A Survey of Human-object Interaction Detection with Deep Learning

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***Abstract*—Human-object interaction (HOI) detection has attracted significant attention due to its wide applications, including human-robot interactions, security monitoring, automatic sports commentary, etc. HOI detection aims to detect humans, objects, and their interactions in a given image or video, so it needs a higher-level semantic understanding of the image than regular object recognition or detection tasks. It is also more challenging technically because of some unique difficulties, such as multi-object interactions, long-tail distribution of interaction categories, etc. Currently, deep learning methods have achieved great performance in HOI detection, but there are few reviews describing the recent advance of deep learning-based HOI detection. Moreover, the current stage-based category of HOI detection methods is causing confusion in community discussion and beginner learning. To fill this gap, this paper summarizes, categorizes, and compares methods using deep learning for HOI detection over the last nine years. Firstly, we summarize the pipeline of HOI detection methods. Then, we divide existing methods into three categories (two-stage, one-stage, and transformer-based), distinguish them in formulas and schematics, and qualitatively compare their advantages and disadvantages. After that, we review each category of methods in detail, focusing on HOI detection methods for images. Moreover, we explore the development process of using foundation models for HOI detection. We also quantitatively compare the performance of existing methods on public HOI datasets. At last, we point out the future research direction of HOI detection.**

***Index Terms*—Deep learning, visual relationship detection, human-object interaction, foundation models, attention mechanism, GNN, transformer.**

I. Introduction

DEEP learning methods have achieved brilliant achievements in object recognition [1, 2] and detection [3, 4], which greatly reduce manual labor in processing mass visual information. Object recognition aims to answer "What is in the image?" while object detection aims to answer "What and where is in the image?" However, an expected intelligent machine should have a complete semantics understanding of a scene. Towards this goal, human-object interaction (HOI) detection is proposed to answer "What are the people doing with what objects?". Fig. 1 gives two examples to show the different goals between object recognition, object detection, and HOI detection. From which we can see, HOI detection can provide more human-centered information at the semantics level. Therefore, HOI detection has plenty of application potential in human-robot interactions [5, 6], security monitoring [7, 8], automatic sports commentary [9, 10], action simulation [11, 12], recognition [13, 14], etc. At the same time, HOI detection plays a crucial role in the embodied artificial intelligence (AI) system [15, 16], which thinks that human intelligence needs to be formed through interaction and iteration with actual scenes.

Object recognition	Woman + Donut	Humans + Soccer
Object detection	Woman + Center Donut + Lower Center	Boy + Center , Girl + Center Left ... Soccer + Lower Center
HOI detection	Woman + Center + Eat + Donut + Lower Center	Boy + Center + Kick + Soccer + Lower Center

Fig. 1. Comparison between object recognition, object detection, and HOI detection.

However, HOI is a challenging visual task since it not only suffers from the common difficulties of machine vision. It also has to face some unique challenges:

(1) Multi-object interactions. In a complex interaction scene, there may be multiple people performing interactions at the same time, one person interacting with multiple objects, and one object interacting with multiple people, such as a crowded party that involves various objects and interactions. Even if all objects and humans could be detected, assembling them into reasonable HOI triplets is still challenging. Some work [17–20] focuses on solving this issue.

(2) Long-tail distribution of interaction categories. Sample imbalance is particularly serious in HOI datasets. In some datasets, the number of instance samples between different categories is unbalanced. Specifically, the number of common interaction samples can be tens or even hundreds of times that

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of uncommon interactions. This leads to the unreliable accuracy of the model after training due to overfitting, underfitting, and other problems. Some work [21–25] is trying to solve this problem by zero-shot and few-shot learning.

(3) Visual distraction under real-world settings. Visual distraction is serious in HOI detection. In order to detect HOI, the model must identify objects. However, there are many interference factors in the natural environment, including occlusion, deformation, lighting changes, background clutter, shooting perspective, etc. This makes HOI detection challenging.

Before reviewing the literature, we first present the purpose of HOI detection. HOI detection aims to detect humans, objects, and interactions (verbs) between each human-object pair in a given image or video. Technically, an HOI instance is generally represented by a ⟨human, verb, object⟩ triplet and denoted by $\langle \boldsymbol{h}, \boldsymbol{v}, \boldsymbol{o} \rangle$. Solving HOI detection consists of three sub-problems. Firstly, detecting an object instance $\boldsymbol{o}$, which needs to indicate its location in the image (bounding box) b_o and its category c_o, i.e., $\boldsymbol{o} = \langle b_o, c_o \rangle$. Similarly, the second is detecting a human instance $\boldsymbol{h} = \langle b_h, c_h \rangle$. The third is predicting the action verb $\boldsymbol{v}$, which is a classification problem. Considering the details of each sub-problem, some papers also present an HOI instance by a quintuple $\langle b_h, c_h, b_o, c_o, \boldsymbol{v} \rangle$, but they are essentially the same.

Different work organizes and solves these three sub-problems in different frameworks. Some papers naturally regard HOI detection as three divided sub-problems and solve them in two subsequent stages [26–32]. In the first stage, they detect the object and human instances by an off-the-shelf detector. In the second stage, they generate the HOI hypothesis for all the human-object pairs. Some papers [33–36] solve HOI detection in one stage by using point or union-box to represent humans, objects, and the interactions between them. Some papers [37–42] treat HOI detection as a set prediction problem, then directly match the predicted and ground-truth HOI triples based on the transformer structure.

Based on these differences, most existing research papers classify their methods into one of the following three categories: two-stage methods, one-stage methods, and end-to-end methods. However, there is still no review literature to clearly define and distinguish between the three categories. Some papers discuss the categorization in their related work section, but they have disagreements with each other. For example, Zhong et al. [35] simply divide HOI detection methods into one-stage and two-stage. However, Antoun et al. [43] illustrate four categories: two-stage, one-stage, end-to-end transformer-based, and two-stage methods using transformers. Chen et al. [40] claim their transformer-based method as the one-stage network, while Zou et al. [37] call their transformer-based method as the end-to-end method. Such a confusing category is inconvenient for beginners to learn and for researchers to discuss. Therefore, one of the main contributions of this paper is to clearly define and differentiate current methods that use deep learning for HOI detection. Instead of making a fresh start, we dig into the root reasons why methods contain a different number of stages, then divide existing methods into two-stage, one-stage, and transformer-based methods. Among them, we group all methods that use transformers into one category to avoid overlapping categories of some methods, such as methods that belong to both two-stage and end-to-end. The new category does not violate the category of most existing work but significantly makes the category clear.

Compared with the currently published HOI detection review papers, our contributions can be summarized as follows:

(1) We review more than 200 references related to HOI detection and 13 datasets from 2015 to 2024, and compare the advantages and disadvantages of HOI detection methods and datasets. Then we summarize the pipeline of all three classes of HOI detection methods and clearly distinguish them in formulas and schematics.

(2) We analyze the impact of foundation models on HOI detection methods, which is not covered in the previous HOI field review.

(3) Based on the analyzed papers, we reasonably deduce and explore future research directions, analyze the current problems and limitations of each research direction, and propose our suggestions to solve these problems.

There have been five reviews on HOI detection. Bergstrom et al. claim their paper [44] to be the first general survey in this field, which mainly focuses on multi-stream CNN architectures but pays little attention to other architectures. Sunaina et al. [45] simply divide existing methods into two categories: handcrafted representation-based approaches and deep learning-based approaches, which do not reflect the specific differences in structure and algorithm of such methods. Li et al. [46] divide existing methods into sequential methods and parallel methods, which is similar to the definition of two-stage methods and one-stage methods. However, they do not consider the transformer-based methods. Antoun et al. [43] classify existing methods into two-stage methods, one-stage methods, end-to-end transformer-based methods, and two-stage methods using transformers. This classification method has partial overlap and does not consider the foundation models on HOI detection. Wang et al. [47] divided the existing HOI detection methods into one-stage and two-stage methods, and further divided the two-stage methods into HOI detection with multi-stream modeling, human parts and pose, compositional learning, graph-based modeling, and query-based modeling. This classification method also overlaps and causes confusion. For example, RPNN [28] is a method with graph-based modeling, and it also incorporates detailed feature information of human body parts and poses to refine the graph structure. This makes it difficult to clearly classify RPNN into HOI detection with graph-based modeling or HOI detection with human parts and pose. At the same time, Wang et al. did not pay attention to the impact of emerging foundation models on HOI detection. Differently, the classification method of our paper is more scientific. Moreover, we have focused on the influence of the foundation model, providing a detailed and comprehensive description of the foundation model methods and development directions. At the same time, the number of articles reviewed is far more than the papers mentioned above. We classify all transformer-based methods into one category instead of separating a two-stage method using transformers like Antoun et al. In conclusion, our review is more comprehensive and specific than existing

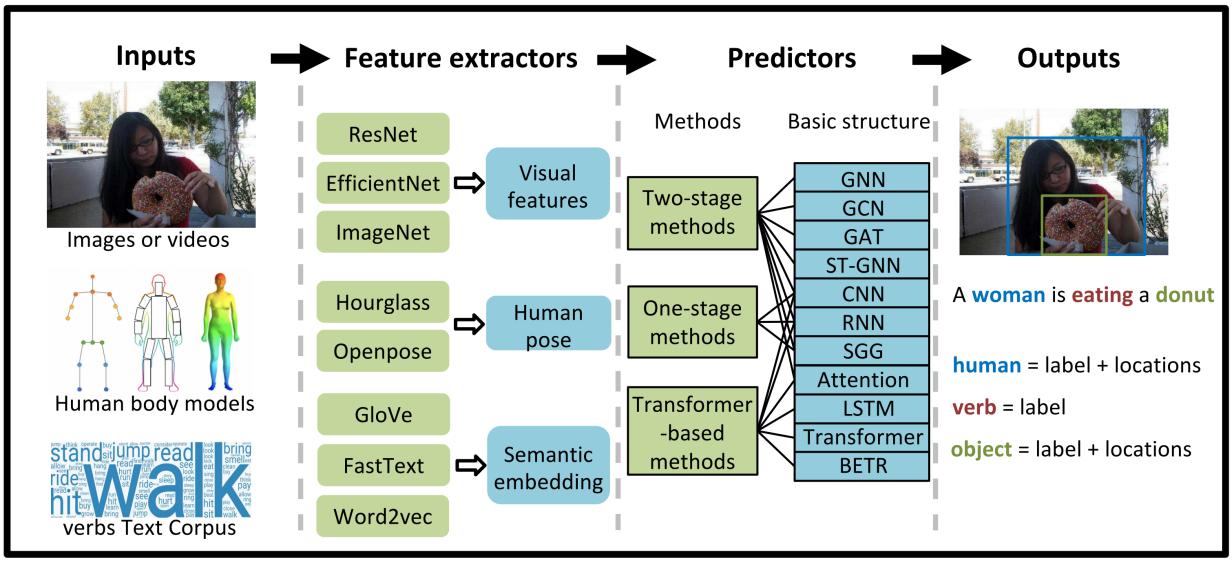


Fig. 2. Pipeline of HOI detection using deep learning methods.

reviews.

The rest of this paper is organized as follows. Section II introduces the HOI detection pipeline, classifies the existing HOI detection methods, defines them with formulas, and describes the advantages, disadvantages, and development process of each method. Section III defines the two-stage methods and further divides them into the attention-based methods and GNN-based methods; Section IV defines the one-stage methods and introduces the current advanced one-stage methods; Section V defines the transformer-based methods and introduces the current advanced transformer-based methods; Section VI introduces the definition of the foundation models and introduces methods using the foundation models to solve the long-tail distribution problem; Section VII introduces the datasets and evaluation metrics in the field of HOI in detail, and analyzes the performance of each method in the dataset; Section VIII and Section IX present the future direction and conclusion, respectively.

II. Overview of HOI detection

In this section, we provide an overview of existing HOI detection, including their pipeline, category, and development time.

