness:** This paper introduces the latest datasets and algorithms (from the year 2019 to June 2022) proposed for multi-modal pre-training which is a long survey, meanwhile, their work belongs to short paper.
- **New insights to MM-PTMs:** By classifying and analyzing the existing MM-PTMs from different perspectives, this article can help readers master the cutting-edge methods and techniques from both detailed and high-level perspectives. In addition, our proposed research directions on the MM-PTMs are deliberate and will provide new clues for the follow-up research.

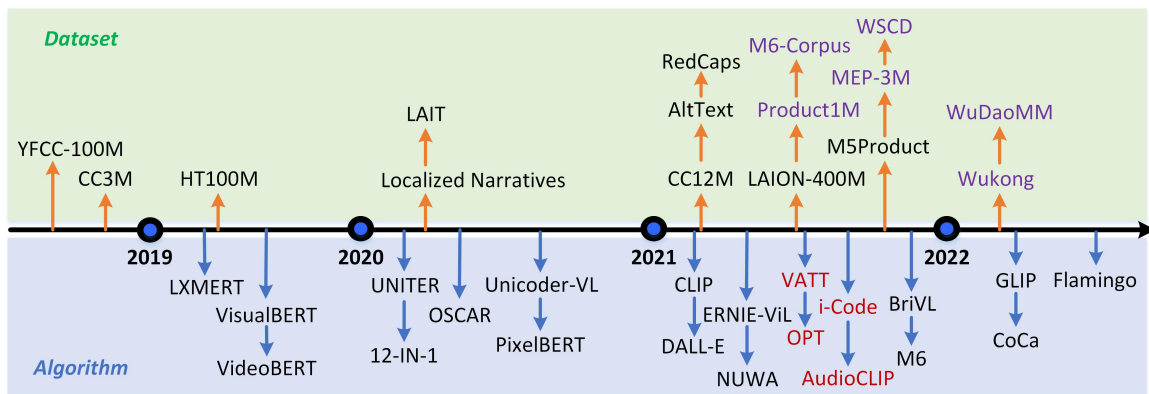
## 2 Background

### 2.1 Conventional Deep Learning

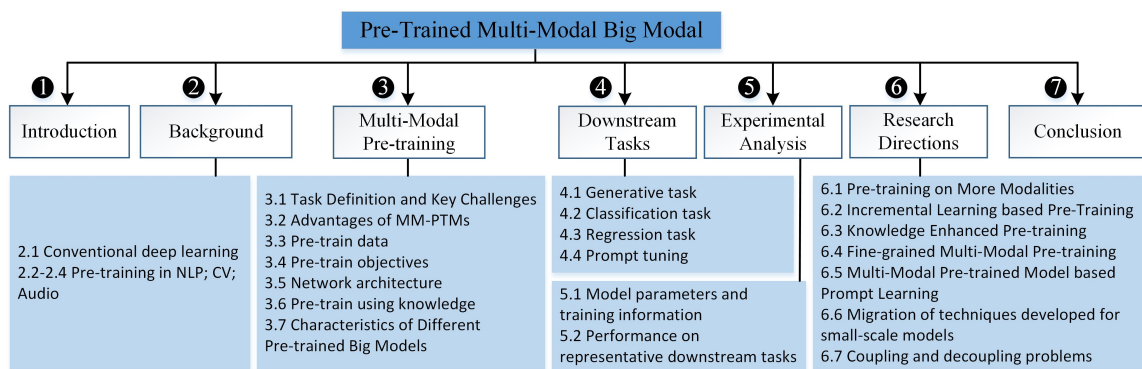
With the release of AlexNet [1], a series of deep learning models are proposed in the artificial intelligence community. These deep models show better capabilities for fitting complex data than conventional machine learning models. From the perspective of its development (LeNet [51] → AlexNet [1] → VGG [3] → ResNet [4] → DenseNet [52]), we can find that their architectures become deeper and deeper, and the corresponding performance accordingly becomes better. The success of these approaches is supported by large-scale annotated training data, such as the ImageNet [2] for the classification task. The scale of used data is much larger than traditional methods, but it’s still limited. The pursuit

**Table 1** Summary of related single- and multi-modal pre-training surveys. SC and DC denotes Single Column and Double Column. Pub. is short for Publication.

No.	Title	Year	Pub.	Topic	Pages
01	A short survey of pre-trained language models for conversational ai-a new age in nlp [26]	2020	ACSWM	NLP	DC, 4
02	A Survey of Controllable Text Generation using Transformer-based Pre-trained Language Models [27]	2022	arXiv	NLP	SC, 34
03	A Survey of Knowledge Enhanced Pre-trained Models [28]	2021	arXiv	KE	DC, 20
04	A Survey of Knowledge-Intensive NLP with Pre-Trained Language Models [29]	2022	arXiv	KE	DC, 8
05	Commonsense Knowledge Reasoning and Generation with Pre-trained Language Models: A Survey [30]	2022	arXiv	KE	DC, 11
06	A survey on contextual embeddings [31]	2020	arXiv	NLP	DC, 13
07	Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing [32]	2021	arXiv	NLP	SC, 46
08	Pre-trained Language Models in Biomedical Domain: A Systematic Survey [33]	2021	arXiv	NLP	SC, 46
09	Pre-trained models for natural language processing: A survey [34]	2020	SCTS	NLP	DC, 26
10	Pre-Trained Models: Past, Present and Future [35]	2021	AI Open	NLP, CV, MM	DC, 45
11	Recent Advances in Natural Language Processing via Large Pre-Trained Language Models: A Survey [35]	2021	arXiv	NLP	DC, 49
12	A Survey of Vision-Language Pre-Trained Models [36]	2022	arXiv	MM	DC, 9
13	Survey: Transformer based video-language pre-training [37]	2022	AI Open	CV	DC, 13
14	Vision-Language Intelligence: Tasks, Representation Learning, and Large Models [38]	2022	arXiv	MM	DC, 19
15	A survey on vision transformer [39]	2022	TPAMI	CV	DC, 23
16	Transformers in vision: A survey [40]	2021	CSUR	CV	SC, 38
17	A Survey of Visual Transformers [41]	2021	arXiv	CV	DC, 21
18	Video Transformers: A Survey [42]	2022	arXiv	CV	DC, 24
19	Threats to Pre-trained Language Models: Survey and Taxonomy [43]	2022	arXiv	NLP	DC, 8
20	A survey on bias in deep NLP [44]	2021	AS	NLP	SC, 26
21	A Survey of Controllable Text Generation using Transformer-based Pre-trained Language Models [27]	2022	arXiv	NLP	SC, 34
22	An Empirical Survey of the Effectiveness of Debiasing Techniques for Pre-Trained Language Models [45]	2021	arXiv	NLP	DC, 21
23	A multi-layer bidirectional transformer encoder for pre-trained word embedding: A survey of BERT [46]	2020	CCDSE	NLP	DC, 5
24	Survey of Pre-trained Models for Natural Language Processing [47]	2021	ICEIB	NLP	DC, 4
25	A Roadmap for Big Model [48]	2022	arXiv	NLP, CV, MM	SC, 200
26	Vision-and-Language Pretrained Models: A Survey [49]	2022	IJCAI	MM	DC, 8
27	Multimodal Learning with Transformers: A Survey [50]	2022	arXiv	MM	DC, 23



**Fig. 1** The chronological milestones on multi-modal pre-trained big models from 2019 to the present (June 2022), including multi-modal datasets (as shown by the orange arrow) and representative models (as shown by the blue arrow). The purple font indicates that the dataset contains Chinese text (other datasets contain English text). The models highlighted in wine red are trained on more than two modalities.



**Fig. 2** The overall framework of this survey.

of robustness and generalization performance of machine learning models has never stopped.

Recently, the results of large-scale pre-trained models obtained by pre-training on massive data are constantly refreshing people’s cognition of artificial intelligence. Compared with previous small-scale deep learning methods, pre-trained big models show obvious advantages in Natural Language Processing (NLP), Computer Vision (CV), and Multi-Modal fields. Such a pre-training scheme take full advantage of the large-scale unlabeled data, therefore, getting rid of expensive annotation costs. Therefore, the study of large-scale pre-trained models is a feasible and necessary way to explore real intelligence.

## 2.2 Pre-training in Natural Language Processing

The large-scale pre-trained models [29, 43, 44, 53–56] first appeared in the NLP field. Their success is mainly attributed to self-supervised learning and network structures like Transformer [9]. Specifically, the advent of Bidirectional Encoder Representations (BERT) [10] based on self-supervised learning has led to revolutionary performance improvements on a wide variety of downstream tasks by fine-tuned on fewer training data [57]. Generative Pre-trained Transformers (GPT) [12, 58, 59] further extends the number of parameters and the training data for better performance. Note that, the GPT-3 [12] has ten times more parameters than TuringNLP [60]. It can not only better fulfill the functions of general NLP tasks, but also has some mathematical calculation ability. The success of the GPT-3 model has made

it widely used in various fields, such as search engines, chatbots, music composition, graphics, and coding. XLNet [14] is developed based on a generalized permutation language modeling objective, which achieves unsupervised language representation learning. PanGu- $\alpha$  [61] is a large-scale pre-trained Chinese model with 200 billion parameters and implemented based on MindSpore Auto-parallel. NEZHA [62] is another Chinese pre-trained big model based on BERT proposed by Wei et al. More large-scale pre-trained models for NLP can be found in surveys [27, 34].

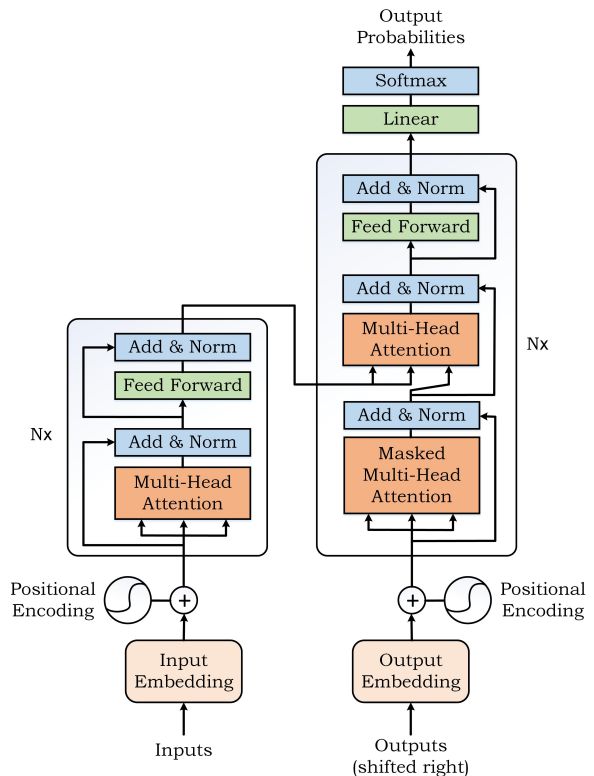
### 2.3 Pre-training in Computer Vision

Inspired by the revolutionary advancement of Transformer for NLP tasks, many large-scale Transformer-based vision models are also proposed in recent years. Chen et al. [63] attempt to auto-regressively predict pixels using a sequence Transformer. The model obtained by pre-training on the low-resolution ImageNet dataset demonstrates strong image representations. The ViT (Vision Transformer) model [64] directly adopts the pure Transformer to handle the sequence of image patches for classification. Many new SOTA performances are achieved on several downstream CV tasks, including object detection [65], semantic segmentation [66], image processing [67], video understanding [67]. The Swin-Transformer [16] is another milestone for computer vision, as a hierarchical Transformer, it adopts shifted windows for representation learning.

For the pre-training methods, the Masked Image Modeling (MIM) [63, 64] is proposed to learn rich visual representations via masked parts prediction by conditioning on visible context. MIM provides another direction for the exploration of the visual large-scale pre-training model. He et al. propose the MAE [68] to re-explore pixel regression in MIM and show more comparable performance on multiple image recognition tasks. BEiT [69] greatly improves MIM’s performance via masked visual token prediction, and PeCo [70] finds injecting perceptual similarity during visual codebook learning benefits MIM pre-trained representation.

### 2.4 Pre-training in Audio and Speech

As one of the most popular modalities, the audio and speech based pre-training also draws the researcher’s attention. For example, the wav2vec [71] is the first work that applies contrastive learning to improve supervised speech recognition by learning the future raw audio based on the past raw audio. The vq-wav2vec [71] uses context prediction tasks from wav2vec to learn the representations of audio segments. DiscreteBERT [72] is BERT-style model by finetuning the pre-trained BERT models on transcribed speech. HuBERT [73] uses self-supervised speech learning where an offline clustering step is used to generate discrete labels of masked speech signals. wav2vec 2.0 [74] solves a contrastive task to predict the masked latent representation. w2v-BERT [75] uses contrastive learning and masked speech modeling simultaneously, where a model predicts discretized speech tokens and another model solves a masked prediction task.



