Hulk: A Universal Knowledge Translator for Human-Centric Tasks

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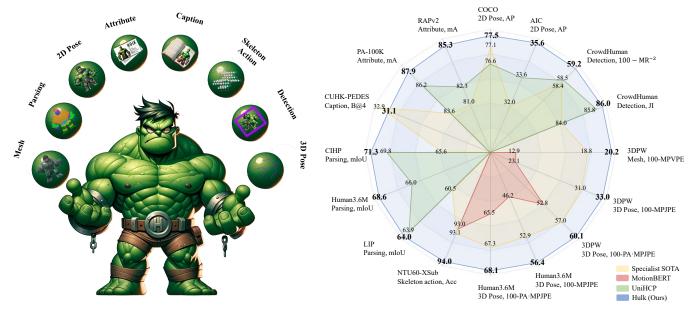


Fig. 1: **Left**: Our proposed Hulk is a general human-centric perceiver that can tackle major 2D vision, 3D vision, skeleton-based, and vision language tasks using a unified framework. **Right**: Hulk pushes the limits on various human-centric tasks when compared with specialist models, pretraining models, *e.g.*, MotionBERT [1], and existing generalist models, *e.g.*, UniHCP [2].

Abstract-Human-centric perception tasks, e.g., human mesh recovery, pedestrian detection, skeleton-based action recognition, and pose estimation, have wide industrial applications, such as metaverse and sports analysis. There is a recent surge to develop human-centric foundation models that can benefit a broad range of human-centric perception tasks. While many human-centric foundation models have achieved success, most of them only excel in 2D vision tasks or require extensive fine-tuning for practical deployment in real-world scenarios. These limitations severely restrict their usability across various downstream tasks and situations. To tackle these problems, we present Hulk, the first multimodal human-centric generalist model, capable of addressing most of the mainstream tasks simultaneously without task-specific finetuning, covering 2D vision, 3D vision, skeleton-based, and vision-language tasks. The key to achieving this is condensing various task-specific heads into two general heads, one for discrete representations, e.g., languages, and the other for continuous representations, e.g., location coordinates. The outputs of two heads can be further stacked into four distinct input and output modalities. This uniform representation enables Hulk to treat humancentric tasks as modality translation, integrating knowledge across a wide range of tasks. To validate the effectiveness of our proposed method, we conduct comprehensive experiments on 11 benchmarks across 8 human-centric tasks. Experimental results surpass previous methods substantially, demonstrating the superiority of our proposed method. The code will be available on https://github.com/OpenGVLab/HumanBench.

Index Terms—Computer Vision, Human-centric Perception, Foundation Models, Multimodal Learning, Multitask Learning.

I. INTRODUCTION

RECENT years have witnessed increasing research attention to human-centric tasks, *e.g.*, person reidentification [3]–[6], pose estimation [7]–[10], and human mesh recovery [1], [11], due to their widespread applications, including sports analysis [12]–[14], surveillance [15]–[18], augmented reality [19]–[21], and video production [22]–[24].

Most of the previous methods have typically emphasized unique designs tailored for individual tasks, involving heavy work for task-specific design, fine-tuning, and deployment. This lack of flexibility and adaptability constrained their applications in real-world scenarios, where multiple tasks are related and need to be addressed using a single model. To this end, some works have explored learning general representative encoders, also known as human-centric foundation

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models, that can be fine-tuned or prompt-tuned for different human-centric visual tasks. These models leverage large-scale pretraining on diverse datasets and have achieved remarkable performance across a wide range of tasks, particularly in 2D vision applications such as person re-identification [3]–[6], pose estimation [7]–[9], and human parsing [25]–[27]. Some notable examples of such models include SOLIDER [28], HCMoCo [62], MotionBERT [1], PATH [29], HAP [30], and SMPLer-X [31].

Despite the success of human-centric foundation models, these models still need to be tuned, making them fall short of the ultimate goal of the *general human-centric perceiver* - one versatile model for all tasks. This goal is inspired by developments in Natural Language Processing (NLP), where one model and one set of parameters, *e.g.*, ChatGPT [32] and InternLM [33], can address all NLP tasks. However, it remains challenging for human-centric tasks because of the diverse data formats and task modeling:

- Heterogeneous and multimodal inputs and outputs. Human-centric perception tasks typically include 2D vision tasks, 3D vision tasks, skeleton-based tasks, and vision-language tasks, whose inputs and outputs cover diverse formats, i.e., images, languages, key points, segmentation maps, and categories. Unifying these incredibly heterogeneous inputs and outputs is nontrivial for a general human-centric perceiver.
- Highly specialized state-of-the-art model designs for individual human-centric tasks. Current state-of-the-art methods for human-centric tasks differ in backbones (e.g., GNN [34] for skeleton-based action recognition and HRFormer [35] for pose estimation) and task heads (e.g., class guidance blocks [104] for human parsing and progressive dimensionality reduction heads [138], [143] for mesh recovery). Unifying these specialized but effective architectural designs for unique tasks is demanding for developing the general human-centric perceiver.

The most recent effort to approximate the abilities of the average human perceiver is represented by UniHCP [2]. This method employs a unified decoder coupled with a versatile yet target-driven interpreter, enabling it to tackle five 2D human-oriented visual challenges. However, the method struggles when dealing with several crucial human-centric tasks, including 3D vision tasks, vision-language tasks, and skeleton-based motion tasks (*e.g.*, skeleton-based action recognition) due to its encoder being only feasible for images. Besides, it fails to enhance the collaboration between various tasks. Consequently, the performance of certain tasks remains significantly lower than the cutting-edge specialized methods.

In this paper, we present Hulk, a <u>H</u>uman-centric <u>universal</u> <u>k</u>nowledge translator, as a *general human-centric percevier*. Hulk is capable of handling major large-scale 2D vision, 3D vision, skeleton-based, and vision-language tasks listed in Table I. Compared to previous methods, its success results from the unification of both diverse input and output formats, and specialized architecture designs. First, Hulk condenses diverse task inputs and outputs into only two basic formats, *e.g.*, continuous digits and discrete words, which can be

further stacked into four modalities, i.e., Text - discrete natural language tokens; Image - normalized RGB images with continuous values from 0 to 1; Sparse Label - 2D/3D continuous location coordinates plus discrete words as its semantic meanings; Dense Label - per-pixel discrete natural language tokens such as segmentation maps. Compared with existing humancentric models, we avoid designing heterogeneous task heads but explore the use of four modality tokenizers/de-tokenizers. These more concise formats facilitate better flexibility and scalability to various tasks and datasets. Second, Hulk reformulates diverse human-centric multimodal tasks into the modality translation task and accordingly unifies different taskspecialist model designs into the encoder-decoder architecture similar to models in the machine translation task. The intuition behind is that if the *general human-centric perceiver* clearly perceives 2D and 3D information of human beings in an image, skeletons, or pedestrian appearance descriptions, we only need to teach it to translate between any input and output modalities. Inspired by advances in machine translation [38], [39], Hulk unifies different task-specialist designs into three simple and effective components: a modality-shared encoder and decoder, a modality-specialised data tokenizers before the encoder and token de-tokenizers after the decoder, and a modality-specialist indicator before the decoder to tell the decoder which modality the inputs should be translated to. Hulk first transforms multimodal data into token sequences in a common manifold space. The modality-shared encoder then extracts general human-centric representations from the token sequence. The modality-specialist indicator guides the modality-shared decoder to translate the human-centric representations into the tokens of the output modality. Finally, the modality-specialist de-tokenizer reconstructs the tokens into the desired output modalities.

To the best of our knowledge, Hulk is the first generalist human-centric perceiver achieving competitive results on major large-scale 2D vision, 3D vision, skeleton-based and vison-language multimodal human-centric tasks¹, including pedestrian attribute recognition, pedestrian detection, 2D pose estimation, human parsing, pedestrian image caption, skeletonbased action recognition, 3D pose estimation and 3D human mesh recovery. Trained on a massive collection of about 30 million labeled human-centric datasets of eight tasks, Hulk can directly handle a broad range of tasks without further taskspecific adaptation, even pushing the performance limits of the existing state-of-the-art methods. Specifically, as shown in Fig. 1, Hulk outperforms current leading human-centric specialist models and pretraining models by +1.5% mIoU on CIHP for human paring, +3.1% mA on RAPv2 for pedestrian attribute recognition, +2.0% AP on AIC for 2D pose estimation, -0.7% MR⁻² (Missing rate) on CrowdHuman for pedestrian detection, -1.4 MPVPE (Mean-Per-Vertex-Position-Error) and -2.0 MPJPE (Mean-Per-Joint-Position-Error) on 3DPW for mesh recovery and 3D pose estimation, respectively.

To summarize, our contributions are three folds:

• We propose Hulk, the first general human-centric per-

¹Tasks such as person re-identification and person search are not explored due to human ethical considerations.

TABLE I

Supporting tasks of existing human-centric pretraining models and generalist models. Pretraining models require fine-tuning for downstream tasks, whereas generalist models like Hulk can be directly used. Compared with other methods, Hulk can perform all mentioned tasks using shared parameters except for Person ReID and Person Search due to ethical concerns.

		Pretraining					Generalist	
Task Type	Tasks	НСМоСо	SOLIDER	PATH	HAP	MotionBERT	UniHCP	Hulk (ours)
	Person ReID		√	√	√		√	
	Person Search		\checkmark					
	Human Parsing	✓	\checkmark	\checkmark			\checkmark	\checkmark
2D Vision Tasks	2D Pose Estimation	✓	\checkmark	\checkmark	\checkmark		\checkmark	\checkmark
	Pedestrian Detection		\checkmark	\checkmark			\checkmark	\checkmark
	Attribute Recognition		\checkmark	\checkmark	\checkmark		\checkmark	\checkmark
Skeleton-based Tasks	Skeleton-based action				✓	✓		✓
Vision-language Tasks	Image Caption							✓
	Mesh Recovery				✓	✓		√
3D Vision Tasks	3D Pose Estimation	\checkmark			\checkmark	\checkmark		✓

ceiver capable of handling 2D vision tasks, 3D vision tasks, skeleton-based tasks, and vision-language tasks without task-specific fine-tuning.

- To facilitate unified modeling, we propose to design only two types of basic blocks, i.e., one for predicting semantics and the other for predicting locations, to establish tokenizers and de-tokenizers of the output modalities.
- Hulk pushes the performance limits of 8 human-centric tasks, including 2D vision tasks, 3D vision tasks, skeleton-based tasks, and vision-language tasks.

II. RELATED WORK

A. Multimodal Foundation Models

Multimodal foundation models have emerged as a significant research direction towards artificial general intelligence (AGI), which aims to synthesize information from various sensory inputs to create more comprehensive AI systems.

Alignment with paired multimodal data, as one common way to develop multimodal foundation models, can be generally divided into two different categories: (1) Contrastive methods, which utilize contrastive loss to pull features with the same content close and push features with different contents apart. A famous example is CLIP [40], which aligns image-text pairs on websites, achieving remarkable zeroshot classification performance. VideoCLIP [41] and Audio-CLIP [42] further extend this idea to alignments text with video and audio, respectively. ImageBind [43] binds five different modalities with images, achieving strong zero-/fewshot performance on cross-modality recognition tasks. (2) Multimodel reconstruction methods, which learn modalityagnostic representation through multi-modal masked autoencoding [44], [45]. For instance, MultiMAE [46] utilizes a modality-share encoder with modality-specific decoders to reconstruct masked RGB, depth and semantic patches, achieving desirable performance on downstream tasks in these modalities. MaskedVLM [47] and SMAUG [48] adopt masked image/text modeling to learn general representations for visionlanguage tasks. However, these methods focus on feature alignment and require additional task heads with fine-tuning for effective application in downstream perception tasks.

The recent emergence of multimodal large language models (MLLM) [49]–[58] proposes a new approach to handling diverse perception tasks: aligning all modalities into language and formatting all perception tasks into Visual Question Answering (VQA) tasks. Leveraging effective adaptation methods, e.g., LoRA [59] and LLAMA-Adapter [60], MLLM generates language answers using the given samples in different modalities, including image [51]–[53], video [54], [55], point cloud [55]-[57], [61] and audio [55], [58]. Despite their versatility, MLLMs have not attained state-of-the-art performance in some perception tasks [49], [50], such as detection and mesh recovery. In this paper, we summarize the input/output of diverse human-centric tasks into four general modalities. Instead of aligning different modalities to a certain modality, we propose to treat all human-centric tasks as modality translation, thereby enhancing the model's adaptability and scalability across diverse human-centric tasks using a versatile and effective framework.

