

SAM a great Semantic Segmentations

LLM to generate the reward function

Hantao Zhou

Universitaet Hamburg

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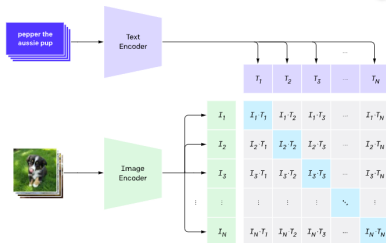
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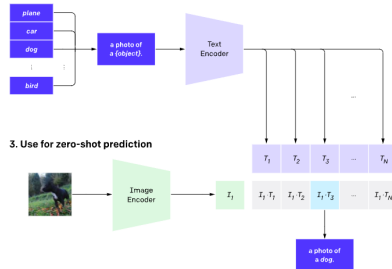
Multi-modal processing structure

1. Contrastive pre-training



CLIP pre-train on image encoder and a text encoder to modify which images were related

2. Create dataset classifier from label text



3. Use for zero-shot prediction

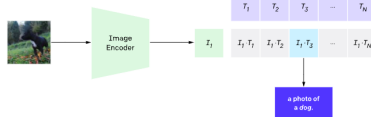
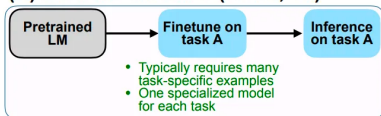


Figure: Multi-modal processing structure

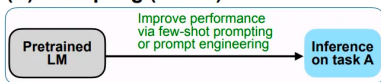
► CLIP

Prompt-based Techniques

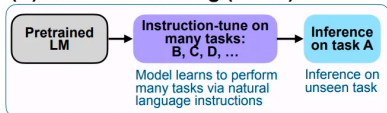
(A) Pretrain–finetune (BERT, T5)



(B) Prompting (GPT-3)



(C) Instruction tuning (FLAN)



1. Instruct Tuning
2. Prompting

Motivation

1. to build a good big-modal based image model
2. to harness the capability of zero-shot

Scientific Questions

1. What task will enable zero-shot generalization?
2. What is the corresponding model architecture?
3. What data can power this task and model?

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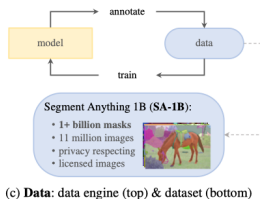
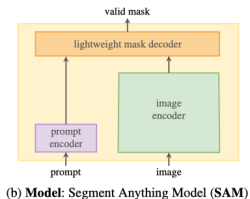
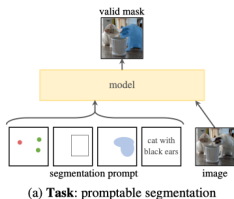
Zero-Shot Transfer

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General Methods



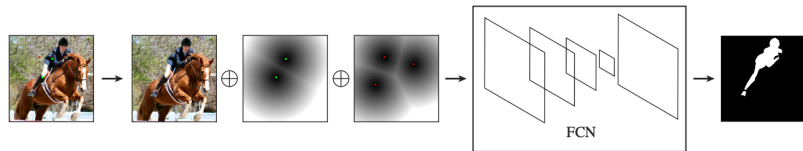
1. Promptable Segmentations
2. Encoder-Decoder Architecture
3. Data Engine with Dataset

Task



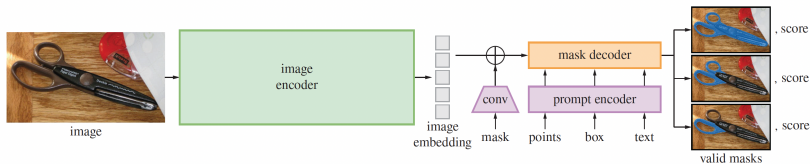
1. Translating the idea of Prompting to the task of semantic segmentation
2. Generate mask for any prompt
3. Leads to a natural pre-training algorithm

Pretrain



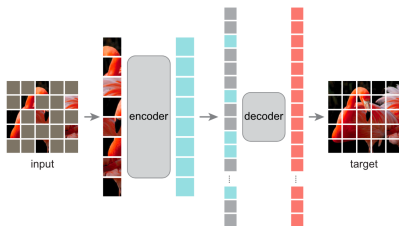
1. Provide with positive and negative clicks
2. Present the answer of correct mask
3. Unlike the classic interactive semantic segmentation, the annotator can provide the mask for any prompt