**Fig. 3** The detailed network architecture of Transformer network [9].

## 3 Multi-Modal Pre-training

### 3.1 Task Definition and Key Challenges

**Task Definition.** Usually, the deep neural networks are trained on a large-scale dataset, for example, the widely used residual network [4] are pre-trained using a classification task on the ImageNet dataset [2]. In contrast, the multi-modal pre-training big models are usually trained on a massive training dataset. Usually, these data are not annotated with labels due to the scale are too large to annotate. On the other hand, the parameters need to reach a certain scale. As illustrated in Fig. 4, the multi-modal data, big model, and computing power are tightly connected. All in all, with the support of computing power, the multi-modal pre-training usually denotes the task that the multi-modality model with huge parameters pre-trained on the massive multi-modal data in an unsupervised way.

**Key Challenges.** It is challenging to attain a great multi-modal pre-training big model according to aforementioned process. More in detail, we summarize the following key challenging factors:

- **Acquisition and clean of large-scale multi-modal data.** The multi-modal data is one of the most important elements in MM-PTMs. The collection of multi-modal data is significantly harder than the single one, due to the scarce of multi-modal imaging devices. The frequently used multi-modal cameras are usually covers two modalities only, such as RGB-Depth, RGB-Thermal, RGB-Radar, RGB-Event cameras, etc. Most of current MM-PTMs are vision-language models, because of the easy access to image and text data from the Internet. But the additional cleaning of these data is also necessary due to the noisy samples.

- **Design of network architectures for large-scale multi-modal pre-training.** The network architecture is another key component for multi-modal pre-training. The networks used for feature encoding of multiple input modalities are worthy carefully tailored, as different modalities may have their own features and particular networks are needed. For example, the Transformer or CNN are suggested for image and text modality, the spiking networks can be used for event

streams. Another problem is the design of multi-modal fusion or cross-modality matching modules. Whether similar modules designed for small-scale multi-modal tasks work for large-scale pre-trained models or not are still remain to be verified.

- **Design of pre-training objectives.** Due to the massive unlabelled multi-modal data, the pre-training tasks usually need to be done in an unsupervised learning manner. Many current works adopt the masked region prediction for each modality as their learning objective. Obviously, the objectives for multi-modal tasks can be directly borrowed from single-modality pre-training, however, the pre-training objectives designed for the multi-modal tasks are also necessary, intuitive and effective. The widely used contrastive learning, modality based matching, and modality translation are all valid and meaningful attempts. How to design new multi-modal pre-training objectives is one of the most challenging tasks for MM-PTMs.

- **Support of large-scale computing power.** The training for traditional deep neural networks can be executed on a server with limited number of GPUs. In contrast, the MM-PTMs needs more computing power due to the large-scale multi-modal data and the super large-scale model parameters. Therefore, the first thing is to prepare a supercomputing device and the subsequent model training also requires a lot of power to support.

- **Skills on parameter tuning.** It is never a simple task to train an effective large model considering aforementioned challenging factors. The tricks used for training the neural networks are also very important. As the research and techniques for the small scale pre-training are relatively more mature, however, there is less accumulation of experience on large-scale pre-training techniques.

### 3.2 Advantages of MM-PTMs

Compared with *single modality pre-trained big models*, the MM-PTMs are more suitable for practical application scenarios. Specifically, the problems like multi-modal collaborative generation, modal completion, cross-domain retrieval, etc, can be addressed well using MM-PTMs. Also, the multi-modal data contains more information which can make up for the defects of a

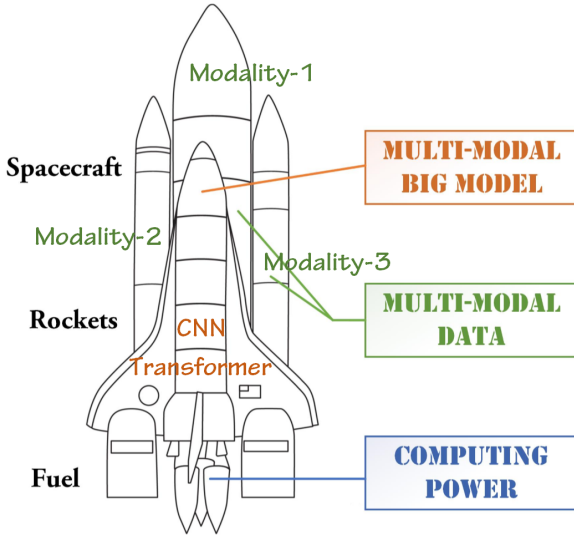


Fig. 4 The relations between multi-modal data, model, and computing power.

single modality. Therefore, the MM-PTMs can help extracting the common features of multi-modalities. Many recent works demonstrate that the utilization of MM-PTMs indeed brings in the additional prior knowledge [76–78].

Compared with *small-scale multi-modal models*, the generalizability of MM-PTMs which are obtained by self-supervised/unsupervised learning can be improved significantly. As some prior knowledge is only contained in massive big data, and a small amount of artificially selected annotated data is biased, therefore, it is hard for the small-scale models to master such knowledge.

### 3.3 Pre-training Data

As shown in Table 2, many large-scale multi-modal datasets are proposed for the pre-training task. In this subsection, we will briefly introduce these datasets to help readers quickly master the data information for pre-training.

- **SBU Captions** [79] is originally collected by querying Flickr <sup>1</sup> using plentiful query terms. Then, they filter the obtained large-scale but noisy samples to get the dataset, which contains more than 1M images with high-quality captions.

- **Flickr30k** [80] is obtained by extending Hodosh et al. [110]’s corpus with 31,783 photographs collected from Flickr. These images cover

everyday activities, events, and scenes. Five sentences are annotated for each collected image via crowdsourcing, therefore, Flickr30k contains 158,915 captions.

- **COCO** [111] is developed based on MS-COCO dataset [111] which contains 123,000 images. The authors recruit the Amazon Mechanical Turk <sup>2</sup> to annotate each image with five sentences.

- **Visual Genome** [82] is proposed to help develop machine learning models that can understand the image by mining the interactions and relationships between objects. Therefore, they perform well on the cognitive tasks, such as the image description and visual question answering, etc. Statistically, the Visual Genome dataset contains more than 108K images and each image has about 35 objects, 26 attributes, 21 pairwise relationships.

- **VQA v2.0** [83] is proposed to reduce the language biases that existed in previous VQA datasets which contain about 1.1M image-question samples and 13M associated answers on 200K visual images from the COCO dataset.

- **FashionGen** [84] contains 325,536 high-resolution images ( $1360 \times 1360$ ), each image has a paragraph-length descriptive captions sourced from experts. Six different angles are photographed for all fashion items.

- **CC3M** [85] is a dataset annotated with conceptual captions proposed in 2018. The image-text samples are mainly collected from the web, then, about 3.3M image-description pairs remained after some necessary operations, such as extract, filter, and transform.

- **CC12M** [88] is the outcome of urgent need of MM-PTMs for large-scale data. The released CC3M dataset is far failed to meet the demand, therefore, the authors further relax the filters used in CC3M for the image and text cleaning. Correspondingly, a four times larger dataset CC12M can be obtained with a slight loss of accuracy.

- **GQA** [86] is mainly proposed for visual reasoning and compositional question answering. A robust question engine is carefully refined by considering *content* and *structure* information. Then, the associated semantic representations are adopted to greatly reduce biases within the

<sup>1</sup><https://www.flickr.com/>

<sup>2</sup><https://www.mturk.com/>

**Table 2** An overview of multi-modal datasets proposed for large-scale pre-training. Lang. and Ava. is short for Language and Available, respectively.

No.	Datasets	Year	Scale	Modal	Lang.	Ava.	URL
01	SBU Captions [79]	2011	1M	image-text	English	✓	<a href="#">Link</a>
02	Flickr30k [80]	2014	145K	image-text	English	✓	<a href="#">Link</a>
03	COCO [81]	2014	567K	image-text	English	✓	<a href="#">Link</a>
04	Visual Genome [82]	2017	5.4M	image-text	English	✓	<a href="#">Link</a>
05	VQA v2.0 [83]	2017	1.1M	image-text	English	✓	<a href="#">Link</a>
06	FashionGen [84]	2018	300k	image-text	English	✓	<a href="#">Link</a>
07	CC3M [85]	2018	3M	image-text	English	✓	<a href="#">Link</a>
08	GQA [86]	2019	1M	image-text	English	✓	<a href="#">Link</a>
09	LAIT [87]	2020	10M	image-text	English	×	-
10	CC12M [88]	2021	12M	image-text	English	✓	<a href="#">Link</a>
11	AltText [89]	2021	1.8B	image-text	English	×	-
12	TVQA [90]	2018	21,793	video-text	English	✓	<a href="#">Link</a>
13	HT100M [91]	2019	136M	video-text	English	✓	<a href="#">Link</a>
14	WebVid2M [92]	2021	2.5M	video-text	English	✓	<a href="#">Link</a>
15	YFCC-100M [93]	2015	100M	image-text	English	✓	<a href="#">Link</a>
16	LAION-400M [94]	2021	400M	image-text	English	✓	<a href="#">Link</a>
17	RedCaps [95]	2021	12M	image-text	English	✓	<a href="#">Link</a>
18	Wukong [96]	2022	100M	image-text	Chinese	✓	<a href="#">Link</a>
19	CxC [97]	2021	24K	image-text	English	✓	<a href="#">Link</a>
20	Product1M [98]	2021	1M	image-text	Chinese	✓	<a href="#">Link</a>
21	WIT [99]	2021	37.5M	image-text	Multi-lingual	✓	<a href="#">Link</a>
22	JFT-300M [100]	2017	30M	image-text	English	×	-
23	JFT-3B [101]	2021	3000M	image-text	English	×	-
24	IG-3.5B-17k [102]	2018	350M	image-text	English	×	-
25	M6-Corpus [103]	2021	60M	image, image-text	Chinese	×	-
26	M5Product [104]	2021	6M	image, text, table video, audio	English	✓	<a href="#">Link</a>
27	Localized Narratives [105]	2020	849k	image, audio, text, mouse trace	English	✓	<a href="#">Link</a>
28	RUC-CAS-WenLan [106]	2021	30M	image-text	Chinese	×	-
29	WuDaoMM [107]	2022	600M	image-text	Chinese	✓	<a href="#">Link</a>
30	MEP-3M [108]	2021	3M	image-text	Chinese	✓	<a href="#">Link</a>
31	WSCD [109]	2021	650M	image-text	Chinese	×	-

dataset and control for its question type composition. Finally, a balanced dataset with 1.7M samples is obtained.

- **LAIT** [87] (Large-scale weak-supervised Image-Text) is a large-scale image-text dataset collected from the Internet in a weak-supervised manner. It contains about 10M visual images, and each image has a corresponding natural language description which contains about 13 words.

- **AltText** [89] is collected by following the rules for constructing Conceptual Captions dataset [85]. To get a large-scale dataset (1.8B image-text pairs), the authors only apply minimal frequency-based filtering for data cleaning. Although the obtained resulting dataset is noisy, the big models obtained by pre-training on this dataset still beats many SOTA works on many downstream tasks.

- **TVQA** [90] is build based on six long-running TV shows from 3 genres, including sitcoms, medical dramas, and crime drama. Then, the Amazon Mechanical Turk is used for VQA collection of video clips. Finally, this dataset contains about 152,545 question-answer pairs from 21,793 video clips.

- **HT100M** [91] contains about 136 million video clips, which are collected from 1.22 million narrated instructional videos. The content of these videos are mainly focus on humans with a total of 23,000 various tasks. The language description for each clip is an automatically transcribed narration. Therefore, the video and text are weakly-paired, compared with other captioning datasets.

- **WebVid2M** [92] is a video-text captioning dataset which contains over two million video alt-text pairs. These data are collected from the Internet following a similar procedure to CC3M



dataset. The authors find that more than 10% of CC3M images are thumbnails from videos, therefore, they scrape these video sources (a total of 2.5M text-video pairs) and create the WebVid2M dataset.

- **YFCC-100M** [93] totally contains 100 million media objects (99.2 million photos, 0.8 million videos) collected from Flickr, the time span of these videos from 2004 and 2014. Note that the YFCC100M dataset is constantly evolving, various expansion packs are unscheduled released.

- **LAION-400M** [94] contains 400 million image-text pairs which is released for vision-language related pre-training. It is worthy to note that this dataset is filtered using CLIP [77] which is a very popular pre-trained vision-language model.

- **RedCaps** [95] is a large-scale dataset with 12M image-text samples collected from 350 subreddits. The authors firstly define the range of subreddit, then, filter the image post and clean the captions. The ethical issue is also considered when building the dataset, and the problematic images are filtered according to privacy, harmful stereotypes, etc.