B. Human-Centric Foundation Models

Human-centric foundation models are pivotal in real-world applications, such as social surveillance, sports analysis, and etc. Depending on the model structures, they can be categorized into two types: (1) Human-centric Pretraining Models [28]–[30], [62], which introduce the human prior to pretrain a versatile backbone for extracting general human-centric representation. Specifically, HCMoCo [62] and HAP [30] leverage the offline extracted human keypoints as the prior knowledge to learn structure-invariant representation across diverse human poses, while SOLIDER [28] proposes to learn representation with more semantic information using tokenlevel semantic classification pretext task. Despite the success, these models still require additional task-specific finetuning for downstream task applications due to their lack of unified task modeling. (2) Human-centric General Perceivers [2], aim for a unified framework to handle diverse human-centric tasks with task-specific finetuning. A notable example, UniHCP [2], introduces a shared decoder head with a task-guided interpreter to handle five 2D vision human-centric tasks without additional task-specific finetuning. Our proposed Hulk aligns with

TABLE II

INPUT AND OUTPUT MODALITIES OF EIGHT COVERED HUMAN-CENTRIC TASKS. HULK TREATS ALL THESE TASKS AS MODALITY TRANSLATION. †IN THE MESH RECOVERY TASK, MANY VERTICES DO NOT HAVE A NAME THEREFORE WE ONLY PREDICT THEIR LOCATIONS.

Task	Input modality	Input sample	Output modality	Output sample
Human Parsing	Image	\mathbf{x}_I	Dense label	semantic map representing the occurrence of "hair"
2D Pose Estimation	Image	\mathbf{x}_I	Dense label	semantic map representing the occurrence of "nose"
Pedestrian Attribute Recognition	Image	\mathbf{x}_I	Text	"female", "age 22-30"
Image Caption	Image	\mathbf{x}_I	Text	"A man with black suit standing near the bus station"
Pedestrian Detection	Image	\mathbf{x}_I	Sparse label	"pedestrian", [0.12, 0.45, 0.21, 0.6]
3D Pose Estimation	Image	\mathbf{x}_I	Sparse label	"nose", [0.45,0.26, -0.18]
Mesh Recovery	Image	\mathbf{x}_I	Sparse label	[0.61,0.42,0.17]†
Skeleton-based Action	Sparse label	[[0.47,-0.21], [0.48,-0.20]], "left knee"	Text	"kicking"

this line and further advances the field by simplifying heterogeneous representation across tasks into only two basic formats - continuous digits and discrete words. This simplification greatly enhances the flexibility and scalability of the model and enables our proposed Hulk to simultaneously address 2D vision, 3D vision, vision-language, and skeleton-based humancentric tasks without any task-specific adaptation.

III. HUMAN-CENTRIC 2D VISION, 3D VISION, SKELETON-BASED AND VISION-LANGUAGE TASKS

Hulk, a *general human percevier*, is designed to handle a wide range of 2D vision, 3D vision, skeleton-based and vision-language tasks in a unified way. We collect vision, skeleton-based and multimodal datasets from 42 publicly available data sources as training datasets for our model. These datasets detailed in Sec. V-A1 cover 8 human-centric tasks.

The inputs and outputs of human-centric tasks can be categorized into 4 different modalities: *Images* - RGB images, whose normalized formulation is the matrix whose elements range between 0 and 1; *Texts* - Discrete words; *Sparse Labels* - the coordinates with its semantic meaning and locations, *e.g.*, "nose, [0.45, 0.26]"; *Dense labels* - per-pixel semantics represented by texts. In the following, we show that eight major human-centric tasks can be viewed as the translations among the four modalities. Examples are illustrated in Table II. **Human Parsing & 2D Pose Estimation.** Given an image, human parsing and 2D pose estimation are required to generate the dense labels which are semantic segmentation maps for human parsing and keypoint heatmap for pose estimation².

Pedestrian Attribute Recognition & Image Caption. The RGB images are projected into texts that describe their semantic meanings. For pedestrian attribution recognition, the output is the name of pedestrian attributes, while for the image caption, the output consists of sentences of discrete words as natural language descriptions of the image.

Pedestrian Detection & 3D Pose Estimation & Human Mesh Recovery. The RGB input images are projected to sparse labels, which include continuous digits to describe their locations and discrete words to describe its semantic meaning. For pedestrian detection, the sparse labels contain the location of the upper left point and bottom right point for bounding boxes and discrete words to describe the object class. For 3D pose estimation, the output is the 3D location of every

²In this paper, we leverage the heatmap-based methods for 2D pose estimation because we experimentally verify that heatmap-based methods generally achieve better performance than keypoint-regression-based methods.

keypoints and its class names, *e.g.*, noses and heads. For human mesh recovery, the output is only the 3D locations of mesh vertices defined in the SMPL model. Since these vertices do not have explicit semantic meaning, we do not predict the class name of every mesh vertex.

Skeleton-based Action Recognition. Given sparse labels that are a temporal sequence of keypoints with their semantic meaning and locations, the skeleton-based action recognition transforms the sparse labels to the texts of the action names.

IV. HULK: A GENERAL HUMAN-CENTRIC KNOWLEDGE TRANSLATOR

We now introduce Hulk, a general human-centric knowledge translator, which can tackle human-centric 2D vision, 3D vision, skeleton-based, and vision-language tasks in one model without any task-specialist adaption. The key challenge is to unify the heterogeneous representations of the inputs and outputs. Our Hulk has two innovations to address the problem. First, our Hulk proposes that heterogeneous inputs and outputs can be unified into four different modalities, i.e., texts, images, sparse labels (locations or location sequences) and dense labels (pixel-wise semantic words), which can be further simplified into two basic input and output formats of discrete semantic words and continuous values such as location coordinates. For instance, the pedestrian caption produces words that describe the appearance, age, dress-ups, etc.; the human parsing task predicts pixel-wise semantic words of the given image; the 3D pose estimation task predicts both the location of joints and their corresponding semantic words such as the nose and the right winkle. Second, our Hulk proposes a modality translation task where the major 2D vision, 3D vision, skeleton-based, and vision-language human-centric tasks can be viewed as its special case. The intuition of the modality translation task is that if a model well understands all human-centric knowledge, it only needs to translate from the input modality to the output modality, e.g., human mesh recovery translates the image into sparse labels that are 3D location of mesh vertices, and skeleton-based action recognition translates the human keypoint temporal sequences into texts that describe the action semantic names.

A. Model Architecture

To realize the general modality translation for humancentric perceptions, our proposed Hulk, *i.e.*, <u>Human universal</u> <u>knowledge translator</u>, consists of three simple yet effective components: a modality-specialist tokenizer and de-tokenizer

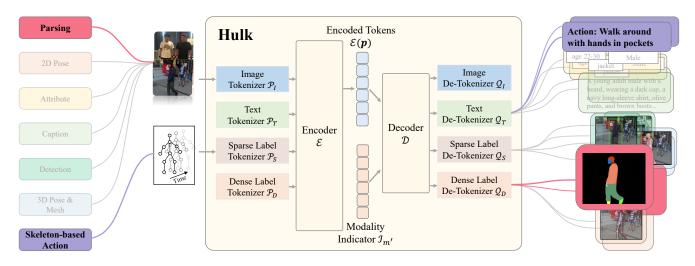


Fig. 2: The framework of our proposed Hulk. The pipeline for human parsing and skeleton-based action recognition tasks are highlighted in pink and purple. Given an input sample from the human parsing task, Hulk first tokenizes the image using the image tokenizer \mathcal{P}_I and sends tokens into the modality-shared encoder \mathcal{E} to learn general human-centric representations. Guided by the output modality indicator \mathcal{I}'_m , the decoder \mathcal{D} translates the encoded tokens to output tokens. Finally, the dense label de-tokenizer \mathcal{P} transforms output tokens into segmentation maps.

(Sec. IV-B) composed of two different heads to predict semantics and locations, a modality-agnostic encoder and decoder (Sec. IV-C) and a modality-specialist indicator (Sec. IV-C) to guide the modality-shared decoder to translate the features extracted by the encoder to the output modality. Finally, we leverage the contrastive loss to supervise the classification of semantic words and L1 loss to supervise the regression of locations. As shown in Fig. 2, the pipeline of our proposed Hulk of translating from the input modality to the output modality can be described as follows:

- 1) Step1 Tokenize modality-specific inputs into a modality-shared manifold space: Given input data \mathbf{x}_m from one of the four modalities, i.e., images I, texts T, sparse labels S and dense labels D, we leverage the modality-specialist tokenizer to project them into tokens \mathbf{p} in the modality-shared manifold, i.e., $\mathbf{p} = \mathcal{P}_m(\mathbf{x}_m)$, where \mathcal{P}_m is the tokenizer of modality m before the transformer encoder \mathcal{E} and $m \in \{I, T, S, D\}$ denotes the modality of input \mathbf{x}_m .
- 2) Step2 Translate the input tokens to the tokens of the output modality with the modality-shared encoder/decoder and the modality indicator for the decoder: Given the input token \mathbf{p} and the output modality indicator \mathcal{I}'_m , we extract the human-centric representations by the encoder \mathcal{E} , and translate it into the output modality with the modality-shared decoder and the output modality indicator, *i.e.*, output tokens $\mathbf{q} = \mathcal{D}(\mathcal{E}(\mathbf{p}), \mathcal{I}_{m'})$, where \mathcal{D} is the transformer decoder and $m' \in \{I, T, S, D\}$ is the output modality.
- 3) Step3 Detokenize the output tokens after the decoder into the target modality and optimize the network with the contrastive loss for classifying the semantic words and L1 loss for regressing locations: Given the translated tokens after the decoder, we generate the output modalities by the modality-specialist de-tokenizer, i.e., $\hat{\mathbf{y}}_s = \mathcal{Q}_s(\mathbf{q})$. Finally, the parameters in the tokenizers $\mathcal{P} \in \{\mathcal{P}_I, \mathcal{P}_T, \mathcal{P}_S, \mathcal{P}_D\}$, the encoder \mathcal{E} , the decoder \mathcal{D} , the de-tokenizers $\mathcal{Q} \in \{\mathcal{Q}_I, \mathcal{Q}_T, \mathcal{Q}_S, \mathcal{Q}_D\}$ and the modality indicators $\mathcal{I}_{m'} \in \{\mathcal{I}_I, \mathcal{I}_T, \mathcal{I}_S, \mathcal{I}_D\}$ are optimized

by the contrastive loss for classifying semantic words and L1 loss for regressing locations.

B. Tokenizer and De-Tokenizer

One of the most critical challenges to developing the *general* human perceiver is to tackle the heterogeneity of the inputs and outputs. While previous methods designed modality-specific projectors and task-specific heads to generate the diverse inputs and outputs, respectively, our Hulk proposes to tokenize task inputs and de-tokenize representations to task outputs in a simple interface: we only need to design two types of tokenizer and de-tokenizer blocks as shown in Fig. 3, *i.e.*, one to classify the semantic texts and the other to regress the locations, based on the intuition that the goal of perception tasks address is to recognize the semantic meaning and locate where it is. We further showcase these two types of blocks can be stacked to construct the tokenizers and de-tokenizers of four modalities in major human-centric tasks.

1) Tokenizer and De-tokenizer Blocks: Based on the observation that the goal of most perception tasks is to recognize the semantic meaning or to localize where the objects and keypoints are. Therefore, we design two pairs of tokenizers and de-tokenizers for classifying semantic words and regressing the digital locations, respectively.

Semantic Tokenizer and De-tokenizer Block. The semantic tokenizer block \mathcal{G}^s aims at tokenizing words in a modality-shared manifold, while the semantic de-tokenizer block \mathcal{H}^s aims at decoding the tokens to the words. The semantic tokenizer and de-tokenizer have dual designs. Specifically, given several words $\mathbf{x}_w = \{\mathbf{x}_1^w, \mathbf{x}_2^w, ..., \mathbf{x}_N^w\}$ representing different semantics, we extract the features $\mathbf{f}_w = \{\mathbf{f}_1^w, \mathbf{f}_2^w, ..., \mathbf{f}_N^w\}$ by the off-shore BERT [63] model, where N is the number of

³According to the vocabulary of BERT, different words will be split into different number of tokens, leading to various lengths of extracted BERT features in different tasks. However, without loss of generality, we use the pooled BERT feature for all tasks.