A. Pipeline of HOI detection

Existing deep HOI detection methods follow a common four-step pipeline, as shown in Fig. 2. **Firstly**, the model takes an image as the main input. We aim to find out all the HOIs in the image. In addition to visual information, human body model has been used as prior knowledge to improve results (figures of human body models are cited from [48]). Text corpus has also been used as external clues to detect unseen objects or actions. **Secondly**, HOI detection methods utilize some off-the-shelf backbone networks to extract features from inputs. For example, ResNet [49], EfficientNet [50], ImageNet [51] are used to extract visual features; Hourglass [52], Openpose [53] are used to estimate the human pose; GloVe [54], FastText [55], Word2Vec [56] are used to generate semantic embedding vectors of objects or verbs. Generally, these backbone networks have been pre-trained on large-scale datasets, and their weights are frozen during HOI detection training. An excellent pre-training method can affect the final detection accuracy [57]. **Thirdly**, the HOI predictor further learns HOI-specific features and then predicts the HOI triplets. The HOI predictor is the core of HOI algorithms, which could be based on various structures, such as CNN, LSTM, GCN, Transformer, etc. **Finally**, HOI detection model outputs the ⟨human-verb-object⟩ triplets existed in the image.

B. Category of HOI detection

The current mainstream classification method for HOI detection is stage-based classification. However, we notice that after the emergence of transformer [58] in 2017, more and more researchers have begun to use transformer-based methods for HOI detection, and some of these papers are unsuitable for using stages for classification. Therefore, we separate the transformer-based methods into a separate category, which can intuitively reflect the progress and impact of transformers on traditional two-stage and one-stage methods.

Two-stage methods use the appearance of detected instances (either humans or objects) as cues to predict the interaction between them. Therefore, the two-stage methods generally consist of two sequential steps: instance detection and interaction classification. In the first stage, they use an object detector, such as a Faster RCNN in [59], to detect the human and object instances. The output of the first stage includes the labels, bounding box, and in-box features of the detected instances. In the second stage, they use features in the detected box to identify the interaction between each possible human-object pair. Note that the weights of the first-stage detector can be either fixed or updated during training.

Given an image $\mathcal{I}$, the computing process of a vanilla two-stage method can be formulated as Eq. (1) - Eq. (2):

$$\mathcal{H}, \mathcal{O} = f_{\theta_d}(\mathcal{I}), \tag{1}$$

$$\boldsymbol{v}_i = f_{\theta_v}(\boldsymbol{h}_i, \boldsymbol{o}_i, \boldsymbol{a}_i), \forall \boldsymbol{h}_i \in \mathcal{H}, \forall \boldsymbol{o}_i \in \mathcal{O}, \forall \boldsymbol{a}_i \in \mathcal{A}, \tag{2}$$

where f_{θ_d} is the object detector, f_{θ_v} is the interaction verb classifier. $\mathcal{H}$ and $\mathcal{O}$ are the human instance set and the object instance set, $\boldsymbol{v}_i$ is the predicted interaction verb between $\boldsymbol{h}_i$ and $\boldsymbol{o}_i$. Note that auxiliary features have also been used in two-stage methods, therefore, we set auxiliary features $\boldsymbol{a}_i$ as the input for the interaction verb classifier and reflect it in Eq. (2). And $\mathcal{A}$ is the set of auxiliary features, such as spatial configuration [26, 27, 60] of detected instances, human pose features [61, 62], and text [63, 64]. However, they all treat the detector output as an input of the interaction verb classifier.

One-stage methods aim to regress a region to represent the interaction. The interaction region could be a point[33, 34], dynamic points [35], a union box [36] or multi-scale boxes [65]. In other words, these methods simultaneously detect human instances, object instances, and some interaction areas or points, where the interaction areas are only used to predict interaction verbs. Therefore, they usually follow a parallel structure as Eq. (3),

$$\{\langle \boldsymbol{h}, \boldsymbol{v}, \boldsymbol{o} \rangle_i\} = f_{\theta_d, \theta_v}(\mathcal{I}), \tag{3}$$

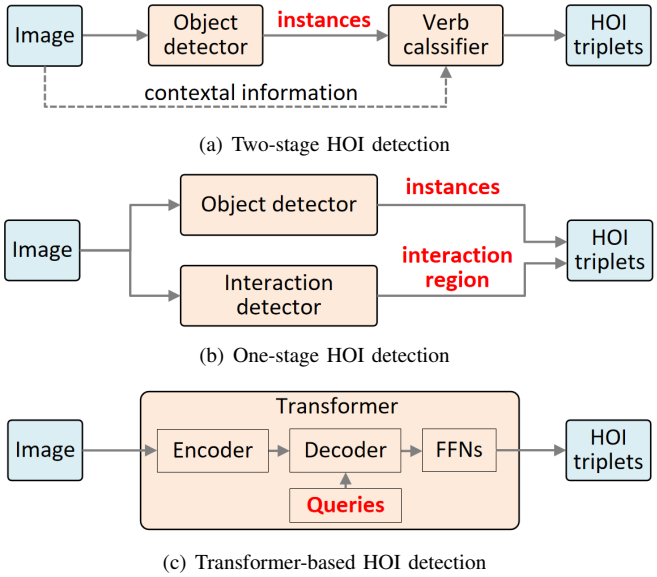
where $\{\langle \boldsymbol{h}, \boldsymbol{v}, \boldsymbol{o} \rangle_i\}$ is the detected HOI triples set in the image $\mathcal{I}$. This parallel structure enables these methods to infer the HOI triples in one stage and be more efficient than most two-stage methods.

Transformer-based methods use trainable query vectors to represent HOI triplets[37–39]. Their basic architecture is a transformer encoder-decoder. The encoder uses an attention mechanism to extract features from the global image context. The decoder takes several learnable query vectors as input, and each query captures at most one interaction action of a human-object pair. Actually, these methods just extend the transformer-based detection model DETR [66] to capture HOI detection and treat HOI detection as a set prediction problem of matching the predicted and ground-truth HOI instances. Transformer-based methods can be formulated as Eq. (4).

$$\{\langle \boldsymbol{h}, \boldsymbol{v}, \boldsymbol{o} \rangle_i\} = f_{\theta_t, Q}(\mathcal{I}), \tag{4}$$

where $\{\langle \boldsymbol{h}, \boldsymbol{v}, \boldsymbol{o} \rangle_i\}$ is the HOI triples set, θ_t means the transformer weights, Q means the query vectors. Q is often treated as parameters of T, but it represents the HOI triplets, so we list it separately in Eq. (4).

Fig. 3 compares the structural differences among the three categories of methods. Nearly all methods utilize a CNN backbone to extract high-level image features, so Fig. 3 does not show it. Two-stage methods generally follow a sequential structure, while one-stage methods follow a parallel structure. However, some two-stage methods [67–69] add a net stream to learn features from the global image, which leads to a hybrid structure. Therefore, we distinguish them by whether they predict an explicit region from the original image to represent the interaction verb or rely on the detected human-object pair to predict the interaction. The transformer-based methods use FFNs to predict HOI triplets based on the latent features extracted by a transformer.



(a) Two-stage HOI detection

(b) One-stage HOI detection

(c) Transformer-based HOI detection

Fig. 3. Schematic comparison between different types of HOI detection methods

The three types of methods have their own advantages and disadvantages:

(1) Two-stage methods can effectively use the information in the picture, but they have the problem of low time efficiency and high computational complexity. They can effectively use the features of instance and additional information from context, body posture, and other aspects to carry out interaction classification. However, due to the separate architecture, detection algorithms require a lot of time to predict each possible human-object pair individually.

(2) One-stage methods have better time efficiency, but they are difficult to quickly deploy to complex environments. They can detect HOI triples directly from the image due to the one-stage object detector [70–72] and parallel structure, so they have an obvious improvement in real-time performance. Although the efficiency has been greatly improved, the performance of the existing methods is limited by the complex handcrafted grouping strategies, which makes it difficult to quickly deploy it to complex or special real-world environments.

(3) Transformer-based methods are currently the best method in terms of real-time performance and accuracy, but they lack interpretability. They can apply transformers with a good ability to capture remote dependencies. They can combine the advantages of one-stage methods and transformers to separately predict human-object proposals and interactions with multiple parallel decoders without requiring complex grouping strategies. This makes them the most studied method in the last two years. However, they lack interpretability and cannot easily configure parameters to fine-tune performance.

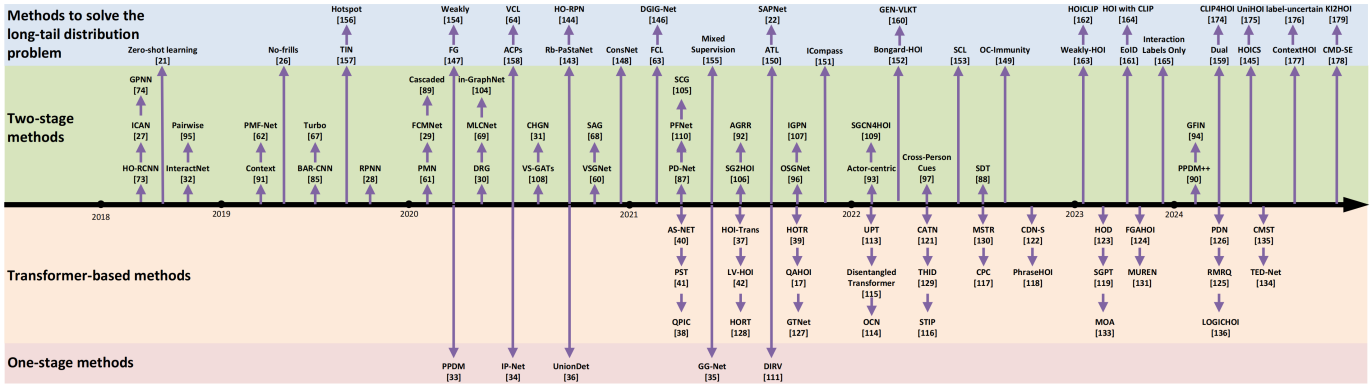


Fig. 4. Development timeline of HOI detection methods.

C. Development timeline of HOI detection

Fig. 4 is the development process of HOI detection methods. For clarity, Fig. 4 only parts but not all existing methods. The listed HOI methods meet the following two conditions: (1) solve a typical HOI detection problem; (2) can be clearly classified into one of the proposed three categories. From Fig. 4, we can find the following development trends:

(1) The multi-stream architecture mainly used in the two-stage methods is proposed by HO-RCNN [73]. Later, attention mechanism [27] and graph neural network [74] are introduced into the field of HOI detection, further enriching the diversity of the two-stage methods and the detection accuracy.

(2) The generation of the one-stage methods benefits from the development of the one-stage object detector. PPDM [33] is the first HOI detection method to achieve real-time performance, which has greatly improved the detection efficiency and accuracy compared with other methods in the same period.

(3) For transformer-based methods, DETR [66] is one of the most advanced visual object detection methods. Most of the current transformer-based methods follow the structure of DETR and are further optimized based on DETR to improve the detection effect. At the same time, after the emergence of DETR, since it has greatly improved the real-time performance and accuracy of HOI detection, the two-stage methods and one-stage methods that do not use transformers have been greatly reduced, and many researchers have begun to pay attention to transformer-based methods.

(4) After the large-scale visual language pre-training foundation model CLIP [75] is established, the mainstream research direction to solve the long-tail distribution problem began to shift to CLIP-based HOI detection.

III. Two-stage methods

The timeline of two-stage methods is shown in Fig. 6. The human-object region-based convolutional neural networks (HO-RCNN) [73] proposed by Chao et al. in 2018 is known as the beginning of the two-stage methods. The multi-stream architecture proposed by them is of great significance for HOI detection research. Before the emergence of the transformer, almost all two-stage methods used multi-stream architecture as their structural framework. The multi-stream architecture includes human stream, object stream, and pairwise stream, as shown in Fig. 5. Among them, the human stream and object stream encode the appearance features of humans and objects, respectively, while the purpose of the pairwise stream is to encode the spatial relationship between humans and objects. The model first generates human-object region pair proposals using humans and object detectors. Then, it feeds each human-object pair proposal into a deep neural network (DNN) to generate HOI classification scores, and the scores in the three streams are fused in a later fusion manner. Finally, the interaction classification is performed according to the fusion scores. Due to the outstanding performance of the attention mechanism and GNN in many aspects, such as feature extraction and object detection, researchers have begun to try to incorporate attention and GNN into the structural components of HOI detection, thereby improving detection accuracy.

The process of the two-stage methods divides the HOI detection task into two subtasks: instance detection and interaction classification. Generally, by sorting out relevant literature on HOI detection, we can divide the two-stage methods into two categories based on the model and overall framework of interaction classification: methods based on attention mechanism and methods based on graph neural networks (GNN).