- **Wukong** [96] is the currently largest dataset collected from the Internet which contains 100 million image-text pairs. A list of 200K queries is maintained to ensure the collected samples cover diverse visual concepts. These queries are fed into the Baidu Image Search Engine, then, the image and its corresponding captions can be obtained. Note that each query can get at most 1000 samples to keep a balance between different queries and a series of filtering strategies are adopted for the final Wukong dataset.

- **CxC** [97] is extended based on MS-COCO dataset by rating existing and new pairs with continuous (0-5) semantic similarity. In general, the CxC contains human ratings for 267,095 pairs which is a significant extension in scale and detail. It can be used for a variety of tasks, such as the image-text, text-text, and image-image retrieval, etc.

- **Product1M** [98] contains 1,182,083 image-caption pairs, 458 categories, 92,200 instance. Each image contains about 2.83 objects. Different from regular object detection benchmark datasets, this dataset obtains the instance locations in a paste manner. They first segment the target object, then, paste them into other images based

on a given bounding box. It can be used for multiple tasks, including weak-supervised, multi-modal, and instance-level retrieval.

- **WIT** [99] is constructed by crawling on Wikipedia <sup>3</sup>. Then, a set of rigorous filtering operations are executed on these data which finally resulting the dataset containing over 37.5 million image-text sets. Note that, the WIT dataset contains multi-lingual, in contrast, other image-text datasets only contain single lingual (for example, English or Chinese).

- **JFT-300M** [100] contains about 300M images and 375M labels, and each image has about 1.26 labels. Note that, 18291 categories are annotated in this dataset, including 1165 animals and 5720 vehicles, etc. A rich hierarchy is formed according to these categories. It is worthy to note that this dataset is not available online.

- **JFT-3B** [101] is also an internal Google dataset, which contains about 3 billion images. These samples are annotated in a semi-automatic way with a class hierarchy of 30,000 labels. In other words, this dataset contains large amount of noisy samples. Note that, this dataset is also not available online.

- **IG-3.5B-17k** [102] is constructed for weakly supervised pre-training by collecting images from Instagram <sup>4</sup>. Similar with JFT-300M [100] and JFT-3B [101], the dataset is also inaccessible and can only be used within the Facebook.

- **M6-Corpus** [103] is specifically constructed for the pre-training of vision-Chinese big model M6 [103]. The samples are collected from various sources, such as the product description, community question answering, forum, etc. It contains 60.5M images and 111.8B tokens.

- **M5Product** [104] is a benchmark dataset specifically proposed for E-commerce. It contains 6 million multi-modal samples which cover 6,000 categories, 5,000 attributes, and five modalities, including the visual image, table, video, language description, and audio. It is worthy to note that the M5Product dataset is different from standard multimodal datasets which have completely paired samples, that is to say, each sample may only contain only a subset of modalities. It also has a challenging long-tailed distribution issue.

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<sup>3</sup><https://www.wikipedia.org/>

<sup>4</sup><https://www.instagram.com/>

- **Localized Narratives** [105] is proposed by Jordi et al. in 2020, which provides a new form of multi-modal image annotations for the connection of vision and language. The image and corresponding spoken description, textual description, and mouse trace are all embodied in this dataset which provides dense grounding between language and vision. It contains 849k images and covers the whole COCO, Flickr30k, and ADE20K [112] datasets and 671k images of Open Images.

- **RUC-CAS-WenLan** [106] is obtained by crawling multi-source image-text data and totally contains about 30M image-text pairs. These samples covers a wide range of topics and categories, such as the sports, entertainment, news, art, and culture, etc. It plays a fundamental role in the WenLan project and supports the training of the BriVL model [106].

- **WSCD** [109] (Weak Semantic Correlation Dataset) is a multi-source dataset, which contains large-scale image-text data samples (650 million). The English texts are all translated into Chinese to support the pre-training of BriVL.

- **MEP-3M** [108] is a large-scale image-text dataset collected from several Chinese large E-commerce platforms which contains 3 million image-text pairs of products and 599 classes. Another key feature of this dataset is the hierarchical category classification, in detail, it covers 14 classes, 599 sub-classes, and 13 sub-classes have further sub-subclasses.

### 3.4 Pre-training Objectives

How to design the learning objectives is a very important step for multi-modal pre-training. Currently, the following learning objectives are proposed, including contrastive loss, generative loss, etc.

- **Contrastive loss (CS)** function usually constructs positive and negative training samples which is widely used in dual-modality. For example, CLIP [77], ALIGN [21] are all trained using contrastive learning loss. The authors of VinVL [113] adopt the *3-way contrastive loss* for the pre-training to replace the binary contrastive loss function utilized in the Oscar model [17].

The contrastive losses in ALIGN are defined as follows:

$$\begin{aligned}\mathcal{L}_{i2t} &= -\frac{1}{N} \sum_i \log \frac{\exp(x_i^T y_i / \sigma)}{\sum_{j=1}^N \exp(x_i^T y_j / \sigma)} \\ \mathcal{L}_{t2i} &= -\frac{1}{N} \sum_i \log \frac{\exp(y_i^T x_i / \sigma)}{\sum_{j=1}^N \exp(y_i^T x_j / \sigma)} \\ \mathcal{L}_{CL} &= \mathcal{L}_{i2t} + \mathcal{L}_{t2i}\end{aligned}\tag{1}$$

where  $\mathcal{L}_{i2t}$ ,  $\mathcal{L}_{t2i}$ ,  $\mathcal{L}_{CL}$  are an image-to-text classification loss function, a text-to-image classification loss function and the total contrastive loss respectively. The  $x_i$  is used to denote the normalized image embedding in the  $i$ -th pair, while the  $y_j$  denote the normalized embedding of text in the  $j$ -th pair. The  $N$  and  $\sigma$  are batch size and temperature parameter.

- **Modality Matching loss (MML)** is widely used in multi-modal pre-training big models due to the explicit or implicit alignment relationships between various modalities. For instance, Unicoder-VL [114] utilizes the Visual-linguistic Matching (VLM) for vision-language pre-training. They extract the positive and negative image-sentence pairs and train their model to predict whether the given sample pairs are aligned or not (in other words, to predict the matching scores). Different from regular negative image-text samples, the authors of InterBERT [115] design the image-text matching with hard negatives (i.e., ITM-hn) by selecting the highest TF-IDF similarities.

- **Masked Language Modeling (MLM)** is another widely pre-training objective, usually, the researchers usually mask and fill the input words randomly using special tokens. The surrounding words and corresponding image regions can be used as a reference for the masked word prediction. Wang et al. train SIMVLM [116] using the Prefix Language Modeling (PrefixLM), which executes the bi-directional attention on the prefix sequence and auto-regressive factorization on the rest tokens, respectively. The words are denoted as  $w = \{x_1, \dots, x_K\}$ , and the image regions as  $v = \{v_1, \dots, v_T\}$ . For MLM, the input words is masked as  $x_m$  by the mask indices  $m$  by generated randomly with a probability of  $p\%$ . The optimizing goal is to predict the masked words based on all image regions  $v$  and remaining words  $x_{-m}$ , by

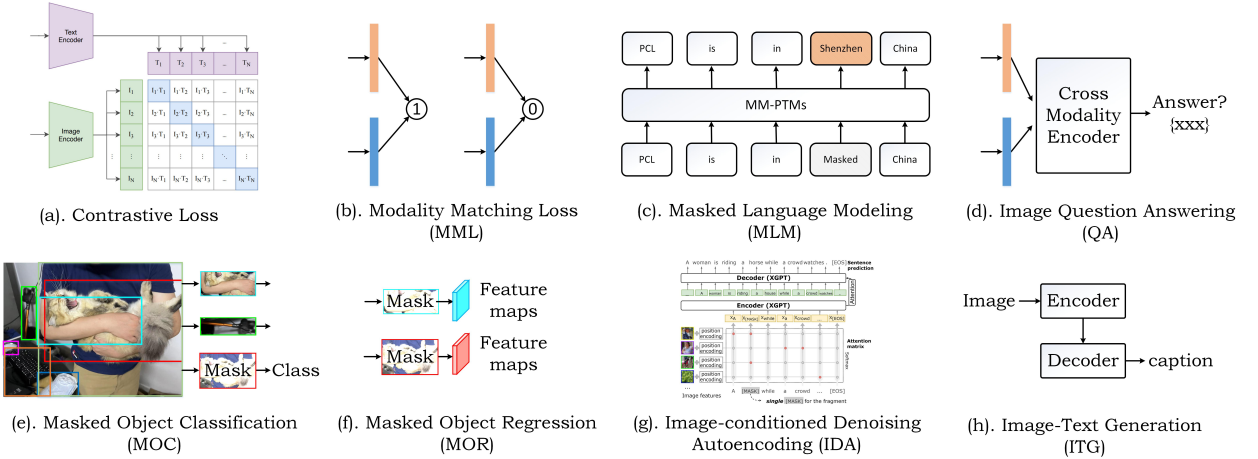


Fig. 5 Representative pre-training objectives used in MM-PTMs.

minimizing the negative log-likelihood:

$$\mathcal{L}_{MLM}(\theta) = -\mathbb{E}_{(x,v)} \log P_{\theta}(x_m | x_{-m}, v), \quad (2)$$

where  $\theta$  is the trainable parameters. Beside MLM, PrefixLM in SIMVLM can also be adopted to pretrain vision-language representation:

$$\mathcal{L}_{PrefixLM}(\theta) = -\mathbb{E}_{\mathbf{x} \sim D} \log P_{\theta}(\mathbf{x}_{\geq T_p} | \mathbf{x}_{< T_p}), \quad (3)$$

where  $\mathbf{x}$  is the given text sequence,  $D$  is the pre-training data and  $T_p$  is the length of a prefix sequence of tokens.

- **Masked Segment Modeling (MSM)** masks a continuous segment of given text using the special token, meanwhile, the MLM masks random words.

- **Image Question Answering (QA)** is used in LXMERT [117] to further expand the pre-training data, as many image-sentence pairs are image and question. The authors train their model to predict the answers as one of their pre-training objectives.

- **Masked Object Classification (MOC)** mainly focuses on masking the visual images using zero values. Then, people often take the predicted labels by object detector as the ground truth labels. This pre-training objective is widely used, such as Unicoder-VL [114]. Similar to MLM, the image regions can be masked by masking their visual feature with a probability of  $p\%$ . The goal is predict the object category of the masked image regions  $v_m^i$ . The encoder output of the masked

image regions  $v_m^i$  is feed into an FC layer to predict the scores of  $T$  object classes, which further goes through a softmax function to be transformed into a normalized distribution  $g_{\theta}(v_m^i)$ . The final objective is:

$$\mathcal{L}_{MOC}(\theta) = -\mathbb{E}_{(w,v)} \sum_{i=1}^M CE(c(v_m^i), g_{\theta}(v_m^i)), \quad (4)$$

where  $c(v_m^i)$  is the ground-truth label.

- **Masked Object Regression (MOR)** is implemented to regress the masked feature or image regions. For example, the LXMERT [117] considers both MOC and MOR for their pre-training.

- **Image-Text Matching (ITM)** aims to align the image-text data. Negative training data is generated by randomly sampling, including negative sentences for each image, and negative images for each sentence.  $y$  is denoted by the ground truth label for each image-text pair  $(v, t)$ . A binary classification loss function is used for optimization:

$$\mathcal{L}_{ITM}(\theta) = -\mathbb{E}_{(v,t)} [y \log s_{\theta}(v, t) + (1 - y) \log (1 - s_{\theta}(v, t))], \quad (5)$$

where  $s_{\theta}$  is the image-text similarity score.

- **Unidirectional LM (UiDT)** Single direction history information is used for masked token prediction only, such as *left-to-right* and *right-to-left* language model objectives. Successful stories includes the ELMo [118], UNILM [119].

- **Bidirectional LM (BiDT)** Different from Unidirectional LM which predicts the masked token from a single direction only, the Bidirectional LM considers contextual information from both directions. Therefore, the contextual representations of text can be encoded more accurately. BERT [10], UNIML [119] and VLP [24] all adopt BiDT as one of their pre-training objective.

- **Sequence-to-Sequence LM (Seq2seq)** is a pre-training objective used in VLP [24], etc. It treats the inputs as different parts, each part can attend to different contexts.

- **Word-Region Alignment (WRA)** is used in UNITER [18] which target at explicitly achieves the fine-grained alignment between the multi-modal inputs via Optimal Transport (OT) [120]. Specifically, the authors learn a transport plan which is a 2D matrix to optimize the alignment and resort to the IPOT algorithm [121] for approximate OT distance estimation. Then, the authors take this distance as the WRA loss to optimize their networks.

- **Action Prediction (AP)** target at evaluating whether the agent developed for vision-language navigation (VLN) can select the right actions based on the current image and instruction [122].