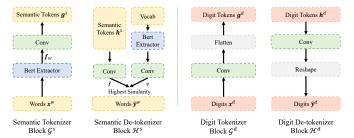


Fig. 3: Two tokenizer and de-tokenizer blocks. Semantic (de-)tokenizer classifies the semantics text and digit (de-)tokenizer regresses the locations.

words. In the skeleton-based action recognition task, semantics of joints are also introduced to enhance Hulk's understanding of the movement of joints (please refer to Fig. 2). To emphasize the semantic correlation among nearing words, we use a convolutional network to generate the text tokens g^s , *i.e.*,

$$\mathbf{g}^s = \mathcal{G}^s(\mathbf{x}_1^w, \mathbf{x}_2^w, ..., \mathbf{x}_N^w) = \text{Conv}(\mathbf{f}_1^w, \mathbf{f}_2^w, ..., \mathbf{f}_N^w), \quad (1)$$

where $\mathbf{f}^i = \text{BERT}(\mathbf{x}_i^w)$ is the BERT feature of the word \mathbf{x}_i^w . Accordingly, the semantic de-tokenizer block \mathcal{H}^s decodes the tokens to words. Given the words in the vocabulary, we extract the features of all words $\mathbf{v} = \{\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_C\}$ by BERT and leverage the convolutional network to project the output semantic tokens \mathbf{h}^s to the BERT feature space $\hat{\mathbf{f}}$,

$$\hat{\mathbf{f}} = \text{Conv}(\mathbf{h}^s).$$
 (2)

Then we select the word $\hat{\mathbf{y}}^w$ whose BERT feature is the most similar to the token feature, *i.e.*,

$$\hat{\mathbf{y}}^w = \mathcal{H}^s(\mathbf{h}^s, \mathbf{v}) = \{ y_j = \operatorname{argmax}_{k \in [1, C]} \mathbf{v}^\top \hat{\mathbf{f}}_{\hat{\mathbf{j}}} \}, j \in [1, N'],$$
(3)

where C and N' denote the number of semantic tokens in \mathbf{v} and output tokens, respectively.

Digit Tokenizer and De-tokenizer Block. The digit tokenizer \mathcal{G}^d and de-tokenizer block \mathcal{H}^d are designed for mutual conversion between continuous digits representing locations and tokens. Given the digit sequence $\mathbf{x} = [\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N]$, where N is the length of digit sequence, we design the convolutional network to extract the information in the digits by transforming the digits to modality-shared tokens, and then flatten it into the token sequence, *i.e.*,

$$\mathbf{g}^d = \mathcal{G}^d([\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N]) = \text{Flatten}(\text{Conv}([\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N])). \tag{4}$$

Accordingly, to decode the digit tokens \mathbf{h}^d into digits indicating locations, we design the convolutional network to generate digits and then reshape the generated digits to the same shape as task outputs \hat{y} , *i.e.*,

$$\hat{y} = [\hat{y}_1, \hat{y}_2, ..., \hat{y}_N'] = \mathcal{H}^d(\mathbf{h}^d) = \text{Reshape}(\text{Conv}(\mathbf{h}^d)), \quad (5)$$

where N' is the length of the output sequence.

2) Stacking Blocks to Modality-specialist Tokenizers and De-tokenizers: As detailed in Sec. III, we categorize the input and output formats of human-centric tasks into 4 different modalities: Text-sentences containing words; Image-RGB images; Sparse labels—a number of location coordinates in the image; Dense labels—per-pixel sentences to describe semantics.

Image. Most human-centric perception tasks rely on the image modality as inputs. An image $\mathbf{x}_I \in \mathbb{R}^{C \times H \times W}$, where C is the number of channels, H is the height of the image and W is the width of the image, is a matrix with continuous digits between 0 and 1 after normalization. Therefore, we directly leverage the digit tokenizer block \mathcal{G}^d as the image tokenizer, *i.e.*,

$$\mathbf{p} = \mathcal{P}_I(\mathbf{x}_I) = \mathcal{G}^d(\mathbf{x}_I), \tag{6}$$

where \mathbf{p} is the input tokens in the modality-shared manifold, and \mathcal{G}^d is the digit tokenizer block defined in Eq. 4. Since Hulk only focuses on human-centric perception tasks, we do not design an image de-tokenizer in this paper and leave it for future works.

Text. The text modality is the important output modality for human-centric perception tasks, including pedestrian caption, skeleton-based action recognition, *etc*. In practice, we directly leverage the semantic tokenizer block as the text tokenizer and the semantic de-tokenizer block as the text de-tokenizer. Given a text inputs of N words, $\mathbf{x}_T = (\mathbf{x}_1^w, \mathbf{x}_2^w, ..., \mathbf{x}_N^w)$, with the text tokenizer, the input tokens \mathbf{p} can be computed by

$$\mathbf{p} = \mathcal{P}_T(\mathbf{x}_T) = \mathcal{G}^s(\mathbf{x}_1^w, \mathbf{x}_2^w, ..., \mathbf{x}_N^w), \tag{7}$$

where \mathcal{G}^s is the semantic tokenizer block defined in Eq. 1.

For attribute or action classification tasks, to obtain the prediction words using the output token ${\bf q}$,

$$\hat{\mathbf{y}}_T = \mathcal{Q}_T(\mathbf{q}) = \mathcal{H}(\mathbf{q}, \mathbf{v}), \tag{8}$$

where \mathcal{H}^s is the semantic de-tokenizer defined in Eq. 3, v denotes the features of attribute or action classes.

For the pedestrian caption task, to auto-regressively decode the word $\hat{\mathbf{y}}^w$ in task outputs $\hat{\mathbf{y}}_T = (\hat{\mathbf{y}}_1^w, \hat{\mathbf{y}}_2^w, ..., \hat{\mathbf{y}}_N^w)$, we define the text de-tokenzier as

$$\hat{\mathbf{y}}_T = \mathcal{Q}_T(\mathbf{q}) = [\mathcal{H}^s(\mathbf{q}_1, \mathbf{v}), \mathcal{H}^s(\mathbf{q}_2, \mathbf{v}), ..., \mathcal{H}^s(\mathbf{q}_N, \mathbf{v})],$$
(9)

where $\mathbf{q}_i, i \in [1, N]$ denotes the *i*-th output tokens in autoregressive manner, \mathbf{v} denotes the features of BERT vocabulary. **Sparse Label.** The sparse labels usually refer to points with semantic meanings. For example, the task outputs of the pose estimation and task inputs of skeleton-based action recognition are the point coordinates and their corresponding semantic meanings. Therefore, the sparse label tokenizer and de-tokenizer combine semantic and digit blocks. We leverage the semantic block to encode the semantics of points and the digit blocks to encode the point locations. Specifically, given the sparse labels $\mathbf{x}_S = (\mathbf{x}_S^s; \mathbf{x}_S^d)$, where \mathbf{x}_S^s denotes the semantics of the sparse labels and \mathbf{x}_S^d denotes the digital locations of the sparse labels. Mathematically, the input tokens \mathbf{p} is computed using the sparse label tokenizer \mathcal{P}_S by

$$\mathbf{p} = \mathcal{P}_S(\mathbf{x}_S) = \mathcal{G}^s(\mathbf{x}_S^s) + \mathcal{G}^d(\mathbf{x}_S^d), \tag{10}$$

where \mathcal{G}^s and \mathcal{G}^d are the semantic tokenzier block (Eq. 1) and the digit tokenizer block (Eq. 4), respectively. Given the output tokens \mathbf{q} after the decoder, the sparse label de-tokenizer \mathcal{Q}_s decomposes it into semantics and digits of sparse label outputs $\hat{\mathbf{y}}_S = (\hat{\mathbf{y}}_S^s, \hat{\mathbf{y}}_S^d)$, where $\hat{\mathbf{y}}_S^s$ and $\hat{\mathbf{y}}_S^s$ are the semantics and digital locations of the output sparse label $\hat{\mathbf{y}}_S$. Specifically,

$$(\hat{\mathbf{y}}_S^s, \hat{\mathbf{y}}_S^d) = \mathcal{Q}_S(\mathbf{q}), \hat{\mathbf{y}}_S^s = \mathcal{H}^s(\mathbf{q}), \hat{\mathbf{y}}_S^d = \mathcal{H}^d(\mathbf{q}), \tag{11}$$

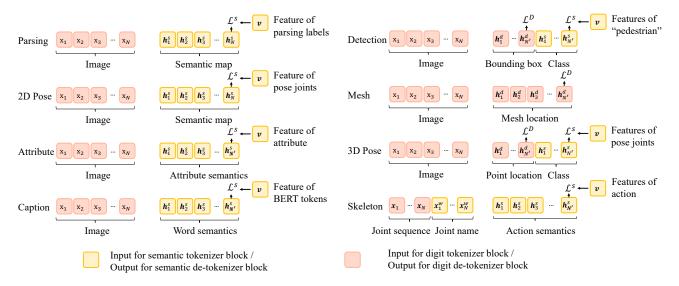


Fig. 4: Input, output tokens and objective functions for eight human-centric tasks. The objective function supervises all the output tokens while only one token's loss is depicted here due to the limited space.

where \mathcal{H}^s and \mathcal{H}^d are the semantic de-tokenzier block (Eq. 3) and the digit de-tokenizer block (Eq. 5).

Dense Label. The dense labels are the semantic words for every pixel of the image. For the dense label tokenizer, given a dense label $\mathbf{x}_D \in \mathbb{R}^{C \times H \times W}$, where C is the number of classes consisting of different words, we leverage the semantic tokenizer block to transform it into input tokens \mathbf{p} , *i.e.*,

$$\mathbf{p} = \mathcal{P}_D(\mathbf{x}_D) = \mathcal{G}^s(\mathbf{x}_D). \tag{12}$$

Different from that in the text de-tokenizer, the decoder output ${\bf q}$ often embeds the information of an image patch instead of a pixel. Therefore, the similarity is computed between the features of words in BERT vocabulary ${\bf v}$ and the feature of upsampled output tokens $\hat{\bf f}$ (Eq. 2). The dense label predictions are then computed by

$$\begin{split} \hat{\mathbf{y}}_D &= \mathcal{Q}_D(\mathbf{q}) \\ &= \{\hat{y}_j = \mathrm{argmax}_{k \in [1,C]} \mathbf{v}^\top \mathrm{Upsample}(\hat{\mathbf{f_j}})\}, j \in [1,N'], \end{split} \tag{13}$$

where C denotes the different semantic classes in \mathbf{v} , N' is the number of output tokens, \mathcal{Q}_D has the additional "Upsample" operator than \mathcal{H}^s defined Eq. 5.

C. Token Translation

Given the modality-specific tokenizer and the modality-specific de-tokenizer, the encoder and the decoder translate the input tokens to output tokens with the guidance of the modality-specialist indicator. The design for token translation is similar to the architecture of "Transformer". Specifically, give the tokens \mathbf{p} of the input modality, the encoder extracts the general human-centric representations, and then the decoder translates the general representation to the output tokens \mathbf{q} , which is guided by the output modality indicator $\mathcal{I}_{m'}$. Mathematically, this process can be defined as

$$\mathbf{q} = \mathcal{D}(\mathcal{E}(\mathbf{p}), \mathcal{I}_{m'}), \tag{14}$$

where \mathcal{E} is the transformer encoder, \mathcal{D} is the transformer decoder, and $\mathcal{I}_{m'} \in \mathbb{R}^{N' \times d_{out}}$, where d_{out} is the dimension of decoder features, N' is the number of output tokens.

D. Objective Functions

As illustrated in Sec. IV-B2, the modality-specific detokenizer will transform output tokens to the semantic part and the digital location part regarding corresponding human-centric tasks. Therefore, the diverse losses proposed in different human-centric tasks can be unified into two, *i.e.*, the contrastive loss to align the predicted semantics and the ground-truth labels, the digit regression loss to supervise the regressed point locations using the ground truth location.

1) Semantic Contrastive Loss: The semantic contrastive loss aims at aligning the predicted semantic words and the semantic labels of the text, the sparse label, and the dense label modality. Mathematically, given the conv-transformed features $\hat{\mathbf{f}}$ of predicted semantic tokens \mathbf{h}^s , the BERT feature \mathbf{v} of the ground-truth semantic label containing the BERT features of all label candidates $(\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_C)$, the semantic contrastive loss is defined as

$$\mathcal{L}^{s} = \frac{\mathbf{v}_{k}^{\top} \hat{\mathbf{f}}}{\mathbf{v}_{1}^{\top} \hat{\mathbf{f}} + \mathbf{v}_{2}^{\top} \hat{\mathbf{f}} + \dots + \mathbf{v}_{C}^{\top} \hat{\mathbf{f}}},$$
(15)

where k denotes the index of the selected semantic label in \mathbf{v} and the computation of $\hat{\mathbf{f}}$ is defined in Eq. 2. Here, $(\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_C)$ are the BERT features that differ in two types of tasks: classification tasks and caption tasks. For the classification task, *i.e.*, skeleton-based action recognition, attribute recognition, the candidate features are the BERT features of all class names in the defined task. For the caption task, *i.e.*, the pedestrian caption, the candidate features are the BERT features of all tokens in the BERT vocabulary.