A. Attention-based methods

The attention mechanism is a signal-processing mechanism discovered by some scientists when they studied human vision in the 1990s. At present, the attention mechanism has become one of the most widely used “components” in the field of deep learning, especially in the fields of natural language processing (NLP) and computer vision (CV). Some prominent examples include image classification [76], object detection [77, 78], semantic segmentation [79], action recognition [80, 81], image generation [82], pose estimation [83], and multi-modal task [84]. Since 2018, more and more researchers have integrated attention mechanisms into the field of HOI detection.

Considering that some attention-based methods also incorporate contextual information and body gestures, the attention-based methods can be further subdivided into generalized attention-based methods, attention-based methods incorporating contextual information, and attention-based methods incorporating body gestures. Among them, the generalized

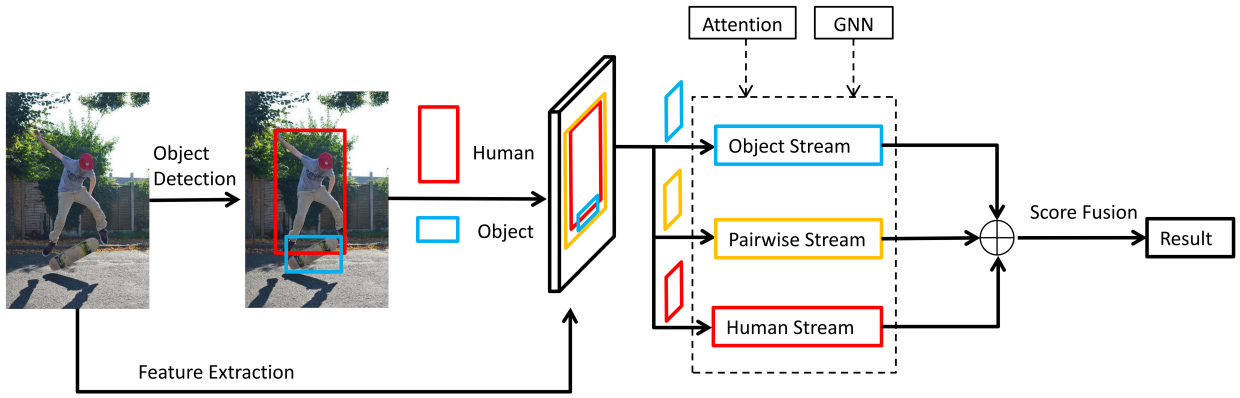


Fig. 5. Framework of two-stage methods.

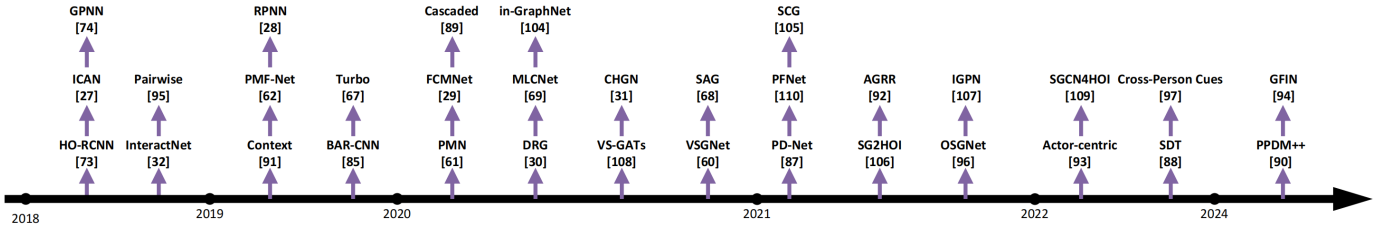


Fig. 6. Development timeline of two-stage methods.

attention-based methods are methods that do not deliberately focus on the context information and body postures.

(1) The generalized attention-based methods. For the generalized attention-based methods, the most representative methods include [27, 32, 85–89]. An instance-centric attention module (ICAN) [27] proposed by Gao et al. in 2018 highlights the important role of attention mechanism in HOI detection for the first time. The module can dynamically highlight important regions by learning the appearance of each instance, which greatly improves the detection effect. Gkioxari et al. [32] proposed a human-centric model named InteractNet in 2018, which can classify actions at target object locations and probability density estimates for specific actions. Box attention R-CNN (BAR-CNN) [85] proposed by Kolesnikov et al. in 2019 is a joint probabilistic model for detecting visual relations. The framework of BAR-CNN is shown in Fig. 7. Kolesnikov et al. use the chain rule to decompose the probabilistic model into two simpler models without using new hyperparameters. Zhong et al. [86] proposed a novel Polysemy Deciphering Network (PD-Net) in 2020. It proposes three methods for decoding HOI to detect visual polysemy of related verbs. And they further augmented PD-Net [87] in 2021. It is also the first attention module that effectively uses language to address verb polysemy in HOI detection. To optimize the performance on distant interactions, SDT [88] proposes a spatially differentiated transformer method and a Far-Near Distance Attention (FNDA) to effectively model distant interactions. Considering the inherent complexity of single-stage inference pipelines, Zhou et al. [89] proposed a multi-stage cascaded architecture. At each stage, an instance localization network refines the HOI proposals and feeds them into an interaction recognition network. The proposal of the PPDM method represents the emergence of the one-stage methods, and the specific content of PPDM will be elaborated in Section IV. However, the author team believes that using only one interaction point for its interaction feature representation is insufficient, so they proposed a new two-stage method called PPDM++ [90]. PPDM++ breaks the limitation from redundant non-interactive human-object proposals by directly locating interactive human-object pairs in the first stage.

By focusing on areas closely related to HOI, the model can capture key information more effectively and ignore irrelevant background noise, allowing the model to better understand the spatial relationship between humans and objects. Thus, the interaction between them can be judged more accurately. At the same time, under limited computing resources, the model is allowed to allocate more computing resources to important information areas, which means that the model can use its processing power more efficiently.

In summary, the attention mechanism has significantly helped HOI detection by improving feature extraction capabilities, enhancing information processing capabilities, improving reasoning and judgment capabilities, optimizing model performance, and reducing background interference. These advantages make the attention mechanism an important research direction in HOI detection.

(2) The attention-based methods incorporating contextual information. For the attention-based methods incorporating contextual information, the most representative methods include [29, 91–93]. Based on ICAN, Wang et al. [91] proposed a contextual attention framework for HOI detection in 2019. Unlike ICAN, which uses standard appearance features to build attention maps, their method builds attention maps

by learning context-aware appearance features of instances. The context-aware appearance features are generated by the context-aware module and encoded by appearance and context information. The attention module can highlight regions that may contain HOI by selecting relevant contextual information. Liu et al. [29] proposed a Fine-grained layout-Context-Motion Network (FCMNet) for localizing and recognizing all HOI instances in an image in 2020. The main role of the model is to amplify and utilize key clues in the image. Considering the huge combination space and non-interactive pair domination problem of multi-stream information, Lin et al. [92] proposed an action-oriented attention mining and relational reasoning network (AGRR). They exploit the compatible consistency between the contexts of human-object pairs to filter non-interactive combinations for relational reasoning. In 2022, Xu et al. [93] proposed an actor-centric HOI detection framework to explore the relationship between one person and multiple objects to solve the ambiguity problem that there may be multiple interactions in images. The Global Context and Pairwise-level Fusion Features Integration Network (GFIN) [94] proposed by Wang et al. in 2024 utilizes an encoder to achieve global context memory extraction. Then, it uses a decoder to transform the query sequences representing human-object pairs into recognizable interactive features.

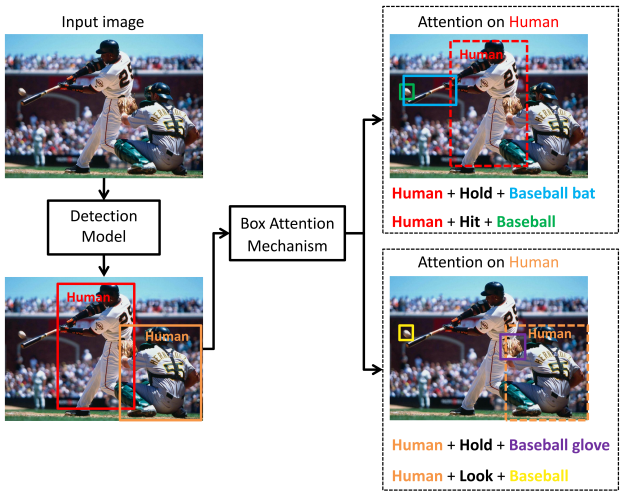


Fig. 7. Framework of BAR-CNN.

By incorporating contextual information, the model can better understand the scene, thereby optimizing the inference process. Contextual information also provides more clues about interaction relationships, helping the model identify interaction types more accurately. At the same time, contextual information can also enhance the generalization ability and robustness of the model, helping the model handle more diverse scenes and interaction types so that it can still accurately identify HOI even when the background noise is large or the target object is partially occluded. In summary, the attention-based methods incorporating contextual information have significantly helped HOI detection by improving detection accuracy, enhancing model generalization ability and robustness, and optimizing the reasoning process.

(3) The attention-based methods incorporating body gestures. Existing research shows that only relying on the appearance features of humans and objects and the spatial relationship between them is far from achieving the needs of HOI detection. Therefore, some studies have begun introducing additional information to improve the accuracy of HOI detection, among which the body part and pose of a human are essential information. Traditional approaches treat the human body as a whole and pay equal attention to the entire body area. Still, they ignore that humans typically use only certain body parts to interact with objects.

For the attention-based methods incorporating body gestures, the most representative methods include [61, 62, 67, 95–97]. Fang et al. [95] believe that different body parts should be given different attention, and the correlation between different body parts should also be further considered, so they proposed a new pairwise body part attention model in 2018. This model is the first to apply an attention mechanism to body part correlation to detect HOI. Considering Fang et al. [95] only use the human body pose as the spatial constraint between the human body part and the object, Wan et al. [62] proposed a pose-aware multi-level feature network (PMFNet) in 2019, which uses the information of human posture to capture the global spatial configuration of relationships. Feng et al. [67] proposed a turbo-learning framework in 2019. They design an HOI-guided pose estimation module and a pose-aware HOI recognition module to enforce information transfer between tasks. Liang et al. [61] proposed a pose-based modular network (PMN) in 2020. It consists of a branch that independently processes the relative spatial pose features of each joint and another that uses graph convolution to update the absolute value of each joint. Lee et al. [96] proposed an on-the-fly stacked generalization deep neural network (OSGNet). To achieve dynamic stacking generalization, they train the submodel and meta-learner simultaneously. The former can provide complementary information, and the latter improves the generalization performance of unseen test data. Wu et al. [97] learn about body part interaction from a global perspective. It constructs a saliency map of body parts based on self-attention to mine cross-human information clues and learn the overall relationship between all body parts.

Body posture information can be combined with visual features to represent richer features. This combination can make up for the shortcomings of a single visual feature in describing interactive relationships and provide more comprehensive information. At the same time, body posture information can reflect the movements and postures of the human body, which is crucial for understanding HOI. By paying attention to body posture, the model can better understand the details and process of interaction and reduce misjudgments and missed detections. Body posture information is also stable and robust, providing valuable clues even when the target is occluded or the background is complex. In summary, the attention-based methods incorporating body gestures have significant advantages in feature representation, information richness, interactive recognition capabilities, and robustness.

B. GNN-based methods

There has been growing interest in extending deep learning methods to graphs in recent years. Driven by the success of multiple factors, researchers have borrowed the ideas of convolutional networks, recurrent networks, and deep auto-encoders to define and design neural network structures for processing graph data. Thus, the graph neural network is born. The GNN mainly includes graph convolution networks (GCN), graph attention networks (GAT) [98], graph autoencoders, graph generative networks (GGN), and graph Spatio-temporal networks (ST-GNN) [99, 100]. One of the most extensive application areas of graph neural networks is computer vision, such as scene understanding [101], object detection and parsing [102], and visual question answering (VQA) [103].

Considering that some GNN-based methods also incorporate attention mechanisms and body gestures, the GNN-based methods can be further subdivided into generalized GNN-based methods, GAT-based methods, and GNN-based methods incorporating body gestures. Among them, the generalized GNN-based methods are methods that do not deliberately focus on attention mechanisms and body postures.