- **Image-conditioned Denoising Autoencoding (IDA)** is adopted in XGPT [11] to align the underlying image-text using an attention matrix. Even without the prior length of the masked fragment, the IDA could still reconstruct the whole sentence successfully.

- **Attribute Prediction (AttP)** is used to recover the masked tokens of attribute pairs, as indicated in ERNIE-ViL [123].

- **Relation Prediction (RelP)** is used in ERNIE-ViL [123] to predict the probability for each masked relation tokens to recover the masked relationship tokens.

- **Aligned Kaleido Patch Modeling (AKPM)** is proposed for the pre-training of Kaleido-BERT [124], which contains five kaleido sub-tasks, i.e., Rotation Recognition (RR), Jigsaw Puzzle Solving (JPS), Camouflage Prediction (CP), Grey-to-Color Modeling (G2CM), and

Blank-to-Color Modeling (B2CM):

$$\begin{aligned}
\mathcal{L}_{RR} &= CE(y_r, \mathcal{F}(T, K, \theta)_{K_1\_hidden}) \\
\mathcal{L}_{JPS} &= CE(y_j, \mathcal{F}(T, K, \theta)_{K_2\_hidden}) \\
\mathcal{L}_{CP} &= CE(y_c, \mathcal{F}(T, K, \theta)_{K_3\_hidden}) \\
\mathcal{L}_{G2CM} &= \sum KLD(k_{4i}, \mathcal{F}(T, K, \theta)_{K_4\_hidden}) \\
\mathcal{L}_{B2CM} &= \sum KLD(k_{5i}, \mathcal{F}(T, K, \theta)_{K_5\_hidden})
\end{aligned} \tag{6}$$

where  $CE$  represents the cross-entropy loss function,  $y_r$  denotes the rotation angle,  $K_p$  is the hidden output patch of size  $p \times p$ ,  $KLD$  denotes the KL-divergence, and  $K_p$  are kaleido patches, among which  $k_{pi}$  is the masked out ones.

- **Object Detection (OBD)** is introduced in the [125] as a direct set prediction to enhance the pre-training. Also, the authors consider object attribute prediction to learn the fine-grained semantic information. A negative log-likelihood loss is defined for OBD as follows:

$$\begin{aligned}
\hat{\sigma} &= \arg \min_{\sigma \in \phi_N} \sum_i^N \mathcal{L}_{match}(y_i, \hat{y}_{\sigma(i)}) \\
\mathcal{L}_{OBD}(y, \hat{y}) &= \sum_{i=1}^N [-\log \hat{p}_{\hat{\sigma}(i)}(a_i) - \log \hat{p}_{\hat{\sigma}(i)}(c_i) \\
&\quad + \mathcal{L}_{box}(b_i, \hat{b}_{\hat{\sigma}(i)}(i))]
\end{aligned} \tag{7}$$

where  $y$  denotes the ground truth set of objects and  $\hat{y} = \{\hat{y}_i\}_{i=1}^N$ , the number of elements is  $N$ ,  $\sigma$  is the cost of a permutation of  $N$  elements,  $\mathcal{L}_{match}(y_i, \hat{y}_{\sigma(i)})$  denotes the pair-wise matching loss between a prediction with index  $\sigma(i)$  and ground truth  $y_i$ ,  $\hat{p}_{\hat{\sigma}(i)}(a_i), \hat{p}_{\hat{\sigma}(i)}(c_i)$  denotes the attribute and class probability,  $\mathcal{L}_{box}(b_i, \hat{b}_{\hat{\sigma}(i)}(i))$  is a normalized loss of bounding box regression.

- **Image-Text Generation (ITG)** also plays an important role in the vision-language related pre-training tasks. The aligned image and text are capable of training a model for text generation based on a given image, for example, Xu et al. train the E2E-VLP [125] with ITG objective:

$$\mathcal{L}_{ITG} = - \sum_{(x,y) \in (\mathcal{X}, \mathcal{Y})} \log \prod_{t=1}^n P(y_t | y_{<t}, x) \tag{8}$$

where  $\mathcal{X}$  represents the visual sequence with context,  $\mathcal{Y}$  denotes the generated set of text, and the length of tokens in text  $y$  is  $n$ .

- **Video-Subtitle Matching (VSM)** considers two targets for the video-text pre-training task, i.e., (i) local alignment, (ii) global alignment, as used in HERO [126]. The score functions and the corresponding loss functions are defined as follows:

$$\begin{aligned}
 S_{local}(s_q, \mathbf{v}) &= \mathbf{V}^{temp} \mathbf{q} \in \mathbb{R}^{N_v} \\
 S_{global}(s_q, \mathbf{v}) &= \max\left(\frac{\mathbf{V}^{temp} \mathbf{q}}{\|\mathbf{V}^{temp}\| \|\mathbf{q}\|}\right) \\
 \mathcal{L}_h(S_{pos}, S_{neg}) &= \max(0, \delta + S_{pos} - S_{neg}) \\
 \mathcal{L}_{local} &= -\mathbb{E}_D \log(\mathbf{p}_{st}[y_{st}] + \log(\mathbf{p}_{ed}[y_{ed}])) \\
 \mathcal{L}_{global} &= -\mathbb{E}_D [\mathcal{L}_h(S_{global}(s_q, \mathbf{v}), S_{global}(\hat{s}_q, \mathbf{v})) \\
 &\quad + \mathcal{L}_h(S_{global}(s_q, \mathbf{v}), S_{global}(s_q, \hat{\mathbf{v}}))] \\
 \mathcal{L}_{VSM} &= \lambda_1 \mathcal{L}_{local} + \lambda_2 \mathcal{L}_{global}
 \end{aligned} \tag{9}$$

where  $s_q$  denotes the sampled query from all subtitle sentences,  $\mathbf{v}$  is the whole video clip,  $\mathbf{V}^{temp} \in \mathbb{R}^{N_v \times d}$  is the final visual frame representation generated by temporal transformer,  $\mathbf{q} \in \mathbb{R}^d$  is the final query vector,  $y_{st}, y_{ed} \in \{1, \dots, N_v\}$  are the start and end index respectively,  $\mathbf{p}_{st}, \mathbf{p}_{ed} \in \mathbb{R}^{N_v}$  represent probability vectors generated from the scores,  $\mathbf{p}[y]$  indexes the  $y$ -th element of the vector  $\mathbf{p}$ ,  $\mathcal{L}_h$  denotes the combined hinge loss over positive and negative query-video pairs,  $(s_q, \mathbf{v})$  is a positive pair while  $(s_q, \hat{\mathbf{v}})$ ,  $(\hat{s}_q, \mathbf{v})$  are negative ones replaced with one other sample in  $\mathbf{v}$  and  $s_q$  respectively,  $\delta$  is the margin hyper-parameter and  $\lambda_1, \lambda_2$  are balancing factors.

- **Frame Order Modeling (FOM)** is treated as a classification problem in HERO [126], which targets reconstructing the timestamps of selected video frames. The objective of FOM is defined as follows:

$$\mathcal{L}_{FOM} = -\mathbb{E}_D \sum_{i=1}^R \log \mathbf{P}[r_i, t_i] \tag{10}$$

where the number of reordered frames is  $R$ ,  $i \in [1, R]$ ,  $t_i \in \{1, \dots, N_v\}$ ,  $r_i$  is the reorder index,  $\mathbf{P} \in \mathbb{R}^{N_v \times N_v}$  is the probability matrix.

- **Textual Aspect-Opinion Extraction (AOE)** aims to extract aspect and opinion terms from the text, as noted in [127]. To handle the lack

of label information required for supervised learning, the authors resort to other models for aspect extraction and opinion extraction. The obtained aspect and opinion terms are treated as labels for the AOE task.

- **Visual Aspect-Opinion Generation (AOG)** targets at generating the aspect-opinion pair detected from the input image [127].

- **Multimodal Sentiment Prediction (MSP)** enhance the pre-trained models by capturing the subjective information from vision-language inputs [127].

- **Modality-Level Masking (MoLM)** is used in [22] to learn the alignment among the text, vision, and audio. The authors mask out each modality independently with a certain probability.

- **Structural Knowledge Masking (SKM)** is proposed in [128] which attempts to mask the tokens selectively based on the cue provided by the knowledge entry. The masking probabilities is calculated to obtain mask indices  $M_w$  and  $M_r$  for each knowledge entry, the two items denote the words of sentences and visual regions of images need to be masked, respectively. The loss function of Structural Knowledge Masking Language Model can be formulated as:

$$\mathcal{L}_{SKMLM}(\theta) = -\mathbb{E}_{(W,R) \sim D} \log P_{\theta}(\mathcal{W}_{M_w} | \mathcal{W}_{\setminus M_w}, \mathcal{R}_{\setminus M_r}) \tag{11}$$

where  $\theta$  is the parameters.  $\mathcal{W}_{\setminus M_w}$  and  $\mathcal{R}_{\setminus M_r}$  represent the non-masked words of sequences and the remaining regions of images, respectively.

## 3.5 Pre-training Network Architecture

### 3.5.1 Self-attention and Transformer

In the large-scale pre-training era, most of current pre-trained models are inspired by the Transformer (which is mainly consisted of self-attention layers). It is originally developed for natural language processing tasks in 2017 [9] which sets new SOTA performance on many downstream tasks by a large margin. Such framework is also introduced into the computer vision community, therefore, the design of unified network architectures for various tasks and inputs is the current research hotspot.

Given the input  $\mathbf{x}$ , an attention module  $A(\mathbf{x})$  is used to generate attention weights, then, some

procedures are conducted based on input  $x$  and  $A(x)$  to get the attended input  $x' = f(A(x), x)$ . Many attention models are designed based on this idea, such as the channel attention, spatial attention, temporal attention, branch attention [129]. The self-attention scheme is a special case of attention mechanism, as shown in Fig. 6. More in detail,

$$Q, K, V = \text{Linear}(x) \quad (12)$$

$$A(x) = \text{Softmax}(QK) \quad (13)$$

$$f(A(x), x) = A(x)V \quad (14)$$

where the Linear denotes fully connected layers. On the basis of self-attention, the work mechanism of multi-head attention is the aggregation of parallel attention layers. Mathematically speaking,

$$\text{MultiHead}(Q, K, V) = [\text{head}_1, \dots, \text{head}_h]W^O \quad (15)$$

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V). \quad (16)$$

where  $[\cdot, \cdot]$  denotes the concatenate operation,  $W_i^Q, W_i^K, W_i^V$  and  $W^O$  are parameter matrices.

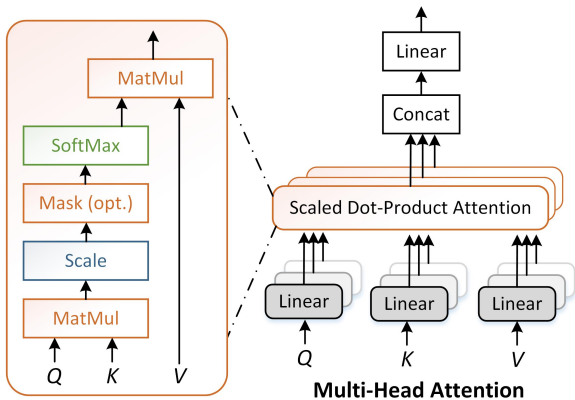


Fig. 6 An illustration of multi-head self-attention (MHSA) [9].

### 3.5.2 Single- and Multi-stream

The multi-layer transformer is widely used in many current MM-PTMs. The input of each modality is first extracted as feature embeddings by the independent encoder and then interacted with other modalities. According to the manner of multi-modal information fusion, two categories

of MM-PTMs can be concluded, i.e., single- and cross-stream. In this subsection, we will present these two architectures separately.

- **Single-stream** Multi-modal inputs such as images and text are treated equally and fused in a unified model. The uni-modal features extracted from each modality are tokenized and concatenated by the separators as the input of the multi-modal transformer for multi-modal fusion, as shown in Fig. 8(a). In the transformer, the MHSA (multi-head self-attention) mechanism is usually adopted to interactively fuse the uni-modal features, then, the multi-modal fusion features are output from the class token of the transformer. Large-scale MM-PTMs based on single-stream structure includes VL PTMs (e.g., Oscar [17] and ALBEF [130]) and vision-language-audio pre-training model OPT [22]. Single-stream pre-training models perform token-level matching based on strong semantic correlation, e.g. object features of the image are matched with semantic features of object tags. It provides realistic interaction between uni-modal features, and multi-modal fusion features contain information from different modalities with better characterization capability.