Model Architecture

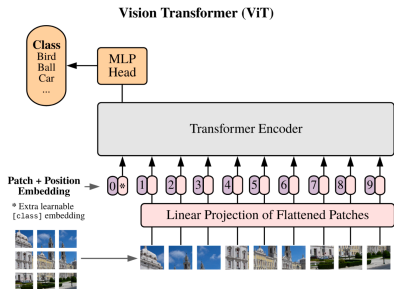


1. Image Encoder
2. Prompt Encoder
3. Mask Decoder
4. Resolving Ambiguity

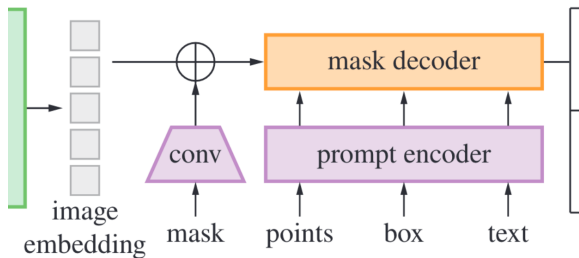
Image Encoder



1. MAE
2. ViT

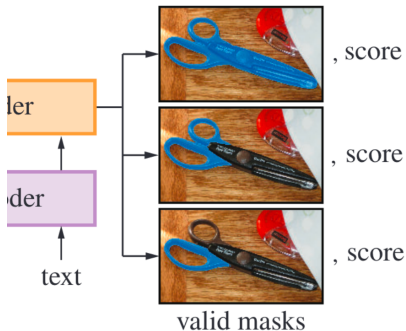


prompt Encoder / Decoder



1. Prompt of Dense and Sparse
2. masks / points, boxes, text
3. Mask encoder map the image embedding, mask and prompts to the result mask

Resolving Ambiguity



1. Three mask is usually sufficient for representing
2. add estimated IoU

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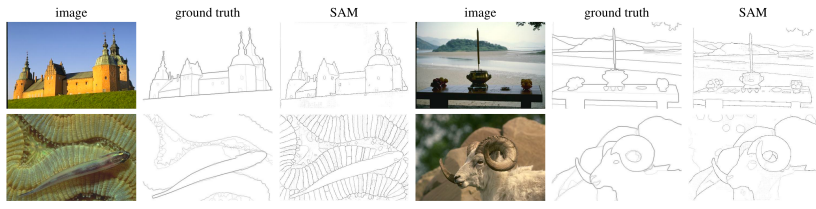
Related Works

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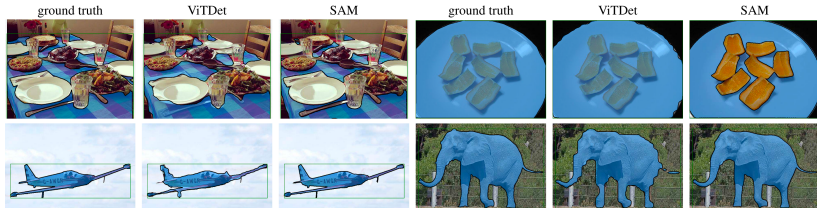
Training

1. Assisted-manual stage
 - 1.1 like classic interactive semantic segmentation
 - 1.2 have mechanism for solving granularity problem
 - 1.3 annotations are based on the models' output
2. Semi-automatic stage
 - 2.1 Aims to increase the diversity of masks in order to improve the model's generalization ability
 - 2.2 Ask the annotators to provide different masks
3. Fully-automatic stage