(1) The generalized GNN-based methods. For the generalized GNN-based methods, the most representative methods include [30, 74, 104–107]. Qi et al. [74] first integrate graph models and neural networks to achieve HOI recognition, and they proposed a graph parsing neural network (GPNN), which is a generalization of message passing neural network (MPNN). The network inherits the learning ability of the neural network and the representation ability of the graph model. Unlike most previous graph or structured deep learning network models using pre-fixed graph structures, in order to seek better generalization ability, GPNN introduces an important connection function to solve the problem of graph structure learning. It learns to infer adjacency matrices in an end-to-end fashion and thus can infer analytic graphs that explicitly explain HOI relationships. In 2020, Gao et al. [30] first use abstract spatial semantic representation when describing each human-object pair and then utilize a dual relational graph (DRG) to aggregate contextual information of the scene. The framework of DRG is shown in Fig. 8. To exploit the implicit interaction semantics between visual objects, Yang et al. [104] proposed a new graph-based interactive inference model (in-GraphNet) to infer HOIs. In 2021, to solve the problem existing in GNN methods, Zhang et al. [105] explored various methods of applying spatial conditioning under a multi-branch structure and demonstrated the advantages of spatial conditioning. Using scene graphs, He et al. [106] proposed HOI detection by exploiting the semantic relationships present in images (SG2HOI). Wang et al. [107] proposed a new model to learn interactive knowledge in Interaction Proposal Graph Network (IPGN).

GNN models HOI through a graph structure, which can not only effectively construct complex dependencies and capture high-order interaction information between nodes, but also naturally integrate visual features, semantic information, spatial relationships, and other information into the graph structure for unified modeling. GNN also makes the reasoning process of the model more intuitive and explainable. In HOI detection, this helps researchers better understand the decision-making process of the model, so as to make targeted improvements and optimizations.

In summary, GNN provides powerful help for HOI detection through its unique graph structure modeling capabilities, multi-stream information processing capabilities, high-order interaction information capture capabilities, and interpretability.

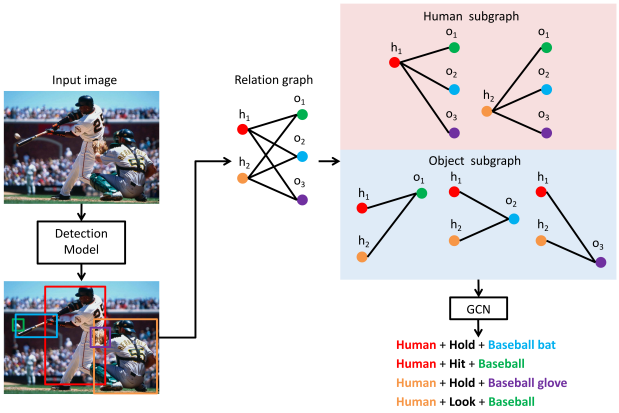


Fig. 8. Framework of DRG.

(2) The GAT-based methods. GPNN's method of representing humans and objects with the same nodes is imperfect because humans and objects play different roles in HOI. There is an inter-class context between heterogeneous entities (human and object) in the activity scene. However, there is an intra-class context between homogeneous entities (human and human, object and object), meaning their relationship is not entirely the same.

For the GAT-based methods, the most representative methods include [31, 60, 68, 108, 109]. Given the above consideration, Wang et al. [31] proposed a context-heterogeneous graph network (CHGN) in 2020. Wang et al. combined context learning with graph attention methods to improve the effectiveness of nodes in gathering knowledge from their neighbors. By investigating HOI detection, Liang et al. [108] constructed a Visual-Semantic Graph Attention Network (VSGATs), a dual-graph attention network aggregating visual-spatial and semantic information in parallel. The Visual-Spatial Graph Network (VSGNet) [60] proposed by Ulutan et al. improves on the traditional three-branch network by exploiting the spatial configuration of human-object pairs to refine visual features and adding a graph convolution branch. However, Zhang et al. [68] test VSGNet and find that its bipartite graph performed worse when more than one message passing iteration is used. They then speculate that this is because adjacency values are not correctly normalized, resulting in node encoding being dominated by incoming messages. In their proposed spatiotemporal attention graph neural network (SAG) for detecting HOI, the message-passing algorithm is more stable and does not show this problem. SGCN4HOI [109] is a skeleton perceptual GCN for HOI detection. Based on VSGNet, it uses the spatial connection between human key points and object key points to capture their fine-grained structural interaction through graph convolution.

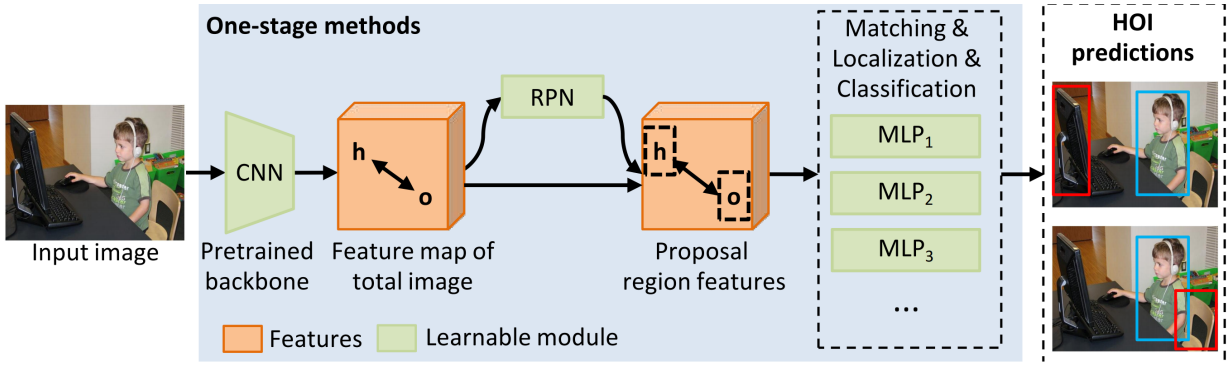


Fig. 9. Framework of one-stage methods.

The GAT enables the model to focus on the key information most relevant to HOI detection when processing graphic data and reduce the interference of irrelevant information, such as specific parts or interactions between the human body and objects. The GAT can also pay more attention to nodes and edges related to HOI during the inference process, thereby accelerating the inference process and reducing the use of computing resources. In summary, the GAT-based methods have significant advantages in focusing on key information, optimizing model reasoning, and reducing computing resource consumption.

(3) The GNN-based methods incorporating body gestures. For the GNN-based methods incorporating body gestures, the most representative methods include [28, 69, 110]. Zhou and Chi pioneered the combination of graph models with body parts and proposed relation parsing neural network (RPNN) [28] in 2019. RPNN is also the first study to focus on pairwise correlations between body parts and objects in HOI detection. RPNN introduces detailed body part features, and the model incorporates a graph structure for feature refinement instead of coarse appearance-based features in GPNN to extend learnable graph models for robust representations. Unlike ICAN, RPNN identifies objects and body parts as the most interesting areas to pay attention to. With further in-depth research, some problems with RPNN surface. Sun et al. [69] find that RPNN uses a backbone of convolutional neural networks (CNN) pre-trained on object detection datasets to extract visual features for HOI inference. This leads to significant deviations in the appearance distributions of interaction phrases and individual objects. Therefore, Sun et al. proposed a multi-level conditioned network (MLCNet) in 2020, which aims to fuse additional explicit knowledge with multi-level visual features. Liu et al. [110] also argue that the pairwise features of RPNN are not comprehensive enough, resulting in a better model of subtle interactions between body parts and objects. The multi-level pairwise feature network (PFNet) they proposed in 2021 contains more comprehensive pairwise features.

Body posture information provides a detailed description of human body movements and postures. Combined with GNN, it can provide a richer feature representation for HOI detection. This feature representation not only includes traditional visual features, but also includes relative position and angle information between various parts of the human body, which helps to understand HOI more accurately. At the same time, the GNN-based methods incorporating body gestures can more intuitively display the interactive relationship between various parts of the human body and objects during the reasoning process, which makes the decision-making process of the model more transparent and explainable. In summary, the GNN-based methods incorporating body gestures have significant advantages in terms of richness of feature representation, optimization of model reasoning, and interpretability.

IV. One-stage methods

The common framework of the one-stage methods is shown in Fig. 9 and the timeline of one-stage methods is shown in Fig. 10. Due to the need to detect humans and objects first and then perform matching and interaction classification, the two-stage methods consume more computing resources and lack flexibility. At the same time, affected by its serial structure, the detection efficiency and real-time performance of the two-stage methods are also flawed. With the development of one-stage object detectors [70–72], scholars have studied more and more one-stage methods. As mentioned above, one-stage methods can reduce HOI detection as a parallel detection problem, detecting HOI triples directly from images. Therefore, compared with the two-stage methods, they have further improved detection efficiency, real-time performance, and accuracy.

In 2020, Liao et al. [33] proposed the first real-time one-stage HOI detection method, named parallel point detection and matching (PPDM). This method uses the center point of the detection frame to represent the human and object points and the midpoint between the human and object points to describe the interaction point. The model uses two parallel branches for point detection and matching, respectively. The point detection branch predicts humans, objects, and interaction points, and the point matching branch predicts two displacements from the human and object points to their corresponding interaction points. Human and object points originating from the same interaction point are treated as matched pairs. But Liao et al. also discovered the limitations of PPDM in interactive feature representation, so four years later, they proposed a two-stage method PPDM++ [90], which uses PPDM to detect HOI, and then extracts the regional features

of each pair to predict actions. More information has been elaborated on in the previous Section III.

Wang et al. [34] also use the idea of points to solve the problem of HOI detection in 2020, called IP-Net. By defining the interaction between humans and objects as interaction points, HOI detection is regarded as an interaction point estimation problem. IP-Net is the first method to treat HOI detection as a key point detection and grouping problem. The method learns to generate interaction vectors about the center points of humans and objects based on the interaction points.

Also, as a point-based method, Zhong et al. [35] proposed a novel one-stage method called Glance and Gaze Network (GGNet) in 2021. It models a set of action-aware points (ActPoints) through Glance and Gaze steps. The Glance step can quickly determine the distribution of interaction points in the feature map. The gaze step uses the feature map generated by the glance step to adaptively infer the ActPoint around each interaction point. Zhong et al. then devise an action-sensing approach to efficiently match each detected interaction with the relevant human-object pair and aggregate the features of ActPoints for interaction classification.

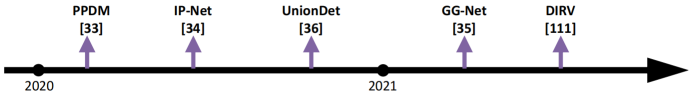


Fig. 10. Development timeline of one-stage methods.

Different from the first three point-based methods, the union-level detector towards real-time HOI detection (UnionDet) [36] is proposed by Kim et al. in 2020. They regard HOI detection as a union box detection process. The obtained feature pyramid is sent to both the union branch and the instance branch. While the joint branch directly captures interaction regions, the instance branch performs traditional object detection and action classification for more fine-grained HOI detection results. It directly detects interacting human-object pairs with the proposed joint detection framework instead of putting each object pair into a separate neural network. This eliminates the need for extensive reasoning after object detection and allows interactions to be detected with minimal extra time.

Fang et al. [111] proposed a region-based HOI detection method named DIRV in 2021. This method aims to solve the problem that the existing one-stage methods will introduce unnecessary visual disturbance information. Therefore, to capture the subtle visual features that are most important for interaction, it focuses more on densely sampled interaction regions at different scales for each human-object pair than previous one-stage methods. And it introduces a new voting strategy to replace the traditional Non-Maximum Suppression (NMS).

In summary, one-stage methods usually predict the input image directly and output all possible HOI triplets. Therefore, one-stage methods usually have higher detection speed and are more suitable for real-time applications. At the same time, the processing flow of one-stage methods is relatively simple, reducing the need for intermediate steps and parameter adjustments. This makes one-stage methods easier to implement and deploy.

V. Transformer-based Methods

The transformer is first proposed in [58] as a novel attention model for NLP. It follows an encoder-decoder structure, which takes a sequence as input and generates an output sequence. Either encoder or decoder contains stacked self-attention layers and position-wise feed-forward layers. Since its self-attention layer uses a multi-head attention mechanism to scan through all elements in the input sequence, the transformer can jointly attend to information from the whole sequence. The transformer's advantages of global computing and perfect memory make it popular in the machine-learning community. We recommend readers refer to paper [58, 66] for details about the self-attention mechanism and transformer model.