2) Digit Regression Loss: The digit regression loss aims at predicting 3D coordinate values (3d pose estimation, human mesh recovery), or coordinate sequence values $(x_1y_1x_2y_2)$

TABLE III
STATISTICS OF TRAINING DATASETS.

Task type	Dataset	Number of samples
Human parsing (7 datasets)	Human3.6M [64] LIP [65] CIHP [66]	1,419,910
2D pose estimation (8 datasets)	COCO [67] AIC [68] Posetrack [69]	3,192,532
Attribute recognition (6 datasets)	RAPv2 [70] PA100k [71] parse27k [72]	10,911,029
Pedestrian detection (6 datasets)	CrowdHuman [73] EuroCity [74] WiderPerson [75]	170,687
Skeleton-based action (6 datasets)	Ntu60 [76] GYM [77] Diving48 [78]	391,685
Image caption (2 datasets)	CUHK-PEDS [79] SYNTH-PEDES [80]	12,206,283
3D pose estimation (7 datasets)	Human3.6M [64] Muco [81]	
Mesh recovery (7 datasets)	GTA [82]	1,895,710
Total	42	30,187,836 ≈ 30M

coordinates in pedestrian detection). Specifically, given the coordinates of the sparse labels, the digit regression is defined as

$$\mathcal{L}^d = Dis(\hat{\mathbf{y}}_S^d, \mathbf{y}_S^d), \tag{16}$$

where $Dis(\hat{\mathbf{y}}_S^d, \mathbf{y}_S^d)$ measures the distance between predicted $\hat{\mathbf{y}}_S^d$ and ground truth \mathbf{y}_S^d , which is different in different tasks, e.g., L1 loss and GIoU loss in the pedestrian detection.

3) Overall Objective function: In general multi-dataset learning of Hulk with K datasets, given the prediction $\hat{\mathbf{y}}_i$ with ground truth $\mathbf{y}_i, i=1,2,...,K$, in i-th dataset, the overall objective function is defined as

$$\mathcal{L} = \sum_{i=1}^{K} \lambda_i \mathcal{L}_i(\hat{\mathbf{y}}_i, \mathbf{y}_i), \mathcal{L}_i \in \{\mathcal{L}^s, \mathcal{L}^d\},$$
(17)

where \mathcal{L}_i is the dataset-specific loss with corresponding weight λ_i . For each task, we illustrate the input, output and the objective function in Fig. 4. Detailed losses for every human-centric task are elaborated in the supplementary material.

V. EXPERIMENT

A. Datasets and Evaluation Metric

1) Training Datasets: To establish a human-centric universal knowledge translator, we train the proposed Hulk at scale on a diverse and numerous collection of human-centric datasets. There are two major types of datasets: (1) datasets that leverage professional capture equipment [64], [83] or proficient human annotators [65]–[68], [70], [71], [73]. These

TABLE IV

PEDESTRIAN DETECTION EVALUATION ON CROWDHUMAN [73] WITH

MAP, MR⁻² AND JI. FOLLOWING UNIHCP [2], WE REPORT THE DIRECT

EVAL AND FINE-TUNE (FT) RESULTS. †INDICATES USING A SMALLER

INPUT RESOLUTION WITH A MAXIMUM HEIGHT/WIDTH OF 1120.

Method		Backbone	mAP	$\mathrm{MR}^{-2} \!\!\downarrow$	JI
	DETR [87]	ViT-B	75.9	73.2	74.4
	PEDR [88]	ViT-B	91.6	43.7	83.3
	DDETR [89]	ViT-B	91.5	43.7	83.1
Specialist	Sparse-RCNN [90]	ViT-B	91.3	44.8	81.3
	Iter-DDETR [37]	ViT-B	92.1	41.5	84.0
	Iter-Sparse-RCNN [37]	ViT-B	92.5	42.6	83.3
	Iter-DDETR [37]	Swin-L	94.1	37.7	87.1
Pretraining	PATH [29]	ViT-B	90.9	-	-
Fietranning	PATH [29]	ViT-L	90.8	-	-
	UniHCP [2]	ViT-B	90.0	46.6	82.2
	UniHCP-FT [2]	ViT-B	92.5	41.6	85.8
	Hulk	ViT-B	90.7	43.8	84.0
Generalist	Hulk-FT	ViT-B	92.4	40.7	86.0
	Hulk	ViT-L	92.2	40.1	85.8
	Hulk-FT	ViT-L	93.0	36.5	87.0

datasets generally provide supervision in high quality but are less scalable due to high costs. (2) pseudo-annotated datasets [6], [80] whose annotations are generated by stateof-the-art methods [84], [85]. Although the annotations of these data are not of high quality, they can greatly enrich the scenarios of the training data, of which the effectiveness has been proven by existing work [80], [86]. Generally, 42 publically available datasets are gathered to form the training set for Hulk, containing 30,187,836 training samples and covering eight different human-centric tasks – human parsing, 2D pose estimation, attribute recognition, pedestrian detection, skeleton-based action recognition, image caption, 3D pose estimation, and mesh recovery. Table III presents the number of datasets and samples in each task. Following the deduplication practice in UniHCP [2], we remove the samples that could appear in the evaluation datasets. More detailed dataset setups can be found in the supplementary.

2) Evaluation Datasets: To evaluate the performance of Hulk across diverse human-centric tasks, following Uni-HCP [2], we select multiple core datasets to form a comprehensive benchmark. Specifically, CrowdHuman [73] is selected for evaluation on pedestrian detection, COCO [67] and AIC [68] are selected for 2D pose estimation, Human3.6M [64], LIP [65] and CIHP [66] are selected for human parsing, PA-100K [71] and RAPv2 [70] are selected for attribute recognition. Additionally, Caltech [91], MPII [92], ATR [93], and PETA [94] are also included to evaluate the transferability of Hulk.

For newly included tasks, we use the most widely-used benchmarks, *i.e.*, 3DPW [83] and Human3.6M [64] for 3D pose estimation and mesh recovery, NTU60-XSUB [76] for skeleton-based action recognition, CUHK-PEDES [79] for image caption on pedestrians.

B. Implementation Details

Following UniHCP [2] and PATH [29], we use the standard ViT-Base [95] as the default backbone and initialize

TABLE V

2D Pose estimation evaluation on COCO [67] val set and on AIC [68] test set with MAP. We compare our method with other SOTA methods, both specialists and generalists, with an input resolution of 256×192 . †indicates the implementation. \pm indicates that multiple datasets are used.

Method		Backbone	COCO	AIC
	HRNet [99]	HRNet-W32	74.4	-
	HRNet [99]	HRNet-W48	75.1	-
	TokenPose-L/D24 [100]	HRNet-W48	75.8	-
	HRFormer-B [35]	HRFormer-B	75.6	-
	ViTPose-B [36]	ViT-B	75.8	-
Specialist	ViTPose-B‡ [36]	ViT-B	77.1	32.0
•	ViTPose++-B‡ [101]	ViT-B	77.0	31.9
	ViTPose-L [36]	ViT-L	78.3	-
	ViTPose-L‡ [36]	ViT-L	78.7	34.5
	ViTPose++-L‡ [101]	ViT-L	78.6	34.3
	HCMoCo† [62]	HRNet-W48	76.9	-
	SOLDIER [28]	Swin-B	76.6	-
Pretraining	HAP [30]	ViT-B	77.0	32.3
Trettaining	PATH [29]	ViT-B	76.3	35.0
	PATH [29]	ViT-L	77.1	36.3
	UniHCP [2]	ViT-B	76.1	32.5
	UniHCP-FT [2]	ViT-B	76.6	33.6
	Hulk	ViT-B	77.0	34.5
Generalist	Hulk-FT	ViT-B	77.5	35.6
	Hulk	ViT-L	78.3	36.3
	Hulk-FT	ViT-L	78.7	37.1

it with unsupervised MAE pretraining [96]. Unless otherwise specified, the input resolution is consistent within each task, *i.e.*, 256×192 resolution for 2D pose estimation and attribute recognition, 480×480 resolution for human parsing, 224×224 resolution for 3D pose estimation and mesh recovery, 17 joints×175 frames for skeleton-based action recognition, 384×384 resolution for image caption, and a maximum height/width of 1120 for pedestrian detection. Due to the high GPU memory demand of detection tasks, we resize the maximum height/width of the input images from the commonly used 1333 to 1120, which has a certain impact on the performance of detection tasks but does not affect the superiority of Hulk over other methods.

Considering the computational and communication efficiency during training, we adopt the practices in UniHCP to run one specific task on each GPU with gradient checkpointing [97]. We use the same Adafactor optimizer as that in UniHCP with $\beta_1 = 0.9$, β_2 clipped at 0.999 and disable the parameter scaling. We adopt a 60000-iteration schedule with a linear warm-up for the first 2000 iterations. We set the base learning rate to 10^{-3} with a cosine decay scheduler. For ViT-B backbone, we use a drop-path-rate of 0.2, a layerwise learning rate decay of 0.75, and set weight decay to 0.05. We also train the ViT-L with a drop-path-rate of 0.5, a layer-wise learning rate decay of 0.85, and a weight decay of 0.1, following the recommendation setup in ViTDET [98]. To better utilize the knowledge in every dataset, we do not restrict that all datasets should take the same epoch during training and provide detailed joint training setup in the supplementary. The whole training takes 70, 144 hours in total on 80 NVIDIA A100 GPUS for ViT-B, ViT-L, respectively.

TABLE VI

Human parsing evaluation on Human3.6m [64], LIP [65] and CIHP [66] with mIoU. We compare our method with other SOTA methods, including specialists, generalists, and pretrainings, with an input resolution of 480×480 . †indicated the re-implementation.

Method		Backbone	H3.6M	LIP	CIHP
	SNT [102]	ResNet-101	_	54.73	60.87
	PCNet [103]	ResNet-101	-	57.03	61.05
Specialist	SCHP [84]	ResNet-101	-	59.36	-
	CDGNet [104]	ResNet-101	-	60.30	65.56
	НСМоСо [62]	HRNet-18	62.50	-	-
	HCMoCo† [62]	HRNet-48	66.01	-	-
	SOLDIER [28]	Swin-B	-	60.50	-
Pretraining	PATH [29]	ViT-B	65.00	61.40	66.80
	PATH [29]	ViT-L	66.20	62.60	67.50
	UniHCP [2]	ViT-B	65.90	63.80	68.60
	UniHCP-FT [2]	ViT-B	65.95	63.86	69.80
	Hulk	ViT-B	68.08	63.95	70.58
Generalist	Hulk-FT	ViT-B	68.56	63.98	71.26
	Hulk	ViT-L	69.31	65.86	72.33
	Hulk-FT	ViT-L	69.89	66.02	72.68

C. Comparison with States-of-the-art Methods

Extensive evaluations are conducted to demonstrate the capabilities of our Hulk across diverse human-centric tasks. Table IV-IX show the experimental results of Hulk on eight different human-centric tasks, i.e., pedestrian detection, 2D pose estimation, human parsing, pedestrian attribute recognition, 3D human pose and mesh recovery, skeleton-based action recognition, and pedestrian image captain.

To facilitate a more detailed analysis, we categorize the comparative methods into three distince classes: (1) Specialist models, referring to models custom-tailored specifically for the target task; (2) Pretraining models, involving models pretrained on datasets distinct from the target task, followed by fine-tuning on the target task; and (3) Generalist models, which are designed as unified frameworks capable of handling multiple tasks simultaneously.

Following the practice in UniHCP, we report two kinds of evaluation results of our Hulk: (1) **direct evaluation**, where the pre-trained model are directly used for evaluation on the target dataset, and (2) **finetuning**, where the pretrained Hulk are first finetuned with the train split of the target dataset and then evaluated.

1) 2D Vision Tasks: As observed, our proposed Hulk demonstrates promising performance on four 2D vision tasks, i.e., pedestrian detection, 2D pose estimation, human parsing, and pedestrian attribute recognition.