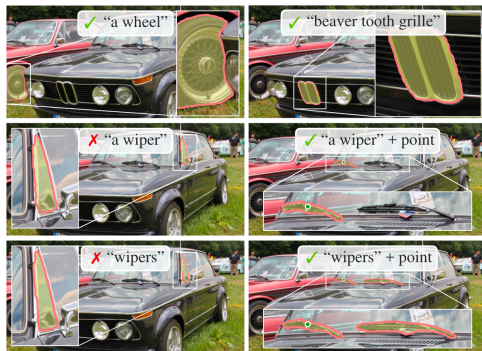
Edge Detection



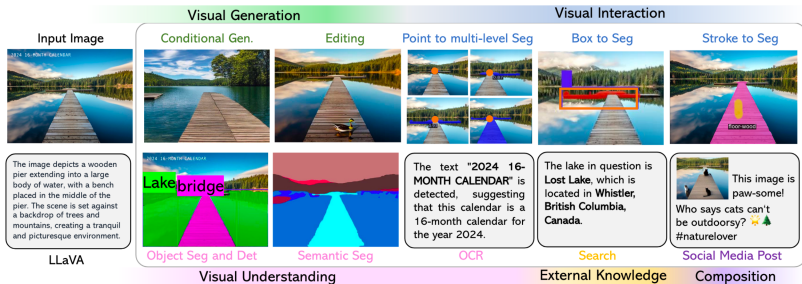
Instance Segmentation



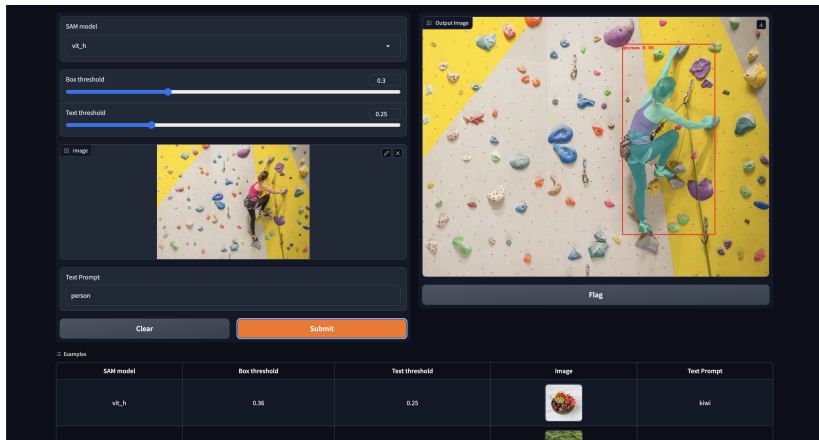
Text-to-Mask





LLAVA-PLUS



Language Segment-Anything

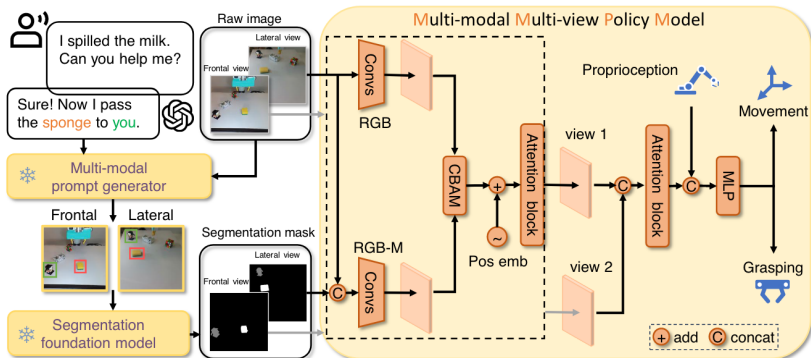


The screenshot displays the SAM (Segment Anything Model) interface. On the left, there are controls for the SAM model (set to 'vit_h'), a 'Box threshold' slider at 0.3, and a 'Text threshold' slider at 0.25. Below these is an 'Image' input field showing a rock climber. A 'Text Prompt' field contains the word 'person'. At the bottom of the controls are 'Clear' and 'Submit' buttons. On the right, the 'Output Image' shows the same rock climber image with a red bounding box around the climber. Below the output image is a 'Flag' button. At the bottom of the interface, there is an 'Examples' section with a table.

SAM model	Box threshold	Text threshold	Image	Text Prompt
vit_h	0.36	0.25		kiwi
				

Running on  Lightning ^{AI}

Transfer



Method	Seen	Unseen	New background	More distractors	Average
Ours	82.5	80.0	65.0	75.0	75.625
-replace mask with bbox	50.0	40.0	25.0	30.0	36.25
-w/o tracking	70.0	50.0	55.0	70.0	61.25
-single view	65.0	80.0	20.0	70.0	58.75
-RGB-M only	85.0	70.0	50.0	70.0	68.75