- **Cross-stream** Features of different modalities are extracted in parallel by independent models and then are aligned by self-supervised contrastive learning in cross-stream architecture. The pre-training models obtain aligned uni-modal features rather than fused multi-modal features. As shown in Fig. 8(b), multi-modal fusion features are obtained by concatenating uni-modal features and fed into a MLP (Multi-Layer Perceptron) for pre-training objective learning. Representative large-scale MM-PTMs based on cross-stream structure include BriVL [106] and CLIP [77], etc. Compared with pre-training models based on single-stream, cross-stream models align different modality features into a consistent high-dimensional feature space, such as text semantics and visual image representation. Cross-stream pre-training models generally contain the CS pre-training objective and achieve embedding-level matching based on “weak semantic correlation” [106]. The structure of cross-stream models is more flexible, and modifying the branching structure of one modality of the model does not affect other modalities, making it easy to deploy in real scenarios. However, cross-stream models extract the aligned multi-modal common features, and how to effectively

exploit the information differences and complementarity between multi-modal data is an issue to be studied.

In addition, depending on the needs of the pre-training objectives, the structure of pre-training models can be divided into with and without a decoder. If pre-training objectives contain generative tasks, such as masked image reconstruction, generating matching images based on the text description, etc., the pre-training model adds a decoder after the encoder for converting multi-modal fusion features into the corresponding output.

### 3.5.3 Modality Interactive Learning

Most of current large-scale pre-trained multi-modal models adopt concatenate, add, Merge-attention, Co-attention, and Cross-attention [132] to achieve interactive learning between modalities. An introduction to these modules are given in the following paragraphs.

- **Merge-attention:** As shown in Fig. 7 (a), a unified feature representation is obtained by concatenating the input modalities. Then, this feature is fed into the fusion network. For example, the i-Code [131] flatten the visual inputs along the temporal and spatial dimensions. Note that the parameters of this attention model is shared by these input modalities.

- **Co-attention:** For the co-attention module, as shown in Fig. 7, each input modality has its own self-attention layers for modality-specific feature embedding. Then, the multiple embeddings are fused using a cross-attention layer.

- **Cross-attention:** For the multi-modal task, the key step is how to design a fusion module to connect the multi-modality inputs effectively. For instance, the cross-attention layer is proposed by Suo et al. [132], which integrate the image and language subtly for visual question answering. Specifically, they mutually input one modality into the Q-branch of another self-attention network. Then, the output of two modalities are concatenated as one unified representation for final prediction.

- **Tangled-transformer:** The TaNged Transformer (TNT) [133] is proposed to handle the action-, regional object-, and linguistic-features, simultaneously, using three Transformer modules. As shown in Fig. 7 (d), the authors

inject one modality to the Transformer network designed for other modality to enhance the interactions.

- **Inter-Modality Contrastive Learning:**

The contrastive learning is widely used for inter-modality relation modelling, such as the CLIP [77] and its following-up works [19, 104, 134–138]. The representative work SCALE [104] is trained with Self-harmonized Inter-Modality Contrastive Learning (SIMCL), which can be written as:

$$\mathcal{L}_{CL}(d_i^{(0)}, d_i^{(1)}) = -\log \frac{\exp(\text{Sim}(f_i^{(0)}, f_i^{(1)})/\tau)}{\sum_{m=0}^1 \sum_{k=1}^N \mathbf{1}_{[k \neq i]} \exp(\text{Sim}(f_i^{(m)}, f_k^{(1-m)})/\tau)}, \quad (17)$$

where  $(d_i^{(0)}, d_i^{(1)})$  is a positive pair, and the pairing of  $d_i^{(0)}$  and other samples will bring us negative training data.  $f_i^{(0)}, f_i^{(1)}$  are feature embedding of  $(d_i^{(0)}, d_i^{(1)})$  respectively. The *Sim* denotes the cosine similarity,  $\mathbf{1}_{[k \neq i]}$  is the binary indicator function,  $\tau$  is a temperature parameter.

### 3.6 Pre-training using Knowledge

Conventional pre-trained models suffer from poor logical reasoning and lack of interpretability. To alleviate those problems, it is straightforward to involve knowledge, deep understanding of data, in pre-training models, i.e., pre-training using knowledge also known as Knowledge Enhanced Pre-Trained Models (KEPTMs) shown in Fig. 9.

**Knowledge Representation Learning** By learning to represent symbolic knowledge, usually in the form of entities and relations, knowledge representation learning enables neural network based models to fuse knowledge and improve their reasoning capabilities. Similarity-based models and graph neural network (GNN) models are two major methods of knowledge representation learning.

- **Similarity-based Models** Given similarity-based scoring functions, similarity-based models measure the similarity of latent semantics between two entities. Translation-based models are representatives of similarity-based models, as the distance in the vector space is often used to describe the similarity. TransE firstly models relations by translations, which operates on entity embeddings at low-dimension [197]. To deal with mapping properties of relations efficiently in complex models, such as reflexive, one-to-many, many-to-one and many-to-many,

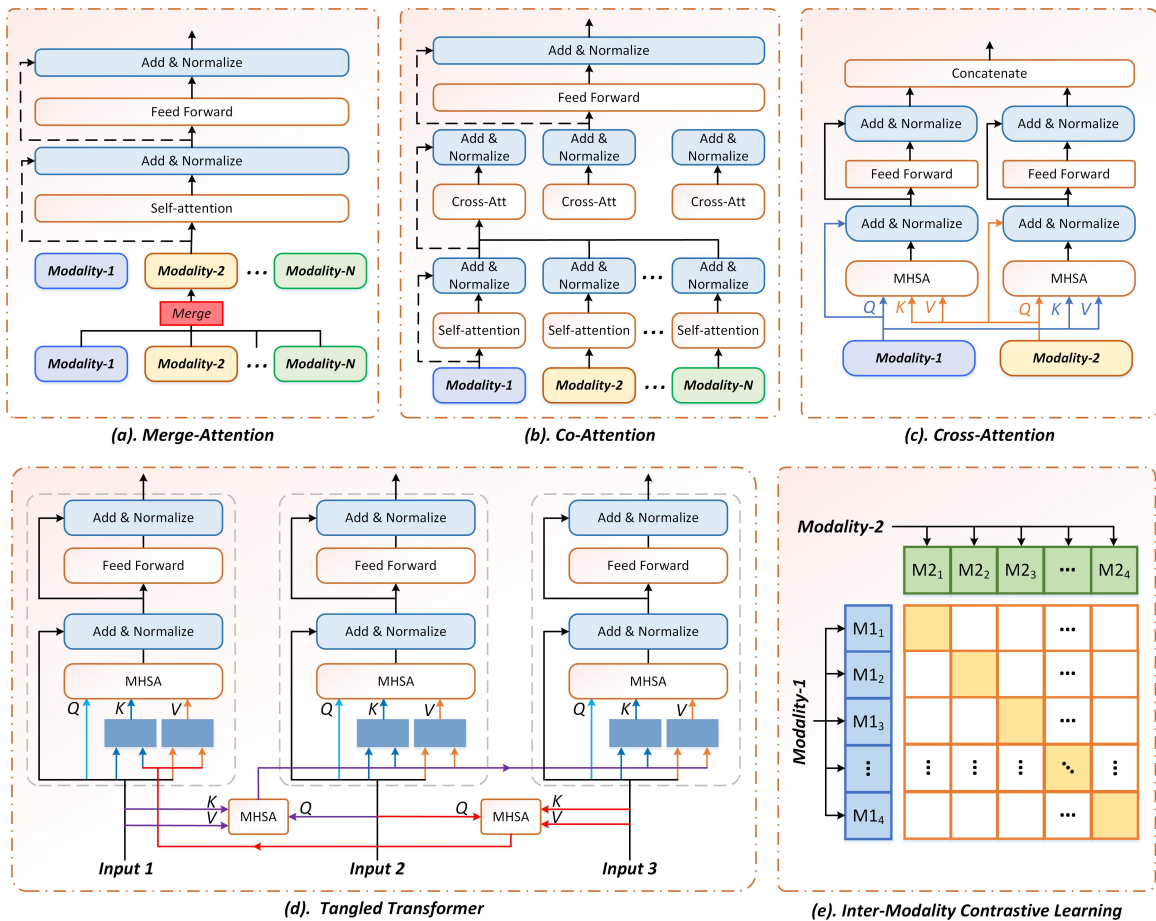
**Table 3** The summary of mainstream multi-modal pre-trained big models (Part-I).

No.	Model	Pub.	Modality	Architecture	Objective	Highlights	Parameters	Code
01	VisualBERT [139]	arXiv-2019	image-text	Trans, BERT	GR, MML	A simple and strong baseline for VLP	170M	<a href="#">URL</a>
02	ViLBERT [140]	NeurIPS-2019	image-text	Trans	CS, GR	First adopt co-attention for MM pre-training	274M	<a href="#">URL</a>
03	LXMERT [117]	EMNLP-2019	image-text	Trans	QA, MOR, MOC, MML, MLM	Propose a cross-modality encoder for vision-language pre-training	183M	<a href="#">URL</a>
04	B2T2 [141]	EMNLP-2019	image-text	ResNet, BERT	MML, GR	Embed bounding box into text transformer in a early fusion manner	-	<a href="#">URL</a>
05	Unicoder-VL [114]	AAAI-2020	image-text	Trans	GR, MML, MOC	Single transformer encoder for VLP	170M	<a href="#">URL</a>
06	VL-BERT [142]	ICLR-2019	image-text	BERT	GR, MOC	MM PTMs and faster rcnn are jointly trained	-	<a href="#">URL</a>
07	VLP [143]	AAAI-2020	image-text	Trans	BiDT, Seq2seq	Unified encoder-decoder network architecture	-	<a href="#">URL</a>
08	UNITER [18]	ECCV-2020	image-text	Trans	MRA, MML	Propose an OT-based Word-Region Alignment objective	110M	<a href="#">URL</a>
09	12-IN-1 [144]	CVPR-2020	image-text	Trans	CS, GR	Training jointly on 12 different datasets in a multi-task learning manner	270M	<a href="#">URL</a>
10	VisDial-BERT [145]	ECCV-2020	image-text	Trans	MLM, NSP, MIR	Pre-training on image-text corpus and finetuning on visual dialog	-	<a href="#">URL</a>
11	ImageBERT [87]	arXiv-2020	image-text	Trans	MOC, MLM, MML, MOR	Indicating that multi-stage pre-training works better	170M	-
12	PREVALENT [122]	CVPR-2020	image-text	Trans	MLM, AP	Pre-training for vision and language navigation	-	<a href="#">URL</a>
13	XGPT [11]	NLPCC-2021	image-text	Trans	IC, MLM, IDA, MOR	Novel IDA pre-training; Share parameters between encoder and decoder	-	-
14	InterBERT [115]	arXiv-2020	image-text	Trans	MSM, MOC, ITM-hn	Finding that all-attention works better than co-attention for modal interaction	173M	<a href="#">URL</a>
15	PixelBERT [20]	arXiv-2020	image-text	CNN, Trans	MLM, MML	First to align vision and language in pixel and text-level	142M	-
16	OSCAR [17]	ECCV-2020	image-text	Trans	CS, MLM	Align the visual patches with word embeddings by using object tags as anchor points	155M	<a href="#">URL</a>
17	pyramidCLIP [146]	arXiv-2022	image-text	CNN+Trans	CS	Hierarchical image-text contrastive learning	-	-
18	FashionBERT [147]	RDIR-2020	image-text	BERT	MLM, MOR, MML	Use image patches for fashion domain instead of Rols	-	<a href="#">URL</a>
19	VILLA [148]	NeurIPS-2020	image-text	Trans	MLM, MOR, MML	Pre-training with adversarial learning	-	<a href="#">URL</a>
20	ERNIE-ViL [123]	AAAI-2021	image-text	Trans	MOC, AttP, ReLP, MLM, MOR, MML	Use the knowledge obtained from scene graph	-	<a href="#">URL</a>
21	KVL-BERT [149]	KBS-2021	image-text	BERT	MOC, MLM	Integrate commonsense knowledge for visual commonsense reasoning	-	-
22	VinVL [113]	CVPR-2021	image-text	Trans	MTL, 3-way CS	Verifying that visual feature matters in VLP, i.e., strong object detector brings better results	157M	<a href="#">URL</a>
23	VL-T5 [150]	ICML-2021	image-text	Trans	MLM, VQA, MML, VG, GC	Unified framework for VL via generating texts	400M	<a href="#">URL</a>
24	ViLT [151]	ICML-2021	image-text	Trans	MLM, MML	Use linear embedding only for Fast VL transformer	87M	<a href="#">URL</a>
25	ALIGN [21]	ICML-2021	image-text	EfficientNet, BERT	CS	Milestone for image-text pre-training using noisy data	300M	-
26	Kaleido-BERT [124]	CVPR-2021	image-text	Trans	MLM, MML, AKPM	Use saliency detector to generate multi-grained patches	-	<a href="#">URL</a>
27	MDETR [152]	ICCV-2021	image-text	CNN+Trans	STP, MML	A text-modulated detection system which can be trained in an end to end way	-	<a href="#">URL</a>
28	SOHO [153]	CVPR-2021	image-text	CNN+Trans	MLM, MOR, MML	Use a dynamic-updated visual dictionary for vision-language alignment	-	<a href="#">URL</a>
29	E2E-VLP [125]	ACL-2021	image-text	Trans	OBD, ITG	The first PTM for vision-language understanding and generation	94M	-
30	PIM [154]	NeurIPS-2021	image-text	Trans	MLM, MML, MOR	Measure and reveal the V+L fusion using the proposed inter-modality flow metric	48M	-
31	CLIP - ViL <sub>p</sub> [137]	arXiv-2021	image-text	Trans	MLM, VQA, MML	Take the CLIP visual encoder as its visual backbone	-	<a href="#">URL</a>
32	ALBEF [130]	NeurIPS-2021	image-text	Trans	CS, GR	Design a momentum model to address noisy data	210M	<a href="#">URL</a>
33	SimVLM [116]	arXiv-2021	image-text	Trans	PrefixLM	Simple VL model using single PrefixLM pre-training objective only	-	-
34	MURAL [155]	arXiv-2021	image-text	Trans	CS	Adopt multi-task contrastive learning objective (image-text, text-text)	430M	-
35	VLMo [156]	arXiv-2021	image-text	Trans	MLM, MML, CS	Jointly learns visual-, text-encoder and a fusion encoder	-	<a href="#">URL</a>