DETR [66] is one of the most advanced transformer-based visual object detection methods, which views object detection as a direct set prediction problem. It consists of a transformer to generate a set of object predictions and a set-based loss that forces correct matching between predictions and the ground-truth objects. The main advantage of DETR is eliminating the need for many hand-designed components. The tremendous success of DETR has led researchers to investigate its adaptation to HOI detection. For example, HQM [112] can enhance DETR's robustness and improve detection accuracy by mining hard-positive queries.

At present, most transformer-based HOI methods follow DETR's pipeline. Their common framework is shown in Fig. 11, which first uses a CNN backbone to extract preliminary visual features from the input image. Then, the 2D feature map is supplemented with a positional encoding and flattened into a 1D sequence. After that, a transformer encoder-decoder architecture further extracts HOI-specific features, where the decoder additionally takes a fixed number of learnable HOI queries as input. Finally, the subsequent feed-forward networks (FFN) process the output of the decoder to generate n HOI prediction results. The timeline of transformer-based methods is shown in Fig. 12.

Some papers adjust the output heads of DETR to predict HOI triplets. HOI-Trans [37] is one of the most straightforward methods based on the transformer for HOI detection. The network architecture of HOI-Trans contains three main parts: a ResNet backbone, a standard transformer encoder-decoder, and five FFNs to predict HOI instances. HOI-Trans defines each HOI instance with a quintuple of ⟨human class, interaction class, object class, human box, object box⟩ and uses five parallel FFNs to predict them separately. QPIC [38] is another intuitive DETR-like method whose idea and proposed time are similar. The main difference between QPIC and HOI-Trans lies in that QPIC represents a HOI instance with a quadruple ⟨human bounding box, object bounding box, object class, action class⟩. Zhang et al. [113] find that their two-stage counterparts can improve performance and memory efficiency while requiring a fraction of the time to train when equipped with the same transformer. Therefore, they proposed a two-stage HOI detector consisting of unary encoding and

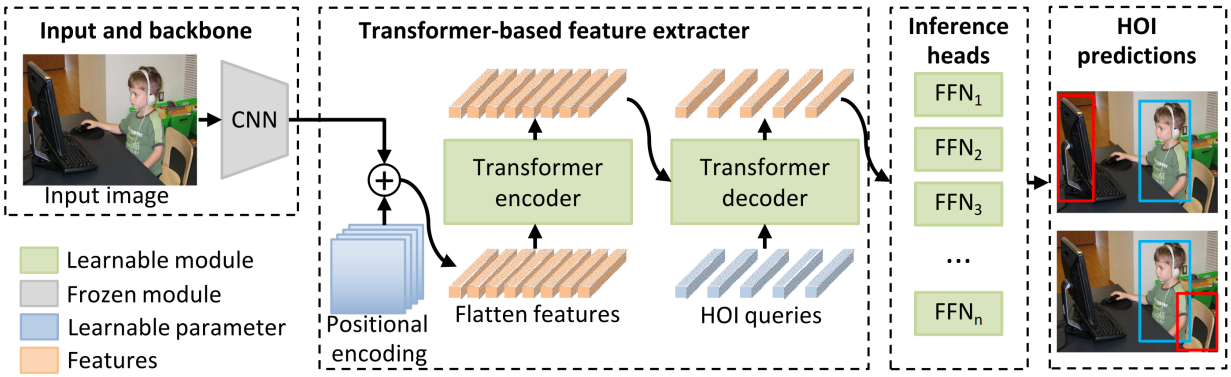


Fig. 11. Common framework of transformer-based HOI detection methods.

pairwise encoding (UPT) and further demonstrated that the two encoder layers have complementary properties.

Some papers improve the standard transformer encoder-decoder architecture to an HOI-dedicated architecture. HOTR [39] realizes it by introducing a shared encoder and two parallel decoders (instance decoder and interaction decoder). Similarly, AS-Net [40] also builds an instance decoder branch and an interaction decoder branch in parallel following a shared transformer encoder. To overcome the problem of static semantic embeddings, Object-guided Cross-modal Calibration Network (OCN) [114] proposes to generate cross-modal perception visual and semantic features through cross-modal calibration (CMC). Zhang et al. [115] proposed a disentanglement strategy for HOI detection by decoupling triple prediction into human-object pair detection and interaction classification via instance flow and interaction flow. STIP [116] decomposes the process of HOI detection into two stages, i.e., interactive proposal generation is first performed, and then non-parametric interactive proposals are transformed into HOI predictions through a structure-aware transformer, which optimizes and strengthen the architecture. CPC [117] optimizes the interactive reasoning path. It improves the HOI detection of transformers by exploiting the enhanced decoding path. PhraseHOI [118] is the first method to creatively use HOI annotations as phrases. It proposes a novel relational phrase learning task based on HOI, which uses natural language phrases to describe interactions between humans and objects. Chen et al. [119] improved on the existing mainstream single-stream detection and proposed SGPT to use the secondary path to guide the primary path.

Some papers mainly focus on the query input of the transformer decoder to address HOI detection. PST [41] creatively introduces a composite transformer-based part-and-sum transformer decoder to replace the standard decoder. Based on this structure, PST passes composite queries into composite decoders to predict composite HOI sets. LV-HOI [42] employs a Fast-RCNN to detect person-bounding boxes and use them as queries for the subsequent transformer. The strategy chosen by Wang et al. [120] is to detect humans in images and use them as queries to search for corresponding interactions and target objects. In leveraging the model's object query capabilities, Category-Aware Transformer Network (CATN) [121] performs better by initializing object queries with category-aware semantic information. CDN-S [122] proposes an efficient knowledge distillation model, which shares parameters between teacher and student networks. QAHOI (Query-Based Anchors for Human-Object Interaction detection) [17] uses multi-scale architecture to extract features from different spatial scales and uses query-based anchors to predict all elements of HOI instances. Zhang et al. [123] decoupled the human and object detection decoder and proposed a new human-object decoupling network (HOD). Zhang et al. [124] proposed a new end-to-end transformer-based framework (FGAHOI) to extract key features from images with complex background information and perform semantic alignment on the extracted features and query embeddings. In response to the potential overlap of multiple interaction actions and the lack of guidance information in existing query designs, Chan et al. [125] proposed Region Minning and Refined Query (RMRQ) in 2024. They utilized Ground Truth Mask Denoise (GTMD) to extract more features from different regions and proposed Dynamic Linguistic Query (DLQ) and Multi-label Focal Loss (MFL) to generate dynamic queries. The Parallel disentangling network (PDN) [126] proposed by Cheng et al. expands the naive query into triple explicit queries in parallel so that each query is focused on a specific task.

Some papers focus on the attention mechanism and the information obtained in the joint feature space to optimize performance. GTNet [127] encodes spatial context information in visual features through a self-attention mechanism and designs a guidance mechanism that combines object semantics and relative spatial configuration to guide the attention mechanism in the framework. The HORT [128] proposed by Ji et al. can greatly improve the understanding of human-object relationships by applying attention mechanisms among features distributed spatio-temporally. THID [129] proposes a new HOI visual encoder to detect interacting humans and objects and maps them to joint feature space for interaction recognition. MSTR [130] is a multi-scale transformer driven by two new deformable attention modules, entity-conditional contextual attention and dual-entity attention. Kim et al. [131] proposed a Multiple Relation Network (MUREN), which uses unary, pairwise, and ternary relationships of humans, objects, and interaction tokens to exchange context between three

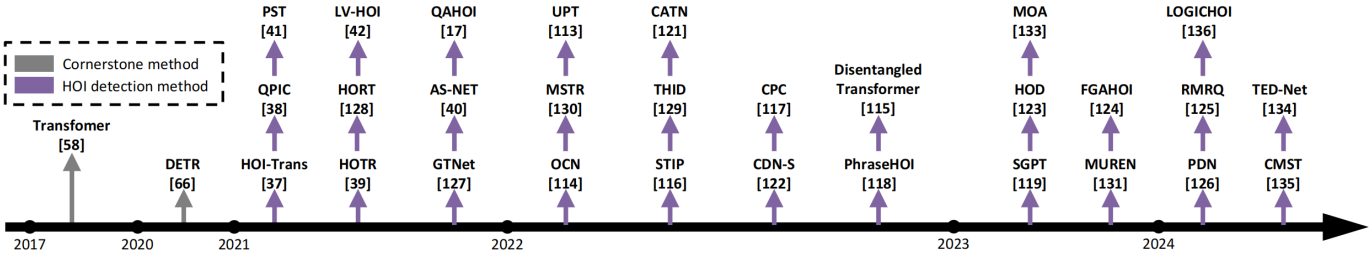


Fig. 12. Development timeline of transformer-based methods.

decoder branches. To solve the quantization problem that traditional feature extraction methods (e.g., ROIAlign [132]) are difficult to directly apply when using the Visual Transformer backbone, Park et al. proposed a feature extraction method, named masking with overlapped area (MOA) module [133], to utilize the overlapped area between the given region and each patch in the attention function. Wang et al. proposed the Triple stream Enhanced encoder-decoder Dispersal Network (TED-Net) [134] in 2024. They designed a dispersal attention mechanism to capture indirect contact interaction information and an auxiliary discrimination mechanism to enhance the decoder's capability to recognize actions. Xia et al. proposed a cascade multi-scale transformer (CMST) [135] and used the multi-scale HOI attention mechanism, solving the problems of slow convergence and high computational complexity related to transformer architecture. Li et al. proposed LOGICHOI [136], which modified the self-attention mechanism in vanilla Transformer to enable it to infer ⟨human, verb, object⟩ triplet and constitute novel interactions.

The transformer-based method achieves end-to-end HOI detection. This means the model can predict HOI triplets directly from the input image without additional post-processing steps. This end-to-end solution simplifies the detection process and improves detection efficiency. Transformer has powerful modeling capabilities. Through its self-attention mechanism, it can not only capture long-distance dependencies in the image, but also pay attention to all positions in the input sequence, which enables the transformer to identify and understand HOI more accurately. At the same time, The transformer-based method is highly flexible and scalable. By adjusting the parameters and structure of the model, it can adapt to different HOI detection tasks and datasets.

In summary, the transformer-based method provides powerful assistance for HOI detection through its end-to-end solution, powerful modeling capabilities, ability to handle complex interactions, flexibility, and scalability. These advantages make the transformer one of the important technologies in HOI detection.

VI. Methods Related to Foundation Models

The "Foundation Models" concept is first defined in the article "On the Opportunities and Risks of Foundation Models" [137] in 2021. Over 200 pages of text, Rishi Bommasani et al. provide a comprehensive introduction to the opportunities and risks of the foundation models, from their capabilities and technical principles to their applications and social impact. Foundation models are defined as an emerging paradigm for building AI systems based on a general class of models. A foundation model generally uses large-scale self-supervision so that it can be adapted to a wide range of downstream tasks. The current examples include BERT [138], GPT-3 [139] InstructGPT [140], GPT-4 [141], BLIP-2 [142] and CLIP [75]. The foundation models have multiple capabilities, such as language, vision, reasoning, interaction, and understanding, which shows that they have the potential to change the pattern of existing industries and expand the influence of AI in society.

We introduce the foundation models because, in the past two years, researchers have discovered that the foundation models can be used to solve the long-tail distribution problem in HOI detection. As we mentioned in Section I, the long-tail distribution problem refers to overfitting, underfitting, and other problems caused by an imbalance in the number of instance samples between different categories in certain datasets. Since 2018, some scholars have begun to notice the seriousness of this problem. In order to solve this problem, most current methods can be divided into three categories:zero-shot/few-shot learning, compositional learning, and weakly-supervised learning.

(1) Zero-shot/Few-shot learning. Shen et al. [21] introduced a factorization model for HOI detection in 2018. Ji et al. [22] formulated HOI as a few-shot task in a meta-learning framework. Rb-PaStaNet [143] uses human prior knowledge to improve rare HOI class detection; HO-RPN [144] designs a zero-shot classification module to identify new HOI class. Jiang et al. proposed an innovative end-to-end parallel HOI detection framework that incorporates compatibility self-learning (HOICS) [145] for zero-shot HOI detection. Furthermore, DGIG-Net [146], FG [147], ConsNet [148], and OC-Immunity [149] achieve excellent results in zero-shot HOI detection experiments with the new model.

(2) Compositional learning. Compositional learning facilitates the affordance recognition of HOI models by enabling the learning of both known and unknown HOI concepts, which provides new directions for solving the problem of long-tail HOI detection, such as FCL [63], VCL [64], ATL [150], ICompass [151], Bongard-HOI [152] and SCL [153].