Pedestrian detection. In the pedestrian detection task, MR⁻² is employed as a more sensitive and crucial metric in detection in the crowd scenes. This metric is particularly sensitive to False Positives (FP), with lower values indicating more desirable performance. We use an input image resolution of a maximum height/weight of 1120, while other methods take a large resolution of 1333 by default. As shown in Table IV, Hulk showcases competitive performance with State-Of-The-ART (SOTA) using a smaller input resolution. Specifically, after finetuning, our Hulk achieves an improvement of **-0.7**%

TABLE VII PEDESTRIAN ATTRIBUTE RECOGNITION EVALUATION ON PA-100K [71] AND RAPV2 [70] WITH MA REPORTED.

Method		Backbone	PA-100K	RAPv2
	SSC [105]	ResNet-50	81.87	-
	C-Tran [106]	ResNet-101	81.53	-
Specialist	Q2L [107]	TResNetL	80.72	-
Specianst	L2L [108]	ViT-B	82.24	-
	DAFL [109]	ResNet-50	83.54	81.04
	SOLIDER [28]	Swin-B	86.37	-
	HAP [30]	ViT-B	86.54	82.91
Pretraining	PATH [29]	ViT-B	86.90	83.10
	PATH [29]	ViT-L	90.80	87.40
	UniHCP [2]	ViT-B	79.32	77.20
	UniHCP-FT [2]	ViT-B	86.18	82.34
	Hulk	ViT-B	82.85	80.90
Generalist	Hulk-FT	ViT-B	87.85	85.26
	Hulk	ViT-L	84.36	82.85
	Hulk-FT	ViT-L	88.97	85.86

MR⁻² on ViT-B and **-1.2%** MR⁻² on ViT-L, respectively, compared to SOTA specialist methods, *e.g.*, Iter-DDETR [37]. **2D pose estimation.** To evaluate the performance of Hulk on 2D pose estimation task, we conduct evaluations on both the COCO and AIC datasets. The results are listed in Table V. Hulk model improves previous SOTA by considerable margins on AIC, *i.e.*, **+0.6%** AP and **+0.8%** on ViT-B and ViT-L, respectively. The performance gain demonstrates the good scalability of Hulk. Hulk achieves on-par performance compared with ViTPose++ [101] on COCO. We attribute the relatively small performance gain on COCO to the distribution gap between the training subset and evaluation subset, where models are trained with on ground-truth boxes but evaluated on estimated boxes with a detector obtaining human AP of 56 on COCO valset [110].

Human parsing. We evaluate the performance of Hulk on the human parsing task on Human3.6M, LIP, and CIHP datasets. As shown in Table VI, when using ViT-B, Hulk surpasses SOTA methods by **+2.36%** mIoU, **+1.46%** mIoU on Human3.6M and CIHP, respectively. On LIP, although Hulk achieves a relatively small performance gain with ViT-B, Hulk showcases considerable performance with ViT-B, *i.e.*, 66.02% mIoU, demonstrating excellent scalability of Hulk.

Pedestrian attribute recognition. We evaluate the performance of our Hulk on PA-100K and RAPv2 datasets to demonstrate its effectiveness on the pedestrian attribute recognition task. Results are listed in Table VII. As can be seen, on ViT-B, Hulk outperforms previous methods by obtaining 87.85% mA and 85.26% mA on PA-100K and RAPv2, respectively. The performance of the large Hulk with ViT-B further increases to 88.97% mA and 85.86% mA, showing competitive results without adopting task-specific heads in human-centric pretraining models [29].

2) Skeleton-based Tasks: In the skeleton-based action recognition task, existing methods utilize three categories of backbones: (1) Graph Convolutional Networks (GCN), which are the most common architecture; (2) Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), and (3) more recently, Transformer architectures. Our Hulk falls

TABLE VIII

SKELETON-BASED ACTION RECOGNITION EVALUATION ON NTU60-XSUB [112] WITH ACCURACY RESULTS REPORTED.

Method		Backbone	Accuracy
	ST-GCN [113]	GCN	81.5
	AS-GCN [114]	GCN	86.8
	AGCN [115]	GCN	88.5
	Shift-GCN [116]	GCN	90.7
	CrosSCLR [117]	GCN	86.2
	MCC [118]	GCN	89.7
	SCC [119]	GCN	88.0
	UNIK [120]	GCN	86.8
	CTR-GCN [121]	GCN	92.4
	MS-G3D [122]	GCN	91.5
Specialist	IndRNN [123]	RNN	81.8
Specialist	MTCNN [124]	CNN	81.1
	HCN [125]	CNN	86.5
	PoseConv3D [111]	CNN	93.1
	ST-TR [126]	Transformer	89.9
	DSTA-Net [127]	Transformer	91.5
	STTFormer [128]	Transformer	89.9
Pretraining	MotionBERT [1]	DSTformer	93.0
	Hulk	ViT-B	93.8
G 11	Hulk-FT	ViT-B	94.0
Generalist	Hulk	ViT-L	94.1
	Hulk-FT	ViT-L	94.3

TABLE IX
PEDESTRIAN IMAGE CAPTAIN EVALUATION ON CUHK-PEDES [79].

Model		Backbone	B@4	CIDEr
Specialist	BLIP [129]	ViT-B	32.9	103.8
	BLIP-2 [51]	ViT-B	32.8	105.8
	Hulk	ViT-B	31.1	91.4
	Hulk-FT	ViT-B	28.3	72.8
Generalist	Hulk	ViT-L	31.6	94.5
	Hulk-FT	ViT-L	30.5	82.8

within the third category. To assess the effectiveness of Hulk, we report results on NTU60-XSub, a well-known dataset on skeleton-based action recognition. The results in Table VIII indicate that even without specific pretraining designs [1], Hulk obtains a remarkable accuracy of 93.8% on ViT-B, better than the SOTA PoseConv3D [111] method. After finetuning Hulk with ViT-L backbone, the performance on NTU60-XSub further increases to 94.3%. This improvement not only highlights the effectiveness of Hulk in the skeleton-based action recognition, but also demonstrates Hulk's ability of tokenizing skeleton and image inputs into a modality-shared manifold space to extract generalized human-centric knowledge.

3) Vision-language Tasks: We also evaluate Hulk on the CUHK-PEDES dataset for the vision-language task, *i.e.*, **pedestrian image captain**. For fair comparisons, we reimplemented the state-of-the-art BLIP [129] and BLIP-2 [51] methods by finetuning its pre-trained weights (on a 129M image-text dataset) on the CUHK-PEDES dataset. As shown in Table IX, Hulk achieves on-par performance with BLIP and BLIP-2 on the B@4 metric but lags behind in terms of CIDEr. This discrepancy in performance can be attributed to

TABLE X MONOCULAR 3D HUMAN POSE AND MESH RECOVERY EVALUATION ON 3DPW [83] AND HUMAN 3.6M [64] AMONG IMAGE-BASED METHODS.

				3DPW		Hun	nan3.6M
Method		Backbone	MPVPE↓	MPJPE↓	PA-MPJPE↓	MPJPE↓	PA-MPJPE↓
	HMR [131]	ResNet-50	-	130.0	76.7	88.0	56.8
	GraphCMR [132]	ResNet-50	-	-	70.2	-	50.1
	SPIN [133]	ResNet-50	116.4	96.9	59.2	62.5	41.1
	I2LMeshNet [134]	ResNet-50	-	93.2	57.7	55.7	41.1
	PyMAF [135]	ResNet-50	110.1	92.8	58.9	57.7	40.5
	ROMP [136]	ResNet-50	105.6	89.3	53.5	-	-
	ROMP [136]	HRNet-W32	103.1	85.5	53.3	-	-
	PARE [137]	ResNet-50	99.7	82.9	52.3	-	-
	METRO [138]	ResNet-50	-	-	-	56.5	40.6
	METRO [138]	HRNet-W64	88.2	77.1	47.9	54.0	36.7
Specialist	PARE [137]	HRNet-W32	88.6	74.5	46.5	-	-
Specialist	MeshGraphormer [139]	HRNet-W64	87.7	74.7	45.6	51.2	34.5
	ProHMR [140]	ResNet-50	-	-	59.8	-	41.2
	OCHMR [141]	ResNet-50	107.1	89.7	58.3	-	-
	3DCrowdNet [142]	ResNet-50	98.3	81.7	51.5	-	-
	FastMETRO [143]	ResNet-50	90.6	77.9	48.3	53.9	37.3
	FastMETRO [143]	HRNet-W64	84.1	73.5	44.6	52.2	33.7
	CLIFF [130]	ResNet-50	81.2	69.0	43.0	47.1	32.7
	VisDB [144]	ResNet-50	85.5	73.5	44.9	51.0	34.5
	MotionBERT [1]	DSTformer	88.1	76.9	47.2	53.8	34.9
Pretraining	HAP [30]	ViT-B	90.1	56.0	106.3	-	-
	Hulk	ViT-B	79.8	67.0	39.9	43.6	31.9
	Hulk-FT	ViT-B	80.7	68.9	41.3	44.9	32.0
Generalist	Hulk	ViT-L	77.4	66.3	38.5	40.3	28.8
	Hulk-FT	ViT-L	79.9	68.3	40.6	41.4	30.2

the extensive pretraining of BLIP and BLIP-2 on large-scale vision-language datasets, while our Hulk is trained solely on smaller human-centric vision-language datasets (about 12M). Furthermore, we observed that finetuning on the CUHK-PEDES dataset led to a decline in the model's prediction accuracy, because better pedestrian captions can learn from diverse annotations in large-scale human-centric datasets.

4) 3D Vision Tasks: In the case of the 3D vision task, i.e., 3D human pose estimation and mesh recovery, our Hulk improves the previous state-of-the-art method CLIFF [130], by -3.8 MPVPE, -2.7 MPJPE, -4.5 PA-MPJPE on 3DPW dataset, and -6.8 MPJPE, -3.9 PA-MPJPE on Human3.6M dataset, in direct evaluation scenarios. Interestingly, comparing with direct evaluation results, we observed that finetuning on both 3DPW and Human3.6M datasets will lead to lower performances, showing the effectiveness of pretraining our Hulk on diverse tasks.

D. Ablation Study

To demonstrate the effectiveness of Hulk, we conduct several ablations on a smaller training set. The ablation set consists of 21 datasets with about 1.7M samples, covering all eight tasks. We provide the detailed dataset combination in the supplementary. Without otherwise specified, we train Hulk for 20k iterations in all ablation variants. While results on different datasets within the same task are highly related, we showcase one dataset per task to represent the performance on the specific task in the main text (all results are provided in the supplementary material). As the metric in 3D pose estimation and mesh recovery computes the error, we use 100 - error when we need to compute average performance among 8 tasks.

1) Weight sharing: As Hulk demonstrates promising performance in various human-centric tasks while sharing mostly all parameters, we explore the impact of incorporating more task-specific parameters into our learning framework. To assess the effectiveness of our weight-sharing approach, we ablate three weight-sharing variants: (a) Our Hulk model, all parameters in both the encoder and decoder are shared across all datasets, and parameters in the tokenizers and detokenizers are shared within the same input/output modality. (b) All parameters in both the encoder and decoder are shared across all datasets, but the parameters in the tokenizers and de-tokenizers are dataset-specific. (c) Only encoder parameters are shared. In Table XI, we observed that more parameter sharing enhances the overall performance of the model. Specifically, introducing decoder parameter sharing (from (b) to (c)) significantly benefits task performances by +12.1% on average. This shows that human-centric tasks require shared human semantic information in different humanrelated annotations. A notable example is the skeleton-based action recognition task. When only the encoder parameters are shared, the model fails to converge, resulting in only 1.7% accuracy on the NTU60-XSub dataset. However, by sharing more model parameters, the general knowledge from other tasks substantially is beneficial to better accuracy in this task.

2) Task Collaboration and Interference: In this section, we explore how various human-centric tasks influence each other. We conduct leave-one-out experiments that we remove one task from our training set every time (as detailed in Table XII). Notably, mesh recovery and 3D pose estimation were always conducted together. We compare these scenarios against a baseline to determine if omitting a task would positively or

TABLE XI Comparison of different parameter-sharing schemes. $\mathcal{E}, \mathcal{D}, \mathcal{P}$, and \mathcal{Q} denote encoder, decoder, tokenizer, and de-tokenizer, respectively. With more task-specific parameters, the average tasks performance of Hulk decline significantly.