**Table 4** The summary of mainstream multi-modal pre-trained big models (Part-II).

No.	Model	Pub.	Modality	Architecture	Objective	Highlights	Params	Code
36	METER [157]	CVPR-2022	image-text	Trans	MLM, MOR, MOC, MML	An empirical study on VLP	-	<a href="#">URL</a>
37	VideoBERT [158]	ICCV-2019	video-text	BERT	MLM	A simple model for video-text feature learning	-	<a href="#">URL</a>
38	CBT [159]	arXiv-2019	video-text	Trans	NCE	Self-supervised contrastive bidirectional Transformer	15M	-
39	UniVL [160]	arXiv-2020	video-text	Trans	MLM, MFM, MML, ITG	A unified model for multimodal understanding and generation	-	<a href="#">URL</a>
40	HERO [126]	EMNLP-2020	video-text	Trans	MLM, MFM, VSM, FOM	Hierarchical Transformer-based model trained with newly proposed VSM and FOM	-	<a href="#">URL</a>
41	MMFT-BERT [161]	EMNLP-2020	image-text	BERT	Classification	Adopt multiModal fusion Transformer for modality fusion	-	<a href="#">URL</a>
42	ActBERT [133]	CVPR-2020	image-text	Trans	CS, GR	Extract actions explicitly as one of the inputs	-	-
43	CLIP [77]	ICML-2021	image-text	Resnet, Trans	CS	Milestone for image-text pre-training using noisy data	88.6M	<a href="#">URL</a>
44	Frozen [92]	ICCV-2021	video/image-text	Trans	MML	Jointly optimize the model on both images and videos	180.4M	<a href="#">URL</a>
45	RegionLearner [162]	arXiv-2021	video-text	Trans	MML	Implicitly learning object region without position supervision	-	<a href="#">URL</a>
46	UNIMO [163]	arXiv-2020	image-text	Trans	CS	Adapt to single-, multi-modal understanding and generation tasks effectively	-	<a href="#">URL</a>
47	DALL-E [164]	ICML-2021	image-text	Trans	ELB	Achieve high quality image generation without using any of the training labels	12B	<a href="#">URL</a>
48	BriVL [106]	arXiv-2021	image-text	Trans	InfoNCE	The first Chinese large-scale MM-PTMs	10B	<a href="#">URL</a>
49	VLC [165]	arXiv-2022	image-text	ViT	MIM, MLM, ITM	Built on top of MAE that does not require trained on ImageNet	87M	<a href="#">URL</a>
50	M6 [103]	arXiv-2021	image-text	Trans	LM	The largest pretrained model in Chinese	100B	-
51	CogView [166]	NeurIPS-2021	image-text	Trans	NLL	The first open-source large text-to-image transformer	4B	<a href="#">URL</a>
52	VATT [167]	NeurIPS-2021	Video, Audio, Text	Trans	NCE, MIL-NCE	Modality-specific or Modality-agnostic triplet modality pre-trained model	306.1M	<a href="#">URL</a>
53	OPT [22]	arXiv-2021	image, Audio, Text	Trans	MLM, MVM, MoLM, MAM, DTR, DIR	The first model pre-trained using triplet modalities	-	-
54	Florence [168]	arXiv-2021	image-text	CoSwin	UniCL	Multi-dimensional expansion of representations	893M	-
55	ROSITA [128]	MM-2021	image-text	Trans	SKM, MLM, MRM	Fuse the intra-, cross-modality knowledge, and SKM	-	-
56	VLCDoC [169]	arXiv-2022	image-text	Trans	CS	Contrastive Pre-Training for document classification	-	-
57	MVP [170]	arXiv-2022	image-text	ViT	MIM	Multimodality-guided visual pre-training leads to impressive gains	-	-
58	GhBERT [171]	IR-2021	image-text	BERT	MLM, MOR	Considers both realistic and synthetic data for VLP	-	-
59	COTS [172]	arXiv-2022	image-text	Trans	CS, KLD, MVLM	Token- and task-level interaction are proposed to enhance cross-modal interaction	-	-
60	U-VisualBERT [173]	NAACL-2021	image-text	Trans, BERT	GR, MML	Unpaired image-text data for pre-training	-	<a href="#">URL</a>
61	Flamingo [174]	arXiv-2022	image-text	NFNet	CS	Pre-training on interleaved visual and text data as input	80B	<a href="#">URL</a>
62	M3P [175]	CVPR-2021	image-text	BERT	xMLM, MC-MLM, MC-MRM	Multitask, Multilingual, Multimodal Pre-training	-	<a href="#">URL</a>
63	BLIP [176]	arXiv-2022	image-text	BERT	CS, MML, MLM	Propose the multimodal mixture of encoder-decoder, and captioning-filtering scheme	224M	<a href="#">URL</a>
64	NUWA [177]	arXiv-2021	image-text	Trans	T2I, T2V, V2V	A 3D transformer framework can handle image, text, and video, simultaneously	809M	<a href="#">URL</a>
65	TCL [178]	CVPR-2022	image-text	BERT	CMA, IMC, LMI, ITM, MLM	The first work considers local structure information for multi-modality representation learning	123.7M	<a href="#">URL</a>
66	SCALE [179]	CVPR-2022	image, text, table, video, audio	BERT	MRP, MLM, MEM, MFP, MFM, MAM	A unified model to handle five modalities	-	<a href="#">URL</a>
67	Clinical-BERT [180]	AAAI-2022	image-text	BERT	CD, MMM, MLM, IMM	The first work to learn domain knowledge during pre-training for the medical domain	102M	-
68	RegionCLIP [181]	CVPR-2022	image-text	Trans	Distillation loss, CS	Learn region-level visual representations based on CLIP	-	<a href="#">URL</a>
69	ProbES [182]	ACL-2022	image-text	LSTM, ViLBERT	Ranking loss	Prompt-based learning for VLN based on CLIP	-	<a href="#">URL</a>
70	GLIP [183]	CVPR-2022	image-text	BERT	CS	Unifying the object detection and grounding into a unified framework	394M	<a href="#">URL</a>



**Fig. 7** The widely used modality interactive learning modules for MM-PTMs. (a) Merge-attention [131], (b) Co-attention [131], (c) Cross-attention [132], (d) Tangled-transformer [133], and (e) Contrastive learning [77].

TransH is proposed to model a relation as a translation operation on a hyperplane [198]. TransR is proposed to embed entity and relation in a separated spaces to capture different aspects of entities over various relations [199]. Compared with TransR, not only the diversity of relations but also entities are considered in TransD [200]. To deal with heterogeneity and imbalance issues brought by knowledge graphs but ignored by aforementioned translation-based models, transfer matrices are replaced with adaptive sparse matrices in TranSparse, because the number of entities linked by relations determines sparse degrees [201]. Besides translation-based models, tensor or matrix factorization approaches have also been proposed for multi-relational data by introducing scoring or ranking functions to measure how likely the semantic matching is correct. With the latent components, RESCAL is capable

of collective learning and can provide an efficient algorithm of the factorization of a three-way tensor [202]. NTN introduces an expressive neural tensor network for reasoning over relationships between two entities [203]. DistMult presents a general framework for multi-relational learning and shows the effectiveness of a simple bilinear formulation [204]. SME designs a new neural network architecture to encode multi-relational graphs or tensors into a flexible continuous vector space, so that multi-relational semantics can be learnt [205]. HoLE is proposed to learn compositional vector space representations of entire knowledge graphs by employing holographic models of associative memory and circular correlation to create compositional representations [206].

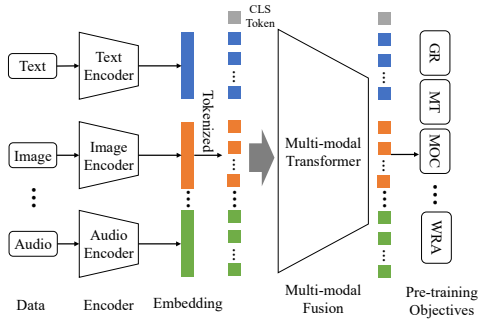
- **Graph Neural Network Models** To further leverage the structure of the graph rather than collections of triplets, graph neural network

**Table 5** The summary of mainstream multi-modal pre-trained big models (Part-III).

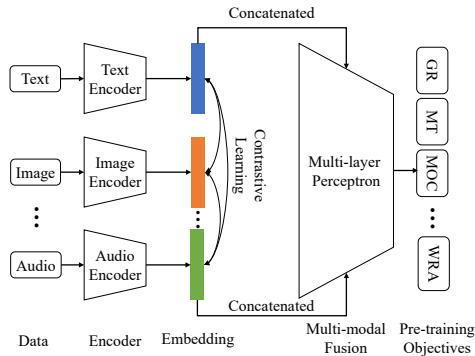
No.	Model	Pub.	Modality	Architecture	Objective	Highlights	Parameters	Code
71	VLP-MABSA [127]	ACL-2022	image-text	BERT	MLM, AOE, MRM AOG, MSP	Task-specific VL-PTMs for multimodal aspect-based sentiment analysis	-	<a href="#">URL</a>
72	R2D2 [184]	arXiv-2022	image-text	ViT, BERT	GCPR, FGR, MLM	A two-way distillation strategy is proposed, i.e., target- and feature-guided distillation	-	-
73	DeCLIP [19]	ICLR-2022	image-text	ViT	InfoNCE, SS MVS, NNS	Learn generic visual features in a data efficient way	276M	<a href="#">URL</a>
74	DeFILIP [136]	arXiv-2022	image-text	ViT, ResNet	CS	A benchmark for CLIP and its variants	-	<a href="#">URL</a>
75	SLIP [185]	arXiv-2021	image-text	ViT	CS, InfoNCE	Combine the self-supervised learning and CLIP pre-training in a multi-task framework	38M	<a href="#">URL</a>
76	FILIP [186]	arXiv-2021	image-text	ViT	CS	Cross-modal interactive learning for finer-level alignment	-	-
77	SemVLP [187]	arXiv-2021	image-text	Trans	MLM, MOP, ITM, QA	Fuse the single- and two-stream architectures	2.1B	-
78	CoCa [188]	arXiv-2022	image-text	Trans	CS, ITG	Jointly pre-train image text model with contrastive loss and captioning loss	-	-
79	HiVLP [189]	arXiv-2022	image-text	Trans	LRM, HRL, VLM	Accelerate image-text retrieval via hierarchical retrieval	-	-
80	CLIP-Event [135]	CVPR-2022	image-text	Trans	CS	Consider event structural knowledge and prompts in the pre-training phase.	-	<a href="#">URL</a>
81	AudioCLIP [190]	ICASSP-2022	image-text-audio	Trans	CS	Build a triplet modality based PTMs like CLIP	30M	<a href="#">URL</a>
82	VL-BEiT [191]	arXiv-2022	image-text	Trans	MLM, MIM, MVLM	Share the Transformer network on both monomodal- and multimodal-data	-	<a href="#">URL</a>
83	MV-GPT [192]	arXiv-2022	image-text	BERT	MLM, LG	Pre-train both a multi-modal video encoder and a sentence decoder jointly.	117M	-
84	MMKD [193]	arXiv-2022	image-text	BERT	ITM	Iteratively execute knowledge discovery and model pre-training for continuous learning	-	-
85	GLIPv2 [194]	arXiv-2022	image-text	Swin, BERT	PGL, CS, MLM	Serves both the localization and understanding tasks.	-	<a href="#">URL</a>
86	LIMoE [195]	arXiv-2022	image-text	Trans	CS	multi-modal pre-training with a sparse mixture of experts model	675M	-
87	VLMixer [196]	arXiv-2022	image-text	Trans	MLM, CMCL, MTM	Implicit cross-modal alignment learning in unpaired VLP.	-	<a href="#">URL</a>
88	ProtoCLIP [138]	arXiv-2022	image-text	Trans	CS	Combine the CLIP loss and prototypical supervisions for VLP.	-	<a href="#">URL</a>
89	i-Code [131]	arXiv-2022	image-text-audio	Trans	MLM, MVM MSM, CS	It can handle different combinations of modalities (such as single-, dual-, and triple-modality) into a single representation space.	906M	-

models are employed to embed entities and relations. As convolutional neural networks (CNNs) are extremely efficient architectures in recognition tasks over different domains, they are generalized to graphs based on hierarchical clustering of the domain and the spectrum of the graph Laplacian in [207]. Inspired by the pioneering work, further efforts have been done on graph convolutional networks (GCNs), such as semi-supervised classification [208], unsupervised learning based on the variational auto-encoder (VAE) [209], inductive representation learning to sample and aggregate features from a node’s local neighborhood [210], and attention mechanism by leveraging masked

self-attentional layers [211]. Beyond GCNs, R-GCNs is developed to deal with the highly multi-relation data characteristic of realistic knowledge bases [212]. A structure-aware convolutional network (SACN) takes the benefit of GCN and ConvE [213] together, where GCN as the encoder utilizes knowledge graph node structure and ConvE as the decoder enables the translational feature [214]. To further enhance Graph Attention Networks (GATs) and capture both entity and relation features within any entity’s neighborhood, another model is proposed for attention-based feature embedding [215]. To leverage various composition operations for embedding entities