(3) Weakly-supervised learning. Baldassarre et al. [154] proposed an explanation-based weakly-supervised method in 2020. In 2021, Kumaraswamy et al. [155] proposed a hybrid-supervised HOI detection pipeline. The method proposed by Nagarajan et al. [156] can infer weakly supervised spatial hotspot maps from a given image.

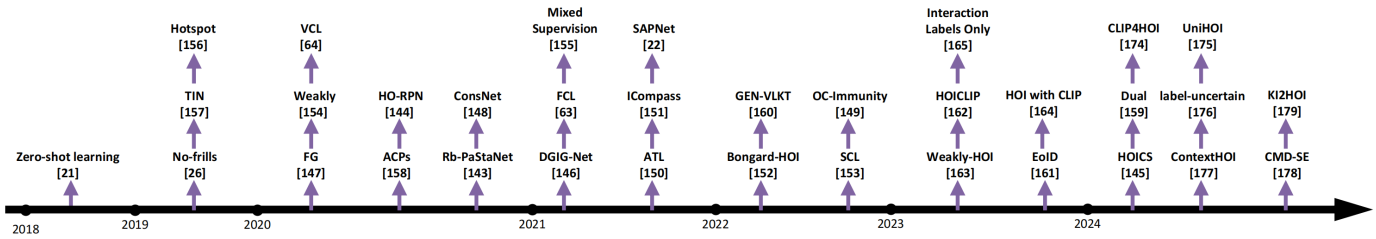


Fig. 13. Development timeline of methods to solve the long-tail distribution problem.

In addition, there are some methods for the long-tail distribution problem that do not fall into the above three categories. Gupta et al. [26] proposed a no-frills model for HOI detection in 2019. Li et al. [157] proposed an interaction identification method named Transferable Interactiveness Network (TIN) in 2019. Kim et al. [158] proposed a new concept of utilizing co-occurring actions (ACPs) to train HOI detectors in 2020. Gao et al. [159] proposed a dual-prior augmented decoding network that utilizes external knowledge to enhance the model's capabilities at a finer granularity.

Since the large-scale visual language pre-training foundation model CLIP is proposed, some studies have gradually focused on CLIP-based HOI detection research. The timeline of methods to solve the long-tail distribution problem is shown in Fig. 13. Liao et al. designed the Guided-Embedding Network (GEN) [160] in 2022. It is a dual-branch pipeline in which an instance decoder uses two independent query sets and a position-guided embedding (p-GE) to detect humans and objects. Another interactive decoder is used to classify interactions, wherein the interactive query is generated by the instance-guided embedding (i-GE) generated by the output of each instance decoder layer. Then, they design a visual language knowledge transfer (VLKT) training strategy to transfer knowledge from CLIP to HOI detectors to enhance interactive understanding without additional computational costs. The THID mentioned above also extracts and leverages transferable knowledge from CLIP to perform zero-shot interaction detection. Wu et al. [161] proposed a new end-to-end zero-shot HOI detection (EoID) framework through visual language knowledge extraction in 2023. They extract interactive knowledge from CLIP and teach HOI models to recognize unseen actions. Ning et al. [162] proposed a new HOI detection framework (HOICLIP) that can effectively extract prior knowledge from CLIP and achieve better generalization. Wan et al. [163] developed a CLIP-guided HOI representation that can incorporate image-level and HOI instance-level prior knowledge and adopt a self-taught mechanism to prune incorrect human-object associations. At the same time, this is also a new weakly-supervised HOI detection strategy. It aims to integrate prior knowledge from pre-trained foundation models to facilitate HOI learning. Wan et al. [164] also design a multi-branch neural network and use CLIP to perform knowledge extraction at multiple levels. They do not use HOI annotations during training, which is a major leap forward in HOI detection. Unal et al. [165] tackle HOI detection in the weakest supervision setting in the system using only image-level interaction labels with the help of pre-trained large language models (LLM) and visual language models (VLM).

After entering 2024, research on HOI detection methods based on foundation models has further become the mainstream direction in the field of HOI. As of the writing of this paper, among the 15 papers related to HOI detection methods produced in 2024, 6 of them used foundation models, accounting for 40% of the total number of papers.

The CLIP4HOI [174] proposed by Mao et al. utilizes the generalizable knowledge of CLIP for unseen interaction recognition. By carefully designing the adaptation modules, CLIP is adjusted to a fine-grained HOI classifier, greatly improving the zero-shot transferability of CLIP4HOI and solving the problem of compromised generalization capability in joint human-object localization. Cao et al. proposed the first visual-textual HOI detection foundation model-based framework (UniHOI) [175], which utilizes LLM and Visual-Language (VL) foundation models to explore universal interaction recognition in open-world environments. Compared with HOI detectors that previously relied solely on specific datasets for training, the framework that combines foundation models significantly improves accuracy and versatility. Cao et al. also proposed HO prompt-based learning, a high-level relation extraction method based on VL foundation models. The designed HO Prompt-guided Decoder (HOPD) helps to associate high-level relation representations in the foundation model with various human-object pairs. In addition, Cao et al. used GPT for interaction interpretation to generate a richer linguistic understanding of complex HOIs. UniHOI effectively unleashes the potential of LLMs and VL foundation models, Breaking through the limitations of traditional zero-shot/few-shot learning methods.

The Bongard-HOI [152] mentioned earlier reflects the problem of few-shot in HOI, and novel label-uncertain query augmentation techniques are introduced in the method proposed by Lei et al. [176] to enhance the diversity of query inputs. By distinguishing positive and negative HOI classes through the pre-trained CLIP image encoder and text encoder, effective learning of Bongard-HOI from a limited number of samples is promoted. To overcome the limitations of previous zero-shot learning methods in understanding context information and comprehensive reasoning, Gao et al. proposed a new HOI learning framework named ContextHOI [177], which serves as an effective contextual HOI detector, including a novel context-mining decoder and a powerful interaction reasoning LLM. The former aims to extract linguistic contextual information from a pre-trained VLM. Based on the extracted context information, the proposed interaction reasoning LLM

TABLE I
HOI DATASETS

Reference	Year	Author	Name	Images	Action categories	Object categories	HOI categories	Parent datasets	Characteristics
[166]	2015	Gupta et al.	V-COCO	10346	26	80	-	MS-COCO	Early, Basic, Widely used
[167]	2015	Chao et al.	HICO	47774	116	80	600	-	New benchmark, Image-level annotations
[73]	2018	Chao et al.	HICO-DET	47776	117	80	600	HICO	New large-scale benchmark, Widely used
[168]	2018	Zhuang et al.	HCVRD	788160	927	1824	28323	Visual Genome	More types, Solve long-tail distribution problem
[33]	2020	Liao et al.	HOI-A	38668	10	11	17	-	Practical application
[169]	2020	Li et al.	HAKE	118000	156	76	-	HICO, HICO-DET, et al.	Human body part-level
[170]	2020	Li et al.	Ambiguous-HOI	8996	48	40	87	V-COCO, HCVRD, et al.	2D pose, Appearance ambiguities
[87]	2021	Zhong et al.	HOI-VP	29190	15	517	5825	HCVRD	Verb polysemy problem
[120]	2021	Wang et al.	SWiG-HOI	59000	406	1000	-	SWiG and DOH	Large vocabulary objects
[171]	2022	Bhatnagar et al.	BEHAVE	15200	-	20	-	-	3D annotations, RGBD sequences
[172]	2022	Li et al.	HAKE-HOI	110714	117	80	520	HICO-DET, HAKE	Larger than HICO-DET
[124]	2023	Ma et al.	HOI-SDC	46821	93	74	321	HAKE-HOI	Two new metrics
[173]	2023	Chen et al.	HOT	35750	-	-	-	V-COCO, HAKE, et al.	2D contact area heatmaps, Associated human part labels

utilizes rich linguistic knowledge to further improve the zero-shot reasoning ability. Lei et al. proposed an end-to-end open-vocabulary HOI detection framework, which features conditional multi-level decoding and fine-grained semantic enhancement (CMD-SE) [178], to address the issue of suboptimal performance of previous zero-shot methods in scenes containing human-object pairs with extensive distances. The framework employs various levels of feature maps from VLM to model HOIs at varying distances in the open-vocabulary scenario. At the same time, by utilizing the extensive world knowledge advantages of LLMs such as GPT, descriptions of human body part states are generated, enhancing the understanding of a large vocabulary of interactions. Xue et al. proposed a novel framework called Knowledge Integration to HOI (KI2HOI) [179], which effectively integrates the knowledge of VLM for zero-shot HOI detection. KI2HOI effectively utilizes prior knowledge and achieves excellent zero-shot transferability. Meanwhile, to deal with zero-shot learning in low-data, Xue et al. utilized prior knowledge from the CLIP text encoder to initialize the linear classifier, enhancing interaction understanding.

LLM has rich semantic knowledge. It acquires a lot of language knowledge through pre-training and provides text descriptions for HOI detection, which helps to understand the semantics of the interaction. GPT has strong zero-shot and few-shot learning capabilities. It can learn and reason without or with only a small amount of specific data, which is particularly important for solving the long-tail distribution problems. At the same time, GPT also has generative capabilities and can generate natural language descriptions to enhance the understanding of interactions.

VLM, such as BLIP-2 and CLIP, has strong cross-modal learning capabilities and can process visual and language information at the same time. This helps to combine visual features and natural language descriptions in HOI detection, which improves detection accuracy. At the same time, for open vocabulary HOI detection, the VLM model can use natural language descriptions to identify new and unseen interaction relationships, thereby expanding the detection capabilities.

The combination of LLM and VLM can provide richer interpretability and higher accuracy for HOI detection. It can not only intuitively display the interaction relationship, but also perform well in dealing with complex scenes and rare interaction relationships, and is better than the first three methods in dealing with the long-tail distribution problems.

In summary, the foundation model has rich semantic knowledge, strong zero-shot and few-shot learning capabilities, generative capabilities, cross-modal learning capabilities, richer interpretability, and higher accuracy. Observing Fig.13, we can find that after 2022, there are more and more methods using the foundation model to solve long-tail distribution problems, which reflects the impact and potential of the foundation model on HOI detection.

VII. Dataset, Metrics and Performance

A. Dataset

This section summarizes the information of popular and widely used HOI detection datasets, as shown in Table I. From 2015 to 2024, a total of 13 datasets for HOI detection have emerged, including HICO, V-COCO, HICO-DET, HCVRD, HOI-A, HAKE, Ambiguous-HOI, HOI-VP, SWiG-HOI, BEHAVE, HAKE-HOI, HOI-SDC, and HOT.

V-COCO (Verbs in Common Objects in Context) dataset [166] is constructed by Saurabh Gupta et al. in 2015. It is a subset of COCO, with annotations of 160K images with 80 different object classes. Its authors add additional annotations to COCO by using Amazon Mechanical Turk (AMT) to connect interacting people and objects and label their semantic roles. The V-COCO dataset contains 10,346 images with 16,199 people instances, of which 2,533 images are used for training, 2,857 images are used for validating, and 4,946 images are used for testing. Each annotated person has 26 different binary action labels, and each image is annotated with 80 object categories. The richness of the data and the

fact that all images inherit the annotations from COCO make V-COCO more suitable for HOI detection. This dataset is the earliest dataset used for HOI detection, so it is also the most basic and commonly used dataset.

HICO (Humans Interacting with Common Objects) [167] is a benchmark dataset proposed by Chao et al. at ICCV (IEEE International Conference on Computer Vision) in 2015, which includes 117 common behaviors from 80 objects. In natural scenes, people may interact with multiple objects simultaneously, so this dataset is object-centric with a large extension of label annotations for interaction categories. Although HICO proposes a new benchmark, it only contains image-level annotations, which makes it inconvenient to use.

HICO-DET [73] is a large-scale benchmark dataset for HOI detection, proposed by the same author as HICO in 2018. They augment HICO with instance annotations by setting up annotation tasks on AMT. HICO-DET has a total of 47,776 images, of which 38,118 are used for training and 9,658 are used for testing. It has 151,276 human instances and 600 HOI categories, including the same 80 object categories as COCO. Those HOI categories with fewer than ten training samples are called "rare" classes, and the rest are called "non-rare" categories; specifically, there are 138 rare categories and 462 non-rare categories. There are two modes of mean average precision on HICO-DET: the Default (DT) mode and the Known-Object (KO) mode. In DT mode, each HOI category is evaluated on all test images, while in KO mode, one HOI is evaluated only on images containing its associated object category. Compared with the V-COCO dataset, the HICO-DET dataset is larger in scale and has more diverse HOI categories. Therefore, it is one of the most commonly used datasets together with the V-COCO dataset.