					Parsing	2D Pose	Detection	Attribute	Caption	Skeleton	Mesh	3D Pose	
Methods	S	hared	modu	le	LIP	AIC	CrowdHuman	RAPv2	CUHK-PEDES	NTU60-Sub	3DPW	3DPW	Avg
	\mathcal{E}	\mathcal{D}	\mathcal{P}	Q	mIoU	AP	AP	mA	B@4	Acc	100-MPVPE	100-MPJPE	8
(a) Hulk	√	√	√	√	56.8	25.5	81.8	77.9	28.0	93.2	-0.3	13.2	41.8
(b)	\checkmark	\checkmark			56.8	25.8	80.6	78.8	26.7	93.8	-3.0	10.7	41.1
(c)	\checkmark				56.3	25.7	75.9	81.3	28.7	1.7	-11.2	2.9	29.0

TABLE XII Alabtion of collaboration and interference between tasks. In green and RED are the gaps of at least ± 0.5 points.

	Parsing	2D Pose	Detection	Attribute	Caption	Skeleton	Mesh	3D Pose	
Method	LIP	AIC	CrowdHuman	RAPv2 CUHK-PEDES		NTU60-Sub	3DPW	3DPW	Avg.
	mIoU	AP	AP	mA	mA B@4		100-MPVPE	100-MPJPE	8-
baseline	56.8	25.5	81.8	77.9	28.0	93.2	-0.3	13.2	-
w/o Parsing	-	$25.2^{\downarrow 0.3}$	$78.5^{\downarrow 3.3}$	$77.3^{\downarrow 0.6}$	$25.8^{\downarrow 2.2}$	$93.2^{\uparrow 0.0}$	$-2.9^{\frac{1}{2}.6}$	$10.8^{\downarrow 2.4}$	-1.6
w/o 2D Pose	$52.3^{4.5}$	-	$65.0^{\text{$\downarrow$16.8}}$	$75.1^{\frac{1}{2}.8}$	$26.6^{\downarrow 1.5}$	$93.5^{\uparrow 0.3}$	$-18.9^{\frac{18.6}{}}$	$-3.5^{\text{$\downarrow$16.7}}$	-8.6
w/o Detection	$57.6^{\uparrow 0.8}$	$26.4^{\uparrow 0.9}$	-	$77.6^{\downarrow 0.3}$	$27.8^{\downarrow 0.2}$	$93.1^{\downarrow 0.1}$	$-4.8^{4.5}$	$10.5^{\stackrel{1}{\downarrow}2.7}$	-0.9
w/o Attribute	$56.9^{\uparrow 0.1}$	$25.6^{\uparrow 0.1}$	79.9 ^{↓1.9}	-	$28.2^{\uparrow 0.2}$	$93.1^{\downarrow 0.1}$	$-2.1^{\downarrow 1.8}$	$13.2^{\downarrow 1.0}$	-0.6
w/o Caption	$57.3^{\uparrow 0.5}$	$25.6^{\uparrow 0.1}$	$80.2^{1.6}$	$77.8^{\downarrow 0.1}$	-	$92.9^{\downarrow 0.3}$	$-2.2^{\downarrow 1.9}$	$11.2^{\frac{1}{2}.0}$	-0.8
w/o Skeleton	57.4 ^{†0.6}	$25.7^{\uparrow 0.2}$	$80.9^{\text{$\downarrow 0.9}}$	$77.4^{\text{$\downarrow$0.5}}$	$28.2^{\uparrow 0.2}$	-	$-4.8^{4.5}$	9.9 <mark>↓3.3</mark>	-1.2
w/o Mesh&3D Pose	57.4 ^{↑0.6}	$25.5^{\uparrow 0.0}$	$81.0^{\downarrow 0.8}$	$78.0^{\uparrow 0.1}$	$27.9^{\downarrow 0.1}$	$93.1^{\downarrow 0.1}$	-	-	-0.1

negatively impact the performance of others.

We observe several key findings. First, removing any task generally leads to lower average performance of human-centric tasks. Particularly, removing the 2D Pose task significantly decreased performance in detection (-16.8 AP), mesh recovery (increased error by 18.6 MPVPE), and 3D pose estimation (increased error by 16.7 MPJPE). We consider that the pose information in 2D is highly important to that in 3D and can help the model perceive the boundary of pedestrians, making the 2D pose estimation task essential in training a human-centric foundation model. Second, tasks such as the performances of pedestrian detection, mesh recovery, and 3D pose estimation are more sensitive to the removal of other tasks. Their performance markedly declined, indicating a high interdependence among these human-centric tasks during training. Third, skeleton-based action recognition was less affected by the absence of other tasks, which may stem from its unique input type (skeleton points) compared to the imagebased input of other tasks. It is also worth noting that the absence of certain tasks resulted in performance gains for human parsing, indicating potential task conflicts with other human-centric tasks that require further investigation.

3) Attention Mask Designs in the Decoder: The receptive field of the attention module in the decoder is crucial for the translation and de-tokenization of features in the unified model. Therefore, we investigate the effects of different attention masks as illustrated in Fig. 5: (a) our Hulk model adopts task-specialized attention masks for different tasks, i.e., for pose estimation and mesh recovery tasks, we employ full attention; for parsing, detection, attribute, and skeleton-based tasks, we use diagonal attention; for caption tasks, we apply a combination of causal and diagonal attention. We also experimented with (b) all tasks using full attention and (c) all tasks using diagonal attention. The results, shown in Table XIII,

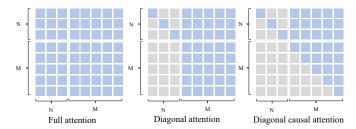


Fig. 5: Given N encoded tokens $\mathcal{E}(\mathbf{p})$ with M modality indicators \mathcal{I}_s , we proposed various attention mask in the decoder \mathcal{D} to facilitate diverse tasks. Left: Full attention enables comprehensive interaction between encoder tokens and modality indicators. Mid: Diagonal attention mitigates potential distortions in encoded tokens due to randomly initialized modality indicators. Right: A combination of the causal and diagonal masks for image captioning.

indicate that employing different attention interaction methods for different tasks can improve the performances, *i.e.*, +0.4% and +1.0% average performance gain on full attention and diagonal attention, respectively.

4) Scaling up data size: To assess the impact of the diverse and sufficient human-centric data, we train Hulk using a longer 60000-iteration schedule on the ablation datasets comprising 1.7M training samples, and full datasets comprising 30M training samples, respectively. Results in Table XIV indicate that incorporating more human-centric data brings considerable performance improvement across all tasks, with notable enhancements in 2D pose estimation (+2.3% AP), pedestrian detection (+1.6% AP), image caption (+2.1 B@4), mesh recovery (-26.0 MPVPE) and 3D pose estimation (-**24.5** MPJPE). Slight improvements are also noted in attribute recognition and skeleton-based action recognition. We attribute these modest gains to the lower quality of data and the significant domain gap in the extended datasets. For instance, in attribute recognition, we include LU-Person [6] with its pseudo labels that offers less informative supervision compared to

TABLE XI	TABLE XIII								
COMPARISON OF DIFFERENT	ATTENTION	MASKS							

	Parsing	2D Pose	Detection	Attribute	Caption	Skeleton	Mesh	3D Pose	
Methods	LIP	AIC	CrowdHuman	RAPv2	CUHK-PEDES	NTU60-Sub	3DPW	3DPW	Avg
	mIoU	AP	AP	mA	B@4	Acc	100-MPVPE	100-MPJPE	
(a) Hulk	56.8	25.5	81.8	77.9	28.0	93.2	-0.3	13.2	47.0
(b) full-attn	57.2	25.4	79.9	77.6	28.6	91.8	-1.0	13.4	46.6
(c) diag-attn	56.6	25.6	80.3	78.0	28.4	93.1	-4.1	10.0	46.0

TABLE XIV

PERFORMANCE OF HULK ON DIVERSE HUMAN-CENTRIC TASKS WHEN SCALING UP DATA SIZE. EXPERIMENTS ARE BOTH TRAINED WITH A FULL 60,000-ITERATION SCHEDULE, SHOWING THAT LEARN FROM ADDITIONAL DATA AND ACHIEVE BETTER PERFORMANCE ON AVERAGE.

	Parsing	2D Pose	Detection	Attribute	Caption	Skeleton	Mesh	3D Pose	
Data samples	LIP	AIC	CrowdHuman	RAPv2	CUHK-PEDES	NTU60-Sub	3DPW	3DPW	Avg.
1	mIoU	AP	AP	mA	B@4	Acc	100-MPVPE	100-MPJPE	Ü
1.7M 30M	63.5 64.0	32.2 34.5	89.1 90.7	80.8 80.9	29.0 31.1	93.7 93.8	-5.8 20.2	8.5 33.0	48.9 56.0

 ${\bf TABLE~XV} \\ {\bf Comparison~of~different~initialization~parameters.}$

	Parsing	2D Pose	Detection	Attribute	Caption	Skeleton	Mesh	3D Pose	
Methods	LIP	AIC	CrowdHuman	RAPv2	CUHK-PEDES	NTU60-Sub	3DPW	3DPW	Avg
	mIoU	AP	AP	mA	B@4	Acc	100-MPVPE	100-MPJPE	8
(a) MAE [96]	56.8	25.5	81.8	77.9	28.0	93.2	-0.3	13.2	47.2
(b) HAP [30]	63.3	33.4	85.4	81.8	29.6	91.5	9.6	22.9	52.2
(c) PATH [29]	63.6	34.5	88.6	80.2	29.9	92.8	8.3	21.3	52.4

other training datasets. Similarly, the Kinetics-400 dataset, which has a substantial domain gap from NTU60, influences the results for the skeleton-based action recognition.

5) Different initialization weights: To examine the influence of model initialization on performance, we conduct additional experiments using pre-training parameters from the human-centric models, i.e., HAP [30] and PATH [29], and compare them with our baseline Hulk initialized by MAE [96]. The results, detailed in Table XV, indicate that initializing Hulk with parameters from human-centric pretraining methods can further enhance its accuracy. This result not only validates the robustness of Hulk but also highlight its potential for further enhancement. Moreover, it is important to note that for a fair comparison with other human-centric models, we refrain from using these specialized pretraining parameters as our default initialization method in main results, ensuring the improvement observed in Hulk are attributed to its novel architecture and learning strategy.

VI. CONCLUSION AND LIMITATIONS

In this paper, we introduce Hulk, a novel general humancentric perceiver that marks the first integration of major 2D and 3D vision tasks, skeleton-based models, and visionlanguage tasks into a unified framework. Diverging from traditional models that rely on task-specific heads, Hulk adopts an innovative approach by decomposing these into two basic heads, thereby enhancing adaptability and simplifying the process. Trained on extensive datasets, Hulk not only achieves state-of-the-art performance across various tasks but does so without the need for dataset-specific fine-tuning. Beyond the success in human-centric tasks, we also shed light on the essential components for developing a human-centric foundation model. Hulk represents a significant step for human-centric foundation models, offering a versatile and effective framework that paves the way for advanced research.

Potential Negatives Impacts. As a foundation model for human-centric tasks, Hulk's extensive data requirements and prolonged training time raise concerns about environmental impact due to high energy consumption. To mitigate this, future research should focus on improving computational efficiency. Additionally, Hulk is trained and evaluated on several human-centric datasets, thus may contain biases in these datasets, which need continuous effort to address to ensure ethical application.

Limitations. Currently, the scope and the capabilities of Hulk is limited by resource constraints and training costs, preventing further exploration of other human-centric tasks, *e.g.*, 3D human generation. Overcoming these barriers remains a lot of future work and will enable us to fully realize the theoretical potential of Hulk. Despite the limitations, Hulk stands as a pioneering framework in human-centric foundation models, offering a glimpse into the future where such models are more inclusive and efficient.

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APPENDIX A FULL ABLATION RESULTS

As shown in Table XVI, we present the full experimental results of the ablation studies. Specifically, we explore the affects of (1) different weight sharing strategies, (2) attention mask designs in decoder, (3) task collaboration and interference, and (4) different initialization weights. One can see that the same conclusion can be observed that as more model components are shared, Hulk can achieve higher performance. Besides, omitting any task generally leads to reduced performance. Furthermore, employing different attention interaction methods for different tasks can optimize the model's performance, compared with using pure full attention or diagnal attention. Last, using the pre-trained weights from other human-centric models (i.e., HAP [30] and PATH [29]) can further boost our hulk's performance. This result not only validates the robustness of Hulk but also highlight its potential for further enhancement.

Moreover, in Table XVII, to assess the impact of the diverse and sufficient human-centric data, we train Hulk using a 60000-iteration schedule on the ablation datasets comprising 1.7M training samples, and full datasets comprising 30M training samples, respectively. Results indicate that incorporating more human-centric data and increasing the training iterations brings considerable performance improvement across all tasks.