(a) Architecture of single-stream pre-training multi-modal model



(b) Architecture of Cross-stream pre-training multi-modal model

**Fig. 8** Pre-training network architecture.

and relations in KGs and ever-increasing number of relations, a composition-based GCN named CompGCN is proposed to embed both nodes and relations jointly [216].

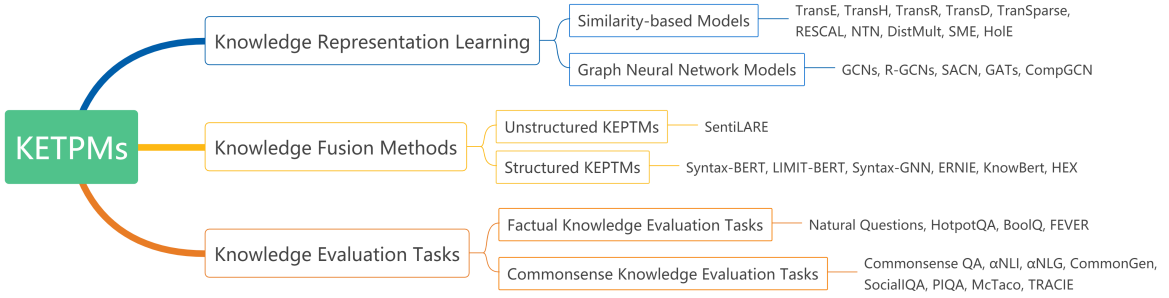
**Knowledge Fusion Methods** How to fuse knowledge into pre-trained models and improve their logical understanding of data after knowledge representation learning remains a challenge to researchers. According to the category of knowledge provided, KEPTMs roughly contain two categories: unstructured knowledge and structured knowledge enhanced pre-trained models.

- **Unstructured KEPTMs** Unstructured knowledge often refers to the knowledge without structures involved, which is in the form of plain text, like the words or phrases. Although some literatures introduce entities as supervised data and achieve promising performance, structural information is ignored while only entities are used to enable PTMs to learn semantics or

attain extra key features from them. Word-aligned attention aligns the character-level attention to the word level to exploit explicit word information in Chinese [217]. SentiLARE also introduces part-of-speech tag and sentiment polarity to build word-level linguistic knowledge [218]. As unstructured text trained neural language models can store knowledge implicitly, PTMs can be further fine-tuned to explicitly retrieve knowledge without access to external knowledge or context [219].

- **Structured KEPTMs** Contrary to unstructured KEPTMs, structured KEPTMs take account of sorts of structural information, including syntax-tree, rules and knowledge graphs. Syntax-BERT incorporates syntax trees effectively and efficiently into pre-trained Transformers [220]. LIMIT-BERT learns language representations across multiple linguistics tasks including constituent and dependency syntactic parsing [221]. Syntax-GNN is proposed to learn syntax representations by using dependency trees and fusing the embeddings into transformers [220]. Knowledge graphs (KGs) provide structural knowledge in the form of entities and relations between them. An enhanced language representation model ERNIE is trained by utilizing both large-scale textual corpora and knowledge graphs, so that it can simultaneously leverage lexical, syntactic and knowledge [222]. Similar work named KnowBert is also proposed for large-scale models to embed multiple knowledge bases with entity linkers, which retrieves relevant entity embeddings and updates contextual word representations by the word-to-entity attention [223]. Moreover, the reasoning capability is also developed by finding supporting-facts, based on a large external knowledge base [224, 225]. Rules, in the form of constraints or even logical expressions, are preferred due to their interpretability and accountability. HEX graphs are proposed to enhance existing models by capturing semantic relations between labels applied to the same object [226].

**Knowledge Evaluation Tasks** Besides conventional performance metrics, more knowledge-oriented tasks are required to evaluate the capability of KEPTMs and inspect whether external knowledge really helps models understand data semantically. Knowledge evaluation tasks are severed as testbeds to ensure the effectiveness of knowledge fusion methods. Currently, knowledge



**Fig. 9** The taxonomy of Knowledge Enhanced Pre-Trained Models (KEPTMs).

evaluation tasks mainly focus on NLP tasks and can be categorized into two groups based on the types of required knowledge: factual knowledge and commonsense knowledge evaluation tasks.

- **Factual Knowledge Evaluation Tasks**

Factual knowledge is the knowledge of facts, including specific details and elements to describe the objective facts [28]. Factual knowledge evaluation tasks focus on testing models’ reasoning ability on factual knowledge over various domains, like answering questions by giving a fact or judging the correctness of a given fact. Natural Questions is the first large publicly available dataset and robust metrics are also introduced to evaluate the performance of question answering (QA) systems [227]. HotpotQA, another QA dataset, provides supporting facts at sentence-level for reasoning and new factoid comparison questions [228]. Different from the above two open-domain QA tasks, BoolQ only involves yes/no naturally occurring questions, namely verifying facts generated in unprompted and unconstrained settings, but those queries involve with complicated and non-factoid information so that make it unexpectedly challenging [229]. Another fact extraction and verification task FEVER is proposed and a new type of claims NotEnoughInfo is introduced beside Supported and Refuted [230]. Entity linking, linking entities from a knowledge base to the corresponding textual mentions in a corpus, can also evaluate how well a model understands the factual knowledge [231].

- **Commonsense Knowledge Evaluation Tasks**

Commonsense knowledge refers to the information generally accepted by the majority of people concerning everyday life, i.e. the practical knowledge about how the world works [29]. Like

factual knowledge evaluation tasks, Commonsense QA also focuses on QA, but such QA requires prior knowledge outside the given document or context [232]. To extend the QA task Abductive Natural Language Inference ( $\alpha$ NLI), Abductive Natural Language Generation ( $\alpha$ NLG), a conditional generation task, is also proposed to explain given observations in natural language [233]. CommonGen further explicitly tests models for the ability of generative commonsense reasoning due to its rigorous requirements on both relation reasoning and compositional generalization [234]. Besides general commonsense evaluation tasks evaluating how well models understand daily scenarios, specific commonsense knowledge ones are further designed for different scenarios. SocialIQA, a large-scale benchmark for social commonsense reasoning, is challenging even for PTMs [235]. Beside human interactions, physical interactions are also important in commonsense knowledge, hence the task of PIQA is introduced for physical commonsense reasoning [236]. Temporal commonsense is crucial for understanding the timing of events, for example duration, frequency, and order, leading to correct reasoning. McTaco defines five classes of temporal commonsense [237], while TRACIE evaluates models’ temporal understanding of implicit events [238].

### 3.7 Characteristics of Different Pre-trained Big Models

In the aforementioned paragraphs, we give a review to the main streams of multi-modal pre-trained models and highlight the features of each model in Table 3, Table 4, and Table 5. In this subsection, we compare and analyze the characteristics of these models. Specifically, the early

multi-modal pre-trained big models usually design an interactive learning module, for example, the ViLBERT [140], LXMERT [117]. They integrate the co-attention or cross-attention mechanism into their framework to boost the feature representation between multiple inputs. Actually, these models obey the idea of interactive fusion of traditional small models. This allows for seamless integration with numerous downstream tasks and providing a high degree of flexibility. In contrast, many current big models directly process the inputs using projection layers and feed them into a unified network like the Transformers, including Unicoder-VL [114], VideoBERT [158], UniVL [160]. More and more works demonstrate that the powerful Transformer network can achieve comparable or even better performance.

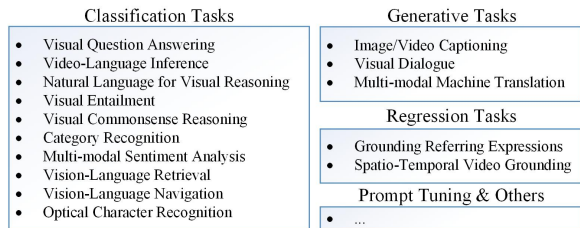
There are also some works make full use of existing big models and carry out secondary development to achieve a higher performance [181, 190]. To address the issues caused by shortage of paired multi-modal data, some researchers propose to training their model using unpaired data [173]. These models show the great potential of processing massive multi-modal data. Unlike general big models, some models are specifically designed for a specific task or domain, like the e-commerce, or Indoor navigation. This provides conditions and convenience for fully mining more detailed domain knowledge assist the pre-training process.

## 4 Downstream Tasks

After the pre-training phase, the researchers usually test their model on many downstream tasks to validate the powerful ability. Specifically, the generative tasks, classification tasks, regression tasks are adopted for the validation which will be discussed below. As a new learning paradigm, the prompt learning which target at modifying the downstream tasks to fit the pre-trained big model draws more and more attention. In this part, several representative prompt learning algorithms are also reviewed. An overview of these downstream tasks are visualized in Fig. 10.

### 4.1 Generative Tasks

**Image/Video Captioning** attempt to describe content of input image or video using a couple of sentences. Usually, a visual encoder is used to



**Fig. 10** An overview of downstream tasks reviewed in this paper.

encode the input image/video, then, a language decoder is adopted for sentence prediction in a word by word manner. NoCaps [239] is proposed by Agrawal et al. in 2019. It is also an image captioning task but focus on developing generalized captioning models.

**Visual Dialogue (VD)** attempt to let the AI agent to talk with humans by holding a meaningful dialog about the visual content [240].

**Multi-modal Machine Translation (MMT)** is a task that targets translating the source sentence into a different language based on the paired image [241].

### 4.2 Classification Tasks

**Visual Question Answering (VQA)** model is provided with an image and a question, and asked to produce an answer [242]. The relations between GQA [86] and VQA is similar to the NoCaps and the standard captioning task. It is introduced to address key drawbacks of previous VQA datasets, and generate novel and diverse questions from a robust question engine, which sufficiently considers the content and structure.

**Video-Language Inference (VLI)** is proposed by Liu et al. [243] in year 2020, which aims at understanding the video and text multimodal data.

**Natural Language for Visual Reasoning (NLVR)** can be seen as a binary classification problem. As noted in [244], the model needs to judge the authenticity of a statement for the image.

**Visual Entailment (VE)** [245] is a triplet-label classification problem derived from Text Entailment (TE) task [246]. The VE model needs to predict whether the given image semantically entails the text. The three labels are *entailment*, *neutral* or *contradiction*.

**Visual Commonsense Reasoning (VCR)** [247] is a variation of VQA, which require a machine to provide a rationale justification and answer correctly for the given challenging problem.

**Category Recognition (CR)** is a classification problem which attempt to predict the category of given image. Many computer vision tasks are belong to this downstream task, such as pedestrian attribute recognition [248], action recognition [134].

**Multi-modal Sentiment Analysis (MSA)** is a multi-modal fusion task proposed for sentiment analysis [249], which attempt to aggregate various homogeneous and/or heterogeneous modalities for more accurate reason. The modalities can be text, visual and acoustic, etc.

**Vision-Language Retrieval (VLR)** can be used in many applications, such as text-based person search [250], or general object retrieval based on language [251].

**Vision-Language Navigation (VLN)** [252, 253] is task that the agents learn to navigate in 3D indoor environments following the given natural language instruction. A benchmark for the popular VLN can be found at the following [leaderboard](#).