HCVRD (Human-Centered Visual Relationship Detection) dataset [168] is proposed by Zhuang et al. in 2018, which is constructed based on the Visual Genome dataset [180]. It is currently the largest human-centric HOI dataset, with 788,160 images and 927 action categories. At the same time, HCVRD has more types, and it is also the first to use the zero-shot method to monitor the labels appearing in the test set, which makes it more suitable and easier to solve the long-tail distribution problem.

HOI-A (Human-Object Interaction for Application) dataset [33] is proposed by Liao et al. in 2020. It consists of 38,668 annotated images with 11 interactive objects and 10 interactive actions. To solve the problem that the V-COCO dataset and the HICO-DET dataset have limited HOI categories that need special attention in practical applications, HOI-A covers different appearance types, low resolution, and images with severe occlusions that are difficult to identify. In addition, to expand the intra-class variation of the data, each type of interaction in the HOI-A dataset is divided into three scenarios: indoor, outdoor, and in-vehicle, including dark, natural, and intense lighting conditions and a variety of different angles. Therefore, this dataset is suitable for testing in the above practical application scenarios.

HAKE [169] is the latest dataset proposed by Li et al. in the field of HOI detection in 2020. It uses a large number of human part states (PaSta) [181] labels to infer human body part states, becoming the first large-scale instance dataset with fine-grained annotations. It covers 247K human instances, 220K object instances, and 7000K local action labels. This dataset is suitable for testing at the human body part level.

Ambiguous-HOI [170] is generated to examine the ability to process 2D pose and appearance ambiguities. It can better evaluate the 2D ambiguity processing capacity of models. It mainly obtains data from V-COCO, HCVRD, and other datasets, forming a dataset with 8996 images, 87 HOI categories, 48 action categories, and 40 object categories.

HOI-VP [87] proposed by Zhong et al. in 2021 is the first database designed explicitly for the verb polysemy problem in HOI detection. Specifically, it consists of 15 common verbs and contains 517 common objects in natural scenes, thus ensuring the richness and variety of semantics. Among them, the images and labels of HOI-VP are collected based on the HCVRD dataset.

SWiG-HOI [120] is a dataset for studying human interactions with large vocabulary objects, consisting mainly of data from the SWiG [182] and DOH datasets [183]. SWiG is initially collected for grounded situational recognition (GSR) missions. SWiG-HOI extracts the top 1000 common object categories and obtains 406 human actions, and there are 45k training images and 14k test images.

BEHAVE [171] is a HOI detection dataset with 3D annotations of humans, objects, and interactions and is the largest dataset of RGB-D sequences. The dataset contains 20 3D objects, eight subjects (five males, three females), and five different locations, totaling about 15.2k records frames. They also provide ground truth SMPL [184] and 3D object meshes. This dataset will be helpful when studying HOI detection related to 3D annotations and RGB-D sequences.

HAKE-HOI [172] is split from the HAKE dataset. To alleviate the impact of missing annotations in HICO-DET, Li et al. exclude 80 non-interacting categories. This dataset has larger training and test sets than HICO-DET, providing 110,714 images.

HOI-SDC [124] is established to solve the two difficulties of the uneven size distribution of humans and objects and excessive distance between humans and objects. Ma et al. proposed two metrics to quantify these two difficulties in this dataset. At the same time, the data of this dataset is selected from the HAKE-HOI. This dataset is suitable for situations where the above two difficulties also need to be solved.

HOT [173] is a new dataset of HOI formed by collecting data from four datasets: PROX [185], V-COCO, HAKE, and Watch-n-Patch [186]. Among them, PROX is a 3D human meshes dataset moving in 3D scenes. Chen et al. used this dataset to automatically annotate 2D image areas for contact and annotate relevant body parts of the human body. Watch-n-Patch is an indoor action recognition dataset, which Chen et al. used along with V-COCO and HAKE to draw polygons around the 2D image areas where contact occurred. HOT has 2D contact area heatmaps and related human body part labels as annotations, using automatic generation and manual annotation.

TABLE II
TEST RESULTS OF TWO-STAGE METHODS ON THE V-COCO DATASET AND THE HICO-DET DATASET.

Reference	Year	Name	Backbone	Structure	AProle	Default			Known Object		
						full	rare	non-rare	full	rare	non-rare
[73]	2018	HO-RCNN	CaffeNet	Other	-	7.81	5.37	8.54	10.41	8.94	10.85
[27]	2018	ICAN	ResNet-50	Attention	45.3	14.84	10.45	16.15	16.26	11.33	17.73
[157]	2019	TIN	ResNet-50	Other	47.8	17.03	13.42	18.11	19.17	15.51	20.26
[28]	2019	RPNN	ResNet-50	GNN	47.5	17.35	12.78	18.71	-	-	-
[29]	2020	FCMNet	ResNet-50	Attention	53.1	20.41	17.34	21.56	22.04	18.97	23.12
[104]	2020	in-GraphNet	ResNet-50	GNN	48.9	17.72	12.93	19.31	-	-	-
[110]	2021	PFNet	ResNet-50	GNN	52.8	20.05	16.66	21.07	24.01	21.09	24.89
[92]	2021	AGRR	ResNet-50	Attention	48.1	16.63	11.30	18.22	19.22	14.56	20.61
[106]	2021	SG2HOI	ResNet-50	GNN	53.3	20.93	18.24	21.78	24.83	20.52	25.32
[97]	2022	Cross-Person Cues	ResNet-50	Attention	63.0	35.15	33.71	35.58	37.56	35.87	38.06
[32]	2018	InteractNet	ResNet-50-FPN	Attention	40.0	9.94	7.16	10.77	-	-	-
[62]	2019	PMFNet	ResNet-50-FPN	Attention	52.0	17.46	15.65	18.00	20.34	17.47	21.20
[30]	2020	DRG	ResNet-50-FPN	GNN	51.0	19.26	17.74	19.71	23.40	21.75	23.89
[31]	2020	CHGN	ResNet-50-FPN	GNN	52.7	17.57	16.85	17.78	21.00	20.74	21.08
[61]	2020	PMN	ResNet-50-FPN	Attention	51.8	21.21	17.60	22.29	-	-	-
[108]	2020	VS-GATs	ResNet-50-FPN	GNN	50.6	20.27	16.03	21.54	-	-	-
[69]	2020	MLCNet	ResNet-50-FPN	GNN	55.2	17.95	16.62	18.35	22.28	20.73	22.74
[148]	2020	ConsNet	ResNet-50-FPN	GNN	53.2	22.15	17.55	23.52	-	-	-
[105]	2021	SCG	ResNet-50-FPN	GNN	54.2	31.33	24.72	33.31	-	-	-
[107]	2021	IGPN	ResNet-50-FPN	GNN	53.8	21.26	18.47	22.07	-	-	-
[88]	2022	SDT	ResNet-101	Attention	61.8	32.97	28.49	34.31	36.32	31.90	31.64
[94]	2024	GFIN	ResNet-101	Attention	70.1	35.28	31.91	36.29	38.80	35.48	39.79
[74]	2018	GPNN	ResNet-152	GNN	44.0	13.11	9.34	14.23	-	-	-
[26]	2019	No-frills	ResNet-152	Other	-	17.18	12.17	18.68	-	-	-
[60]	2020	VSGNet	ResNet-152	GNN	51.8	19.80	16.05	20.91	-	-	-
[87]	2021	PD-Net	ResNet-152	Attention	52.2	22.37	17.61	23.79	26.86	21.70	28.44
[96]	2021	OSGNet	ResNet-152	Attention	53.4	21.40	18.12	22.38	-	-	-
[93]	2022	Actor-centric	HRNet-W32	Attention	51.7	27.39	21.34	29.20	30.87	24.20	32.87
[90]	2024	PPDM++	Hourglass-104	Attention	54.3	30.10	23.73	32.00	31.80	24.93	33.85

B. Metrics

In this section, we introduce the accuracy evaluation metrics and calculation process for HOI detection in detail.

Early HOI detection mainly uses the accuracy rate (A_{cc}) to evaluate, which is defined as the proportion of correct samples detected in all samples. However, when the sample data distribution is uneven, the use of accuracy evaluation is prone to bias, and the type of error cannot be objectively described.

Currently, HOI detection uses mean average precision (mAP) and average precision (AP) as the standard evaluation criteria. The AP used in the HOI detection task is the AP of the triplet ⟨human, verb, object⟩, called "role AP"(AP_{role}). In the object detection task, if the Intersection over Union (IoU) of the object bounding box and the ground-truth bounding box is 0.5 or higher, it is considered a true positive (TP). The HOI detection task is modified based on this discriminant. A triplet is considered as a true positive if :(i) the predicted human box b_h has IoU of 0.5 or higher with the ground-truth human box, (ii) the predicted object box b_o has IoU of 0.5 or higher with the ground-truth target object, and (iii) the predicted and ground-truth actions match.

To calculate AP, a confusion matrix is needed. The confusion matrix includes four calculation variables: TP, FN (false negative), FP (false positive), and TN (true negative).

Precision refers to the proportion of true positive samples to all positive samples predicted by the HOI detection model. It is defined as Eq. 5, in which DE represents the number of all prediction boxes.

$$Precision = \frac{TP}{TP + FP} = \frac{TP}{DE} \tag{5}$$

Recall refers to the proportion of positive samples predicted by the human-object interaction detection model to be correct among all real positive samples. It is defined as Eq. 6, in which GT represents the number of true bounding boxes for all objects.

$$Recall = \frac{TP}{TP + FN} = \frac{TP}{GT} \tag{6}$$

AP refers to the proportion of all the accuracy rates and the number of images in the category, and it measures the quality of the model's judgment results in a single category.

TABLE III
TEST RESULTS OF ONE-STAGE METHODS ON THE V-COCO DATASET AND THE HICO-DET DATASET.

Reference	Year	Name	Backbone	AProle	Default			Known Object		
					full	rare	non-rare	full	rare	non-rare
[34]	2020	IP-Net	Hourglass-104	51.0	19.56	12.79	21.58	22.05	15.77	23.92
[33]	2020	PPDM	Hourglass-104	-	21.73	13.78	24.10	24.58	16.65	26.84
[35]	2021	GGNet	Hourglass-104	54.7	29.17	22.13	30.84	33.50	26.67	34.89
[36]	2020	UnionDet	ResNet-50-FPN	47.5	17.58	11.72	19.33	19.76	14.68	21.27
[111]	2021	DIRV	EfficientDet-d3	56.1	21.81	16.35	23.44	25.84	21.02	27.28

It is defined as Eq. 7:

$$AP = \int_0^1 p(r)dr \tag{7}$$

In the above formula, p represents Precision, r represents Recall, and $p(r)$ is a function with r as a parameter, which is called Precision-Recall curve (PR curve). The integral of the function represents the average precision rate. The AP value represented by this formula can also be regarded as the area under the PR curve. PR curve is widely used in object detection, saliency detection, and other fields. AP is under a single category, and mAP is the mean of AP values under all categories, which measures how well the model judges the results across all categories.

C. Performance

Considering that the V-COCO dataset and the HICO-DET dataset are the two most commonly used datasets, and basically all HOI detection methods have been tested on them, we extract the test results on these two datasets from the articles mentioned above. We rank the test results of each method according to backbones as the main influencing factor and paper publication time as the secondary influencing factor. The test results of the two-stage, one-stage, transformer-based, and foundation model methods are presented in Table II, Table III, Table IV, and Table V.

By analyzing the accuracy of each method in the above tables, we can draw the following conclusions.

(1) With the advancement of technology, the accuracy of HOI detection methods has been continuously improved, showing an overall upward trend. It can be inferred that with the further development of technology in the future, the accuracy of HOI detection will be further improved.

(2) From Table II, we can see that for the attention-based and GNN-based methods, the methods of incorporating body gestures, the methods of incorporating contextual information, and the GAT-based methods introduce additional information and features, making the accuracy significantly improved compared to the previous generalized methods.

(3) Compared with the two-stage and one-stage methods, we can find that the overall accuracy of the transformer-based methods and the foundation model methods are the best. The transformer-based methods and the foundation model methods have the highest accuracy in both the V-COCO dataset and the HICO-DET dataset. Moreover, the mAP average value of the listed foundation model methods is 61.68, slightly higher than the mAP average value of 61.07 for the transformer-based methods. And both of these methods are significantly higher than the mAP average value of 52.21 for the two-stage methods and the mAP average value of 52.33 for the one-stage methods. In summarizing the research time of each method, it can be found that in the past two years, there have been more and more papers on transformer-based methods and foundation model methods, indicating that these two types of methods have become the main research directions for HOI detection.