APPENDIX B ADDITIONAL ARCHITECTURE DETAILS

A. Modality indicator

Modality indicators $\mathcal{I}_{m'}$ are learnable tokens that are appended with encoded tokens \mathbf{p} to generate the output tokens \mathbf{q} through the modality-shared decoder. In the decoder, modality indicators $\mathcal{I}_{m'}$ have a default shape of $\mathcal{R}^{1 \times d_{out}}$, where d_{out} is the dimension of output tokens. For a certain task that requires N' output tokens, we repeat the modality indicator N' times, resulting in a shape of $\mathcal{R}^{N' \times d_{out}}$.

- 1) Weight sharing.: As an indicator, modality indicators $\mathcal{I}_{m'}$ are shared within the same modality but across different tasks, e.g., the dense labeling modality indicator \mathcal{I}_D is utilized for both human parsing task and 2D pose estimation task. This design together with the modality-shared encoder and decoder helps Hulk learn human-centric knowledge, remedying task bias from a certain task.
- 2) Shape of modality indicators.: While the aligning text features $\mathbf{v} \in \mathcal{R}^{C \times d_{out}}$ always have a length of C denoting the number of semantics/classes, N' varies among different human-centric tasks. For **action and attribute recognition tasks**, N' = C where C is the number of action or attribute classes. After aligning with BERT semantic features \mathbf{v} , the similarity in the i-th index represents the existence probability of the i-th action/attribute. For the **image caption task**, N' = 40 means the length of caption tokens. For dense label output tasks, i.e., **human parsing and 2D pose estimation tasks**, N' equals the number of input image tokens N, generating predicted semantic maps with the same resolution. For sparse label output tasks, i.e., **pedestrian detection, 3D**

pose estimation, and mesh recovery task, N' equals the number of predicted boxes/joints/vertices.

B. Positional Embeddings

- 1) Positional embeddings in the encoder: Different from UniHCP [2], we do not use a learnable positional embedding, instead, we use the bilinear interpolation of fixed MAE [96] positional embeddings in the encoder.
- 2) Positional embeddings in the decoder: As the inputs for the decoder contain two parts, i.e., encoded tokens \mathbf{p} and modality indicator $\mathcal{I}_{m'}$, therefore, positional embeddings in the decoder have two parts.

For the encoded tokens part, positional embeddings are set as the bilinear interpolation of fixed MAE positional embeddings.

For the modality indicator part, we prepare three types of positional embeddings for better experimental results across diverse human-centric tasks:

- Anchor points. For the pedestrian detection task, we follow anchor DETR [?] to integrate the location information into modality indicators for achieving better performance. To ensure compatibility with the MAE positional embeddings, which have a shape of 14 × 14, used in the encoded tokens part, we generate 17 × 17 positional embeddings as fixed anchor points. This approach enables Hulk to focus on regressing the distances between these anchor points and the actual ground truth boxes. By doing so, the detection task is simplified, effectively reducing the complexity and difficulty of convergence.
- 3D positional embeddings. For 3D pose estimation and mesh recovery tasks, Hulk needs to predict 3D digit locations using 3D positional embeddings. Following the practice in [?], we separate the 3D positional embeddings into a fixed 2D positional embedding and a fixed 1D positional embedding with $PE_{3D} = PE_{2D} + PE_{1D}$, introducing strong 3D location information into 3D regression tasks. The 2D positional embedding and 1D positional embedding can be generated by interpolating from fixed MAE positional embeddings.
- Simple interpolation. For tasks encompassing 2D vision, vision-language, and skeleton-based applications, we employ a straightforward approach to generate the positional embeddings in the modality indicator part. These embeddings are inherently two-dimensional or one-dimensional and are derived through a process of simple interpolation from the fixed MAE positional embeddings.

C. Objective function details

In this section, we present the objective functions in Sec. IV.D in the main text. Given the prediction $\hat{\mathbf{y}}_m'$ where $m' \in \{I, T, S, D\}$ is the output modality, we compute the losses according to different human-centric tasks. As modality-specific de-tokenizers transform output tokens to the semantic part and the digital location part, we adopt two types of losses, *i.e.*, semantic contrastive loss and digit regression loss.

For **semantic constrasitve loss**, we first compute the convtransformed output tokens $\hat{\mathbf{f}} \in \mathbb{R}^{N' \times d_{out}}$ with $\hat{\mathbf{f}} = \text{Conv}(\mathbf{q})$,

TABLE XVI

COMPLETE EXPERIMENTAL RESULTS OF DIFFERENT ABLATION STUDIES. THE AVERAGE PERFORMANCES IN THE ABLATION OF TASK COLLABORATION AND INTERFERENCE ARE NOT COMPUTED AND REPLACED BY N/A.

		Parsing		2D P	ose	Detection	Att	ribute	Caption	Skeleton		:	3D Pose & Mesi	h		
Methods	H3.6	LIP	CIHP	COCO	AIC	Crowd	PA	rapv2	CUHK	ntu60	Hun	nan3.6M		3DPW		Avg.
Treations .	mIoU	mIoU	mIoU	AP	AP	AP	mA	mA	B@4	Acc	100-MPJPE	100-PA-MPJPE	100-MPVPE	100-MPJPE	100-PA-MPJPE	
(a) baseline (Hulk)	62.4	56.8	59.7	70.8	25.5	81.8	79.4	77.9	28.0	93.2	45.9	60.5	-0.3	13.2	49.0	53.6
Weight sharing																
(b) only enc./dec. shared	63.4	56.8 56.3	59.6 60.5	71.1 71.3	25.8	80.6	80.8 82.2	78.8	26.7 28.7	93.8 1.7	45.2	60.3	-3.0	10.7	47.0	53.2 44.0
(c) only enc. shared	51.6	30.3	60.5	/1.3	25.7	75.9	82.2	81.3	28.7	1.7	35.9	56.5	-11.2	2.9	41.3	44.0
Attention Mask Designs in	the Dece	oder														
full-attn	62.6	57.2	59.9	70.9	25.4	79.9	79.2	77.6	28.6	91.8	44.3	60.1	-1.0	13.4	48.1	53.2
diag-attn	62.7	56.6	59.9	70.6	25.6	80.3	79.3	78.0	28.4	93.1	40.3	57.6	-4.1	10.0	46.3	52.3
Task Collaboration and In	terference	?														
w/o attribute	62.4	56.9	59.9	70.7	25.6	79.9	-	=	28.2	93.1	44.4	60.0	-2.1	12.2	47.9	N/A
w/o caption	62.7	57.3	59.9	70.7	25.6	80.2	79.3	77.8	-	92.9	46.5	61.3	-2.2	11.2	47.5	N/A
w/o skeleton	62.3	57.4	60.1	70.7	25.7	80.9	79.1	77.4	28.2	-	45.7	59.6	-4.8	10.0	46.7	N/A
w/o mesh&3d pose	62.6	57.4	60.3	70.8	25.5	81.0	79.8	78.0	27.9	93.1	-	-	-	-	-	N/A
w/o detection	63.2	57.6	60.9	71.4	26.4	-	79.9	77.6	27.8	93.1	46.0	59.8	-4.8	10.5	47.6	N/A
w/o 2d pose	56.6	52.3	53.0	-	-	65.0	75.3	75.1	26.6	93.5	24.5	48.4	-18.9	-3.5	37.2	N/A
w/o parsing	-	-	-	70.2	25.2	78.5	79.4	77.3	25.8	93.2	42.5	57.5	-2.9	10.8	46.7	N/A
Different initialization wei	ghts															
MAE (baseline)	62.4	56.8	59.7	70.8	25.5	81.8	79.4	77.9	28.0	93.2	45.9	60.5	-0.3	13.2	49.0	53.6
HAP	65.8	63.3	68.8	76.5	33.4	85.4	85.5	81.8	29.6	91.5	55.2	66.6	9.6	22.9	55.6	59.4
PATH	66.3	63.6	69.2	76.8	34.5	88.6	83.3	80.2	29.9	92.8	54.6	66.7	8.3	21.3	54.5	59.4

TABLE XVII

COMPLETE EXPERIMENTAL RESULTS OF OUR HULK PERFORMANCE ON DIVERSE HUMAN-CENTRIC TASKS WHEN SCALING UP DATA SIZE. EXPERIMENTS ARE BOTH TRAINED WITH A **FULL 60,000-iteration** schedule, showing that learn from additional data and achieve better Performance on average. .

		Parsing		2D P	ose	Detection	Att	ribute	Caption	Skeleton	on 3D Pose & Mesh					
Methods	H3.6	LIP	CIHP	COCO	AIC	Crowd	PA	rapv2	CUHK	ntu60	Hun	nan3.6M		3DPW		Avg
	mIoU	mIoU	mIoU	AP	AP	AP	mA	mA	B@4	Acc	100-MPJPE	100-PA-MPJPE	100-MPVPE	100-MPJPE	100-PA-MPJPE	
30M 1.7M	68.1 66.9	64.0 63.5	70.6 68.4	77.0 76.0	34.5 32.2	90.7 89.1	82.9 82.1	80.9 80.8	31.1 29.0	93.8 93.7	56.4 36.0	68.1 60.3	20.2 -5.8	33.0 8.5	60.1 44.9	62.1 55.0

where N' is the number of output tokens, d_{out} is the output dimension, and $\mathbf{q} \in \mathbb{R}^{N' \times d_{out}}$ are output tokens. Given $\mathbf{v} = (\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_C)$ containing the BERT features of C ground truth classes, the semantic contrastive loss is defined as

$$\mathcal{L}^{s} = \frac{\mathbf{v}_{k}^{\top} \hat{\mathbf{f}}}{\mathbf{v}_{1}^{\top} \hat{\mathbf{f}} + \mathbf{v}_{2}^{\top} \hat{\mathbf{f}} + \dots + \mathbf{v}_{C}^{\top} \hat{\mathbf{f}}},$$
(18)

where k is the index of the selected semantic token.

For **digit regression loss**, we compute the distance between predicted coordinate values $\hat{\mathbf{y}}^d$ and corresponding ground truth coordinate values \mathbf{y}^d with

$$\mathcal{L}^d = Dis(\hat{\mathbf{y}}^d, \mathbf{y}^d), \tag{19}$$

where $Dis(\mathbf{a}, \mathbf{b})$ measures the distance between \mathbf{a} and \mathbf{b} , which is different in different tasks, *i.e.*, L1 loss and GIoU loss in the pedestrian detection.

Human Parsing. Human parsing aims to segment human parts. As human parts can be represented by their BERT features, we align the output tokens with BERT features of semantic classes using per-pixel contrastive loss. Following the practice in UniHCP [2], we also supervise the global probability of a certain semantic class to enhance the performance. Given the conv-transformed output tokens $\hat{\mathbf{f}}$, we simply average pool them to represent the predicted probability of occurrence of certain semantic class $\hat{\mathbf{f}}_{avg}$. Given extracted BERT features \mathbf{v} of C parsing classes, , the total objective function for human parsing is as follows:

$$\mathcal{L}_{par} = \mathcal{L}^{s}(\hat{\mathbf{f}}, \mathbf{v}_{pix}) + \mathcal{L}^{s}(\hat{\mathbf{f}}_{avg}, \mathbf{v}) + \mathcal{L}_{dice}(\hat{\mathbf{y}}, y), \tag{20}$$

where $\mathbf{v}_{pix} \in \mathbb{R}^{N \times C \times d_{out}}$ denotes the per-pixel BERT features, L_{dice} is adopted as an auxiliary loss to enhance the human parsing performance. In the dice loss, $y \in \mathbb{R}^{N \times C}$ denotes the ground truth heatmaps with C parsing classes and $\hat{\mathbf{y}}_D \in \mathbb{R}^{N \times C}$ is the predicted heatmaps computed by $\hat{\mathbf{y}} = \{\hat{y}_j = \mathrm{argmax}_{k \in [1,C]} \mathbf{v}^{\top} \mathrm{Upsample}(\hat{\mathbf{f_j}})\}, j \in [1,N'].$

2D Pose Estimation. We follow the common top-down setting for 2D pose estimation. As we leverage the heatmap-based methods for 2D pose estimation for better experimental results, the objective function is similar to that in human parsing. Mathematically, given extracted BERT features ${\bf v}$ of C joint names, we have

$$\mathcal{L}_{pose} = \mathcal{L}^{s}(\hat{\mathbf{f}}, \mathbf{v}_{pix}) + \mathcal{L}^{s}(\hat{\mathbf{f}}_{avg}, \mathbf{v}), \tag{21}$$

where $\mathbf{v}_{pix} \in \mathbb{R}^{N \times C \times d_{out}}$ denotes the per-pixel BERT features

Pedestrian Attribute Recognition. Pedestrian Attribute Recognition predicts whether an attribute exists in the input image. Therefore, we only supervise the output tokens $\hat{\mathbf{f}} \in \mathbb{R}^{C \times d_{out}}$ by aligning them to C different attribute semantics. High similarity means the existence of a certain attribute. Given extracted attribute BERT features $\mathbf{v} \in \mathbb{R}^{C \times d_{out}}$, the objective function can be computed by:

$$\mathcal{L}_{attr} = \mathcal{L}^s(\hat{\mathbf{f}}, \mathbf{v}). \tag{22}$$

Pedestrian Image Caption. We predict the image caption in an auto-regressive manner. For each predicted token, we

adopt the semantic constrastive loss \mathcal{L}^s to supervise. The total objective function is similar to that in attribute recognition,

$$\mathcal{L}_{cap} = \mathcal{L}^s(\hat{\mathbf{f}}, \mathbf{v}), \tag{23}$$

where $\hat{\mathbf{f}} \in \mathbb{R}^{N' \times d_{out}}$ are the features representing predicted caption tokens, N' is 40 by default. $\mathbf{v} \in \mathbb{R}^{C \times d_{out}}$ denotes the features of BERT vocabulary, where C = 30522 denotes the length of BERT vocabulary.