**Optical Character Recognition (OCR)** target at convert the images of Diverse text information into machine-encoded text. Usually, the OCR system contains both text detection and text recognition modules.

### 4.3 Regression Tasks

**Grounding Referring Expressions (GRE)** takes the visual image and language description as input, and output the location of target object described by the language [254–256]. Similar tasks defined on videos are termed **Spatio-Temporal Video Grounding (STVG)** [257] or **Tracking by Natural Language** [258–260].

### 4.4 Prompt Learning

To make full use of pre-trained big models, the prompt learning (also called prompt tuning) is proposed to re-formulate the downstream tasks to fit the objectives of pre-trained models, including CPT [261], CPL [262]. Also, some prompt tuning schemes are designed to fix the parameters of

the large model and adjust the parameters as little as possible to achieve good results, such as the VPT [263], CoOp [264], CoCoOp [265]. To be specific, the VPT [263] fixes the parameters of ViT models and integrates the prompt vectors as additional input. It achieves good performance even only tune the parameters of classification head and prompts. CoOp [264] achieves huge improvements by tuning the context words into a set of learnable prompt vectors. Conditional Context Optimization (CoCoOp) [265] is developed based on CoOp which learns an external network to generate input-conditional tokens for each image. It addresses the issue of class shift significantly using such dynamic prompts.

## 5 Experimental Analysis

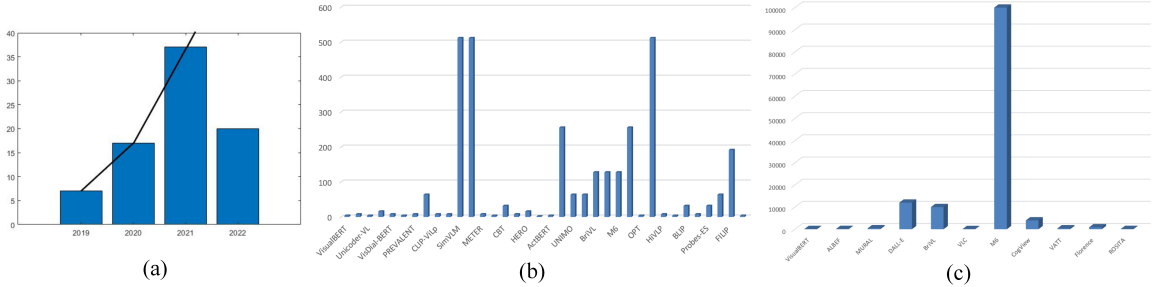
Considering the complexity and numbers of MM-PTMs, it is almost impossible to reproduce pre-training tasks in a short amount of time. Therefore, the experiments and related analyses of the pre-training are ignored in this paper. However, we still want to summarize a more complete review paper for the readers, thus, we extract the experimental results of the corresponding downstream tasks from their paper and compare them to the shared benchmark datasets. More detailed results can be found in Table 3 and Table 4.

### 5.1 Model Parameters and Training Information

As shown in Fig. 11 (a), the large-scale MM-PTMs are emerging in the year 2019 and the number of papers shows an increasing trend year by year <sup>5</sup>. From the Fig. 11 (b), it is easy to find that current large-scale PTMs are optimized on servers with more than 8 GPUs. Also, many of them are trained using more than 100 GPUs, such as BriVL (128) [106], VLC (128) [165], M6 (128) [103], SimVLM (512) [116], MURAL (512) [155], CLIP (256) [19], VATT (256) [167], Florence (512) [168], FILIP (192) [186]. Some MM-PTMs are trained on TPUs with massive chips, for example, the largest model of Flamingo [174] is trained for 15 days on 1536 chips. From all these cases, we can see the

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<sup>5</sup>Note that only half a year’s results (the year 2022, from January to June) have been counted.



**Fig. 11** (a). Number of MM-PTMs papers published from year 2019 to 2022; (b). Number of GPUs used for pre-training of selected models; (c). Parameters of selected MM-PTMs.

huge demand of computing power for pre-trained big MM-PTMs.

Based on Fig. 11 (c), it is also easy to find that many large-scale MM-PTMs are still with limited parameters, but some of them indeed reached new heights. For example, the DALLE-E [164] (12000 MB), BriVL [106] (10000 MB), M6 [103] (100000 MB), and CogView [166] (4000 MB). The reasons for this phenomenon may be as follows: 1). Many MM-PTMs are trained on several public datasets. The scale of parameters is greatly improved compared to traditional models, but not by a shocking amount. 2). The development of big models is also limited by the need for large-scale computing power, and only a few giant companies or research institutes have such computing power platforms.

## 5.2 Performance on Representative Downstream Tasks

Here, we report the experimental results of zero-shot image retrieval, image captioning, and visual question answering. From Fig. 12 (a), we can find that the performance of different MM-PTMs have a big difference on the zero-shot image retrieval task. The blue and red vertical bar denotes the results of Rank-1 and Rank-5, respectively. Some models achieve high performance on this task which demonstrates the effectiveness of large-scale pre-training. For example, the ALBEF [130] and METER [157] achieves 82.80, 96.30 and 79.60, 94.96 on both evaluation metric.

For the image captioning task, we can find that the compared models achieved close performance on the COCO dataset according to Fig. 12 (b). Specifically, OSCAR [17] obtains 41.7, 30.6, 140, 24.5; VinVL attains [113] 41, 31.1, 140.9,

25.2; SimVLM achieves [116] 40.6, 33.7, 143.3, 25.4, respectively. These results are significantly better than traditional image captioning models pre-trained in a supervised manner through ImageNet [2] classification task. Similar results can also be concluded from Fig. 12 (c).

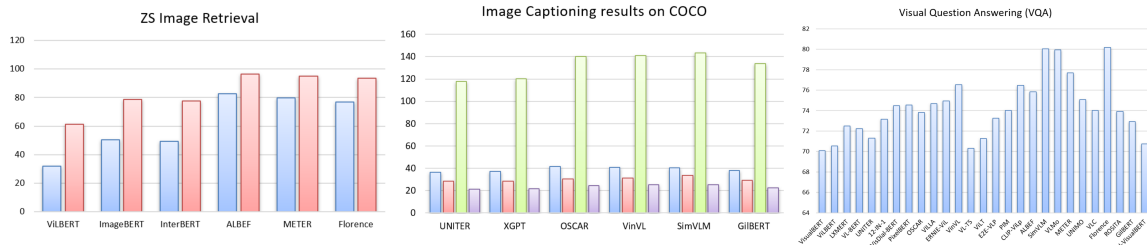
## 6 Research Directions

Although the multi-modal pre-trained big models have obtained huge development, however, it is still a young research direction. Many problems and opportunities are still waiting for researchers to solve. In this section, we summarize several research points which are worthy to be tried.

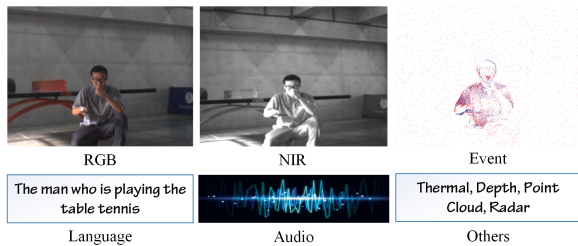
- **Pre-training on More Modalities:** Existing large-scale PTMs are usually pre-trained on two modalities, e.g., the vision and language. The missing of large amount aligned multi-modal data may be a key reason. As an old saying goes, “Sharpening your axe will not delay your job of chopping wood”. The acquirement of real multi-modal data is the most important thing for large-scale pre-training, as shown in Fig. 13, such as visual image, text, audio, radar, event streams, depth image, thermal image, etc. To the best of our knowledge, no imaging device can capture so many modalities at the same time. Therefore, the manufacture of multi-modal imaging equipment can be a very significant thing. The pre-trained big model based on these data may have a wider potential for applications.

- **Incremental Learning based Pre-training:** Currently, existing pre-trained big methods are used for downstream tasks through feature finetuning or prompt learning [266]. This standard deep learning procedure works well in a





**Fig. 12** Experimental results of selected MM-PTMs on zero-shot image retrieval (Rank-1, Rank-5), image captioning (BLEU, METEOR, CIDEr, SPICE), and visual question answering (Test-std).



**Fig. 13** Representative samples of mainstream modalities frequently used.

short time, but pre-training is an expensive process. Specifically, the collection and cleaning of data, the electric charge used for pre-training, and the hardware device all cost a huge amount of human and material resources. When we gathered another group of data, the pre-training on the mixed data are expensive, redundant, and not environmentally friendly. However, seldom of them consider incremental learning for big models, and it is still unclear if the incremental learning algorithms developed for traditional deep learning work well for big models.

In addition to the aforementioned data incremental learning, there are still many aspects that can be exploited for multi-modal pre-trained big modals. For example, the class (or category) incremental learning is a classical machine learning problem. Another interesting problem is modality-incremental learning, in another word, how to introduce and absorb the new modality into the already pre-trained multi-modal model. Because the new sensors (modalities) will appear at some indefinite time in the future, the designed multi-modal big models should be flexible enough to handle this situation.

• **Knowledge Enhanced Multi-Modal Pre-training:** Based on aforementioned reviews on MM-PTMs, we can find that the study of

knowledge-assisted pre-training is still in the starting stage. Current works simply adopt external knowledge-graph or knowledge base in the pre-training phase, but they are usually single-modal, independent of multi-modal data, and limited to improving the understanding of data for models. Although commonsense knowledge is more ubiquitous, it is also abstract and introduces ambiguities, leading to challenges when applying to specific data. Therefore, we believe that further explorations on knowledge enhanced multi-modal pre-training are worth investigating. First, specified knowledge for multi-modal data is demanded to collect or extract through self-supervised learning. Second, more general knowledge fusion methods designed for multi-modal data are needed, beyond the limitations of vision and language modalities. Third, knowledge evaluation tasks specific for pre-training are required to inspect the enhancement of knowledge at this early stage, because pre-training is the first phase of the entire training procedure while downstream tasks are to be determined.

• **Fine-grained Multi-Modal Pre-training:** Most existing MM-PTMs are pre-trained from a global-view, for example, the researchers adopt the matching between the whole image and language as a supervised signal for the pre-training. The representative works are CLIP [77], ALIGN [21], etc. Note that, the fine-grained local information mining or instance-level pre-training may further improve the overall performance of multi-modal pre-training. Some researchers have exploited the possibilities of fine-grained pre-training strategies [98]. We hope more researchers can focus on this direction to further boost the final results.

• **Multi-Modal Pre-trained Model based Prompt Learning:** Current pre-trained big models are usually used in a “pretrain-finetuning”

way, specifically, the users need to initialize their model using pre-trained weights, then, finetune on downstream tasks. Although it works well in many tasks, however, the finetune maybe not be the most direct way. Because current multi-modal big models are pre-trained via modality matching, masked token prediction, and the downstream tasks are usually classification and regression tasks. Therefore, it exists a gap between multi-modal pre-training and finetuning. Recently, a new framework (termed prompt learning) is developed for big model based downstream tasks, which slickly transforms the setting of downstream tasks to make them consistent with pre-training [266]. Many works have demonstrated its effectiveness [76, 135, 261, 264, 265] in CV and NLP tasks. The research in this direction is also interesting and has great potential.

- **Migration of techniques developed for small-scale models:** The small-scale multi-modal models have been exploited for many years, and many representative models are proposed for deep multi-modal tasks [267–269]. Among these works, diffusion, cross-attention, and dynamic neural networks are useful for specific multi-modal tasks. Part of these techniques is exploited in VL-PTMs, such as the cross-attention based ViL-BERT [140]. There are still many algorithms or tricks that have not yet been explored on large model tasks. We believe the transfer from small-scale to large-scale PTMs is worthy to be studied.

- **Coupling and decoupling problems in cross-modal pre-training models:** The coupling involves establishing the correlation between different modalities and the “cross” can be only realized through such correlation. The decoupling can further expand the modality dynamically. It is worth studying how to give feasible solutions to the two problems from the aspect of framework design.

## 7 Conclusion

We give a comprehensive review of large-scale Multi-Modal Pre-Trained Models (MM-PTMs) in this paper. Firstly, we introduce the background of MM-PTMs, with a focus on conventional deep learning, and pre-training in NLP, CV, and speech. Then, the task definition, key challenges, and benefits of MM-PTMs are discussed. After that, we dive into the reviews of MM-PTMs

and discuss the pre-training data, objectives, networks, knowledge enhanced pre-training, etc. We review the downstream tasks including generative, classification, and regression tasks, and also give an overview of model parameters of MM-PTMs and hardware for the pre-training. Experimental results of several representative tasks are also discussed and visualized. Finally, we point out some research directions that are worth to be focused on. We summarize this paper and hope our survey can provide some useful insights for the MM-PTMs.

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