(4) Since the backbone network will directly affect the feature extraction process in the HOI detection process, the selection of the backbone network will also affect the accuracy. At present, for the two-stage methods, transformer-based methods, and foundation model methods, the mainstream backbone networks are ResNet [49] and the feature pyramid networks (FPN) [187] based on ResNet. For the one-stage methods, Hourglass-104 [52] is mainly used to extract features.

Regarding the detection speed, not all methods currently provide their own real-time test results. Moreover, the GPU model, parameters, test datasets, etc., used in the papers that provide detection speed are inconsistent. PPDM [33] tested its efficiency on the HOI-A dataset using Titan Xp GPU and CUDA 9.0, outperforming ICAN and TIN. UnionDet [36] used NVIDIA GTX1080Ti GPU to test the additional inference time on V-COCO and HICO-DET datasets, and the results show that it outperformed ICAN, TIN, GPNN, and InteractNet. DIRV [111] outperformed PMFNet, InteractNet, VSGNet, PPDM, and UnionDet by testing inference time on V-COCO and HICO-DET datasets using NVIDIA RTX2080Ti GPU. AS-Net [40] tested the inference speed on the HICO-DET dataset using GeForce GTX 1080Ti GPU and CUDA 9.0, outperforming InteractNet, ICAN, no-frills, PMFNet, DRG, VSGNet, PPDM, and UnionDet. OCN [114] tested the detection time on the HICO-DET dataset using Tesla V100, and its performance was better than PPDM, HOTR, and ASNet, while QPIC performed slightly better than OCN. HOICLIP [162] tested the inference time using NVIDIA A100 GPUs, and its performance (55.52 ms/img) was almost the same as GEN-VLKT (52.80 ms/img). ViPLO [133] tested the inference speed on the HICO-DET dataset using a Geforce RTX 3090 GPU. It used 3119 MiB of GPU memory and had a speed of 131ms, compared to SCG which used 3423 MiB of GPU memory and had a speed of 106ms.

Although the GPU model, parameters, and test datasets are inconsistent, we can still find from the results of PPDM, UnionDet, and DIRV that the one-stage method has better

TABLE IV
TEST RESULTS OF TRANSFORMER-BASED METHODS ON THE V-COCO DATASET AND THE HICO-DET DATASET.

Reference	Year	Name	Backbone	AProle	Default			Known Object		
					full	rare	non-rare	full	rare	non-rare
[39]	2021	HOTR	ResNet-50	55.2	25.10	17.34	27.42	-	-	-
[41]	2021	PST	ResNet-50	-	23.93	14.98	26.60	26.42	17.61	29.05
[40]	2021	AS-Net	ResNet-50	53.9	28.87	24.25	30.25	31.74	27.07	33.14
[116]	2022	STIP	ResNet-50	66.0	32.22	28.15	33.43	35.29	31.43	36.45
[117]	2022	CPC	ResNet-50	63.1	29.63	23.14	31.57	-	-	-
[121]	2022	CATN	ResNet-50	60.1	31.86	25.15	33.84	34.44	27.69	36.45
[122]	2022	CDN-S	ResNet-50	63.5	33.28	29.19	34.50	-	-	-
[130]	2022	MSTR	ResNet-50	62.0	31.17	25.31	32.92	34.02	28.83	35.57
[131]	2023	MUREN	ResNet-50	68.8	32.87	28.67	34.12	35.52	30.88	36.91
[125]	2024	RMRQ	ResNet-50	61.1	31.11	25.16	32.88	33.89	27.78	35.72
[135]	2024	CMST	ResNet-50	63.9	32.20	27.95	33.56	34.90	30.04	36.33
[134]	2024	TED-Net	ResNet-50	63.4	34.00	29.88	35.24	37.13	33.63	38.18
[136]	2024	LOGICHOI	ResNet-50	64.4	35.47	32.03	36.22	38.21	35.29	39.03
[37]	2021	HOI-Trans	ResNet-101	52.9	26.61	19.15	28.84	29.13	20.98	31.57
[38]	2021	QPIC	ResNet-101	58.8	29.90	23.92	31.69	32.38	26.06	34.27
[114]	2022	OCN	ResNet-101	65.3	31.43	25.80	33.11	-	-	-
[118]	2022	PhraseHOI	ResNet-101	-	30.03	23.48	31.99	33.74	27.35	35.64
[119]	2023	SGPT	ResNet-101	60.3	30.08	24.00	31.89	32.40	26.49	34.16
[123]	2023	HOD	ResNet-101	64.0	34.48	30.38	35.71	-	-	-
[126]	2024	PDN	ResNet-101	64.7	33.18	27.95	34.75	35.86	30.57	37.43
[113]	2022	UPT	ResNet-101-DC5	61.3	32.62	28.62	33.81	36.08	31.41	37.47
[127]	2023	GTNet	ResNet-152	58.3	29.71	23.23	31.64	31.64	24.42	33.81
[17]	2023	QAHOI	Swin-Large$^{*}_{+}$	-	35.78	29.80	37.56	37.59	31.66	39.36
[124]	2024	ViPLO	ViT-B/16	62.2	37.22	35.45	37.75	40.61	38.82	41.15

TABLE V
TEST RESULTS OF FOUNDATION MODEL METHODS ON THE V-COCO DATASET AND THE HICO-DET DATASET.

Reference	Year	Name	Backbone	AProle	Default			Known Object		
					full	rare	non-rare	full	rare	non-rare
[162]	2023	HOICLIP	ResNet-50	63.5	34.69	31.12	35.74	37.61	34.47	38.54
[174]	2024	CLIP4HOI	ResNet-50	66.3	35.33	33.95	35.74	37.19	35.27	37.77
[179]	2024	KI2HOI	ResNet-50	63.9	34.20	32.26	36.10	37.85	35.89	38.78
[160]	2022	GEN-VLKT	ResNet-101	63.6	34.95	31.18	36.08	38.22	34.36	39.37
[163]	2023	Weakly-HOI	ResNet-101	44.7	25.70	24.52	26.05	-	-	-
[175]	2024	UniHOI	ResNet-101	68.1	40.95	40.27	41.32	43.26	43.12	43.25

detection speed than the two-stage method due to the influence of the one-stage detector and parallel detection. The results of AS-Net and OCN also further show that the one-stage method has no advantage in detection speed compared with the transformer-based method. This is also the main reason why the progress of the one-stage methods has stagnated after the emergence of DETR.

In summary, the overall results of the two datasets and different papers on detection time show that HOI detection is developing towards improving detection accuracy and speed. Accuracy and real-time performance indicate whether the HOI detection method is excellent.

VIII. FUTURE DIRECTIONS

Deep learning-based HOI detection methods are still in development, and there are many difficulties that need to be explored and solved. Future research can be carried out from the following aspects.

(1) Domain adaptations for various scenes. The future HOI detection algorithm should be both general and professional. Generality refers to the ability to apply models trained on existing data to unseen scenarios. Professional refers to the ability to train models for specific usage scenarios based on existing data. Domain adaptations can effectively reduce the dependence on labeled training data [188, 189]. At present, the most advanced research directions in this area are few-shot and zero-shot learning, both of which are the application of Meta-Learning in the field of supervised learning. The two hope that the machine learning model can quickly learn new categories with only a small number of samples or zero samples. At present, some early work has begun to explore their application

value in the field of HOI detection, such as [143, 144, 190].

(2) Transformer models are getting increasing attention. Transformer's advantages of global computing and perfect memory make it popular in the machine-learning community. As we mentioned above, the transformer-based methods are slightly more efficient than the one-stage methods in grouping results and interaction classification, and they are also better than the two-stage methods in terms of real-time and accuracy performance. We can find that transformer-based HOI detection methods have become the main research direction in 2024 [134–136, 126, 125] and they are likely to get more attention in the future. At present, transformer-based methods still face difficulties such as long convergence time, poor interpretability, high computational complexity, weak deployment ability in natural environments, and substantial memory needed for model computation. In the future, further research can be conducted on optimizing decoder computing power, mining more interaction information between human pose and contact environment, extracting features from objects that are too small in images, simplifying configuration parameters and fine-tuning processes, and enhancing real-time application performance and generalization performance.

(3) Foundation models to solve the long-tail distribution problem. Nowadays, the popularity of ChatGPT has caused more and more researchers to focus on the foundation models. In the field of HOI detection, there have been some articles using the foundation models, such as CLIP, GPT, and BLIP-2, to solve the long-tail distribution problem, such as [174–179]. The foundation models also perform excellently in solving problems such as excessive reliance on a large number of HOI text labels for classification, poor transferability, complex and diverse HOIs in the real world, poor ability to understand contextual information, and weak comprehensive reasoning ability in previous HOI detection methods. It is conceivable that with the further development of foundation models, more researchers will try to use foundation models to optimize existing HOI detection methods. In the future, further research can be conducted through foundation models to generate and capture uncommon interactions in the long-tail distribution problem, enhance the interaction interpretation and language understanding of complex HOIs using prior knowledge, enhance contextual context and zero-shot reasoning ability, and generate human body part state descriptions using the extensive world knowledge.

(4) More comprehensive and professional datasets. The existing mainstream datasets all have room for further optimization. For example, in [73, 166, 167], the number of instance samples between different categories is unbalanced, which will cause long-tail distribution. At the same time, there is also the problem that the interaction categories are not comprehensive. Although the current largest dataset HCVRD [168] has 9852 behavior categories, it still cannot cover the relationship category between all humans and objects. In addition, datasets with more professional characteristics also have research value. For example, to solve the common occlusion problem in visual perception, Hu et al. [191] proposed a hidden human object detection dataset inspired by physiological features; In the field of human-robot handover, Wiederhold et al. [192] proposed the HOH (Human-Object-Human) Handover dataset to overcome the problem of previous datasets requiring specific body tracking; MECCANO [193] and EgoISM-HOI [194] are proposed to study HOIs in the industrial environment; Li et al. developed V-HICO [195] to solve the problem of traditional video datasets Charades [196], EpicKitchens [197], VidVRD [198], VidOR [199], YouCook [200, 201], being unsuitable for HOI detection, while VidHOI [202], D3D-HOI [203], HOI4D [204], etc. were also proposed to study the video field. Extracting synthetic data from games is also an excellent way to augment the dataset.

(5) Multi-modal optimizes HOI detection performance. In recent years, multi-modal fusion target detection has become a new direction to solve problems such as the poor performance of traditional target detection in complex environments. Similarly, multi-modal fusion can also use information from different modalities to more comprehensively capture interactive information, further improving the robustness, accuracy and versatility of the HOI detection model. In addition to traditional visual information, the available modal information can also be obtained from sensor [205], radar [206], LiDAR [207], sound [208], 3D pose and mesh reconstruction [209], etc.

(6) Beyond HOI detection: HOI generation. In the HOI motion generation field, various innovative methods have emerged in recent years. These methods aim to simulate and generate HOI motions that conform to real physical rules and semantic logic based on the characteristics of scenes [210], text [211, 212] or objects [213]. Combining physical simulation, reinforcement learning, modular design, and deep learning technologies makes the HOI motion generation more natural, accurate, and widely applicable. These research results provide strong support for virtual reality (VR), augmented reality (AR), and human-machine interaction (HMI).

IX. Conclusion

HOI detection plays an essential role in many research fields, but there is no comprehensive and precise method to define and classify all HOI detection methods. This paper fills this gap with the following content. Firstly, this paper introduces the definition, application, and main problems of HOI detection. At the same time, we describe the innovations of this paper compared with previous HOI detection reviews. Then, this paper gives our classification criteria and formula definitions for HOI detection methods and expounds on each method's advantages, disadvantages, and development process. After that, starting from the overall structure of the model, this paper divides the HOI detection methods into the two-stage methods, one-stage methods, and transformer-based methods and expounds them, respectively. At the same time, we introduce the definition of the popular foundation models and a series of methods successfully using the foundation model to solve the long-tail distribution problem faced by HOI detection. Then, this paper introduces the datasets and metrics commonly used in the HOI field specifically and analyzes the performance of each method on the V-COCO dataset and the HICO-DET dataset. Finally, this paper points out future development directions.

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