Pedestrian Detection. Different from widely adopted designs in transformer-based pedestrian detectors that rely on object queries, we directly decode N' modality indicators as the sparse prediction results. Given predicted digital location $\hat{\mathbf{y}}^d$, predicted semantic features $\hat{\mathbf{f}}$, ground truth location \mathbf{y}^d and ground truth semantic features \mathbf{v} representing the word "pedestrian", we utilize optimal bipartite matching to determine the matched pairs. The objective function can be computed by the combination of semantic contrastive loss and digit regression loss:

$$\mathcal{L}_{det} = \mathcal{L}_{L1}(\hat{\mathbf{y}}^d, \mathbf{y}^d) + \mathcal{L}_{iou}(\hat{\mathbf{y}}^d, \mathbf{y}^d) + \mathcal{L}^s(\hat{\mathbf{f}}, \mathbf{v}), \quad (24)$$

where \mathcal{L}_{L1} , \mathcal{L}_{iou} are L1 loss and GIoU loss, respectively.

3D Pose Estimation & Mesh Recovery. Following common practice [130], [138], [143], we train Hulk to learn 3D pose estimation task and mesh recovery task jointly. Similar to the pedestrian detection task, the 3D pose estimation task also has a combined objective function of semantic contrastive loss and digital regression loss while the mesh recovery task only has the digit regression loss due to undefined semantics of numerous vertices. Given predicted digital location $\hat{\mathbf{y}}^d$, predicted semantic features $\hat{\mathbf{f}}$ representing C different joint semantics, we compute the objective function for 3D pose estimation and mesh recovery as

$$\mathcal{L}_{3dpos} + \mathcal{L}_{mesh} = \mathcal{L}_{2d}(\hat{\mathbf{y}}^d, \mathbf{y}) + \mathcal{L}_{3d}(\hat{\mathbf{y}}^d, \mathbf{y}) + \mathcal{L}_{vertice}(\hat{\mathbf{y}}^d, \mathbf{y}) + \mathcal{L}_{normal}(\hat{\mathbf{y}}^d, \mathbf{y}) + \mathcal{L}_{edge}(\hat{\mathbf{y}}^d, \mathbf{y}) + \mathcal{L}^s(\hat{\mathbf{f}}, \mathbf{v}),$$
(25)

where y is the ground truth location, v denotes BERT features of joint names. \mathcal{L}_{2d} , \mathcal{L}_{3d} , $\mathcal{L}_{vertice}$, \mathcal{L}_{normal} , and \mathcal{L}_{edge} are all L1 loss

Skeleton-based action Recognition. Skeleton-based action recognition predicts the action based on input skeleton sequence. Therefore, given action semantic features $\mathbf{v} \in \mathbb{R}^{C \times d_{out}}$ where C is the number of actions, and the predicted semantic tokens $\hat{\mathbf{f}} \in \mathbb{R}^{C \times d_{out}}$, the objective function can be computed by:

$$\mathcal{L}_{ske} = \mathcal{L}^s(\hat{\mathbf{f}}, \mathbf{v}). \tag{26}$$

APPENDIX C DETAILS OF TRAINING DATASETS

A. Full setting

As shown in Table XVIII, we utilize 42 publically available datasets to form the training set for training our Hulk model, containing 30,187,836 training samples and covering eight different human-centric tasks, including human parsing, 2D pose estimation, attribute recognition, pedestrian detection, skeleton-based action recognition, image caption, 3D pose estimation, and mesh recovery.

TABLE XVIII
STATISTICS OF TRAINING DATASETS IN THE FULL SETTING.

Task type	Dataset	Number of samples
	Human3.6M [64]	62,668
	LIP [65]	30,462
II	CIHP [66]	28,280
Human parsing	ModaNet [?]	52,245
(7 datasets)	VIP [?]	18,469
	Deep fashion [?]	191,961
	Paper Doll [?]	1,035,825
	COCO [67]	149,813
	AIC [68]	378,352
2D mass satimation	Human3.6M (pose) [64]	312,187
2D pose estimation	Posetrack [69]	97,174
(8 datasets)	3DPW [83]	68,663
	JRDB-Pose [?]	139,385
	MPI-INF-3DHP [?]	1,031,701
	AIST++ [?]	1,015,257
	RAPv2 [70]	67,943
A 44:1	PA_100k [71]	90,000
Attribute recognition	Parse27k [72]	27,482
(6 datasets)	Market [?]	12,926
	HARDHC [?]	28,336
	LU-Person [6]	10,684,342
	CrowdHuman [73]	15,000
Pedestrian detection	EuroCity [74]	21,785
redestrail detection	CityPersons [?]	2,778
(6 datasets)	WiderPerson [75]	9,000
	WiderPedestrian [?]	58,009
	COCO-person [67]	64,115
	NTU60 [76]	40,091
Skeleton-based action	NTU120 [112]	63,026
Skeletoli-based action	GYM [77]	2,778
(6 datasets)	Diving48 [78]	15,027
	UCF101 [?]	13,320
	Kinetics-400 [?]	239,737
Image caption	CUHK-PEDS [79]	68,126
(2 datasets)	SYNTH-PEDES [80]	12,138,157
	Human3.6M [64]	312,188
	3DPW [83]	22,735
3D pose & Mesh	COCO [67]	40,055
JD pose & Mesil	MUCO [81]	101,883
(7 datasets)	UP-3D [?]	7,126
	MPII [92]	14,810
	GTA [82]	1,396,913
Total	42	30,187,836≈ 30M

B. Ablation setting

In ablation stuides, to demonstrate the effectiveness of Hulk and further explore the potential of a human-centric foundation model, we conduct several ablations on a smaller training set. In Table XIX, the ablation set consists of 21 datasets with about 1.7M samples, covering all eight tasks.

APPENDIX D DETAILS OF DATASET-WISE CONFIGURATIONS

A. Training

We provide detailed dataset-wise training configurations in Table XX, including total batch size, batch size per GPU, the number of GPUs, and task weights. In order to better unify different tasks and different datasets, the different datasets of certain tasks (i.e., attribute recognition, pedestrian detection, skeleton-based action, image caption, 3D pose and mesh

Task type	Dataset	Number of samples
Human parsing	Human3.6M [64]	62,668
numan parsing	LIP [65]	30,462
(3 datasets)	CIHP [66]	28,280
2D pose estimation	COCO [67]	149,813
(2 datasets)	AIC [68]	378,352
	RAPv2 [70]	67,943
Atteilauta magaamitian	PA_100k [71]	90,000
Attribute recognition	Parse27k [72]	27,482
(5 datasets)	Market [?]	12,926
	HARDHC [?]	28,336
Pedestrian detection	CrowdHuman [73]	15,000
Skeleton action	NTU60 [76]	40,091
(2 datasets)	NTU120 [112]	63,026
Image caption	CUHK-PEDS [79]	68,126
(2 datasets)	SYNTH-PEDES [80]	132,000
	Human3.6M [64]	312,188
	3DPW [83]	22,735
2D 0 M 1	COCO [67]	40,055
3D pose & Mesh	MUCO [81]	101,883
(6 datasets)	UP-3D [?]	7,126
	MPII [92]	14,810
Total	21	1,693,302≈ 1.7M

recovery) are stacked together as a integrated dataset for training, and the datasets of some other tasks (i.e., human parsinga nd 2D pose estimation) are separately trained on different GPUs with diverse task weights.

B. Fine-tuning

For fine-tuning porcess, we carefully tune the learning rate, total batch size, the number of iterations, and drop path rate, and report the best performances. In details, the ViT-base backbone (i.e., in Table XXII) and ViT-large backbone (i.e., in Table XXII) are tuned, respectively.

TABLE XX HULK JOINT TRAINING SETUP.

Task Type	Dataset	Batch Size	Batch Size per GPU	GPUs	Task Weight
	LIP	108	27	4	1.8
	CIHP	104	26	4	3.6
	Human3.6M	217	31	7	2.25
Human parsing	ModaNet	27	27	1	0.021
B	VIP	27	27	1	0.021
	Deepfashion	54	27	2	0.042
	PaperDoll	27	27	1	0.021
	COCO	528	176	3	28000
	AIC	1323	189	7	56000
	Human3.6M	264	132	2	3192
	Posetrack	340	170	2	12335
2D pose estimation	JRDB	340	170	2	8223
	MPI-INF-3DHP	340	170	2	8223
	3DPW	170	170	1	2055
	AIST++	170	170	1	2055
Attribute recognition	RAPv2 PA Parse27k Market HARDHC	147	147	1	5
	LUPerson	300	300	1	5
	CrowdHuman	32	4	8	15
Pedestrian detection	EuroCity CityPersons WiderPerson WiderPedestrian COCO	80	4	20	42.4
	Ntu60 Ntu120 gym	240	120	2	4.4
Skeleton action	Diving48 UCF101 K400	90	90	1	1
Image caption	SYNTH-PEDES CUHK-PEDES	300	100	3	90
3D pose & Mesh	3DPW Human3.6M COCO mMUCOuco UP-3D MPII GTA	495	165	3	0.5

 $\label{thm:thm:thm:configs} TABLE~XXI\\ Detailed fine tuning configs~\mbox{\it with ViT-base backbone}~\mbox{for human-centric tasks}.$

Task Type	Dataset	Learning Rate	Batch Size	Iterations	Drop Path Rate
2D	COCO	3.00E-05	1024	20k	0.3
2D pose estimation	AIC	3.00E-04	1024	15k	0.2
	3DPW	3.00E-05	512	10k	0.2
3D pose & Mesh	Human3.6M	3.00E-05	512	10k	0.2
Pedestrian detection	CrowdHuman	1.00E-04	32	80k	0.2
	LIP	1.00E-04	1024	20k	0.3
Human parsing	CIHP	1.00E-04	1024	20k	0.3
Tuman parsing	Human3.6M	5.00E-04	1024	20k	0.3
	RAPv2	6.00E-04	128	8k	0.2
Attribute recognition	PA	3.00E-04	128	5k	0.2
Skeleton action	NTU60	1.00E-04	48	10k	0.2
Image caption	CUHK-PEDES	1.00E-06	256	3k	0.2

 $TABLE\ XXII$ Detailed finetuning configs with VIT-large backbone for human-centric tasks.

Task Type	Dataset	Learning Rate	Batch Size	Iterations	Drop Path Rate
2D pose estimation	COCO	3.00E-05	1024	10k	0.6
	AIC	3.00E-04	1024	15k	0.3
3D pose & Mesh	3DPW	3.00E-05	512	10k	0.2
	Human3.6M	3.00E-05	512	10k	0.2
Pedestrian detection	CrowdHuman	1.00E-04	32	10k	0.5
Human parsing	LIP	5.00E-05	512	10k	0.5
	CIHP	5.00E-05	512	10k	0.5
	Human3.6M	1.00E-05	512	10k	0.5
Attribute recognition	RAPv2	1.00E-03	128	6k	0.5
	PA	7.00E-04	128	3k	0.5
Skeleton action	NTU60	1.00E-05	48	10k	0.5
Image caption	CUHK-PEDES	1.00E-06	256	3k	0.5