Grasp Anything

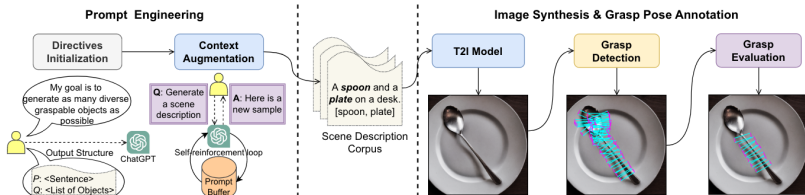
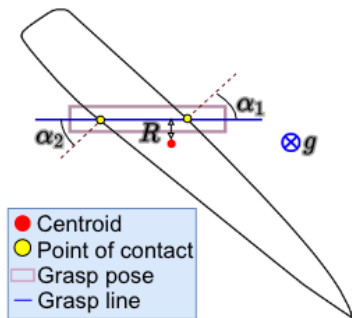
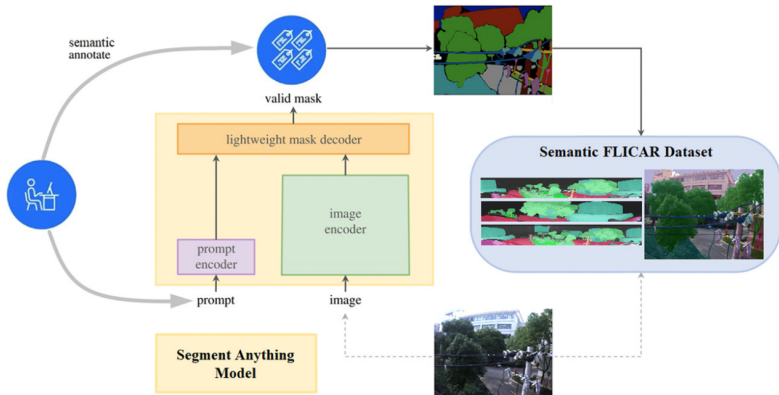


Fig. 2. Dataset creation pipeline.



FLICAR



Instruct2Act

LLM Generated Policy



Instruction

Put the green and purple polka dot block into the green container.

Put <dragged_obj>  into <base_obj> .Put the first clicked object  into the second one .

Generated Policy

```
def main() -> dict:
    image = GetImage()
    masks = SAM(image=image)
    obj1, masks = ImageCrop(image=image, masks=masks)

    # Retrieve the polka dot block, with the pure text model
    block = CLIPRetrieval(obj1, "the polka dot block")

    # Retrieve the polka dot block, with the visual model
    block = CLIPRetrieval(obj1=obj1, query=templates.get("dragged obj"))
    ...
    info = RobotExecution(action=action)
    return info
```

Python Interpreter

Input Image



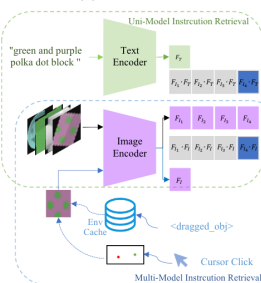
SAM(...)



ImageCrop(...)



CLIPRetrieval(...)



Pixel2Loc(...)



Coord. Mapping

PickPlace(...)

Skill Primitive:

Pick Place

Rotate

...



Action Construction

RobotSetting(...)

Parameter Setting:

Speed

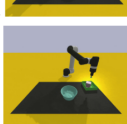
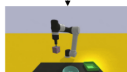
Action Space

...



Robotic Executor

Low-level Controller



Agriculture Robots

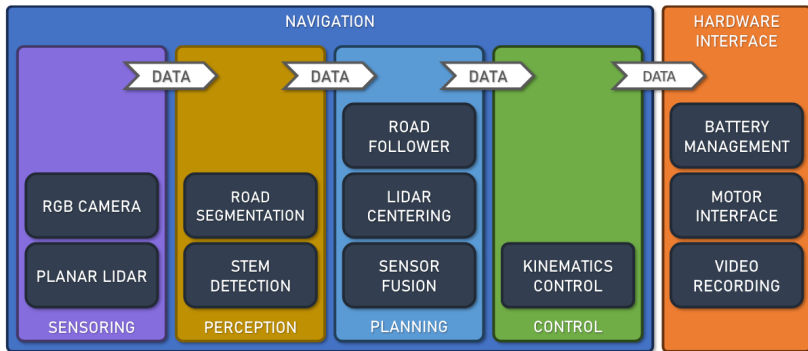


Fig. 1: Overview of the robot platform architecture showing its components and relations

OVIR-3D

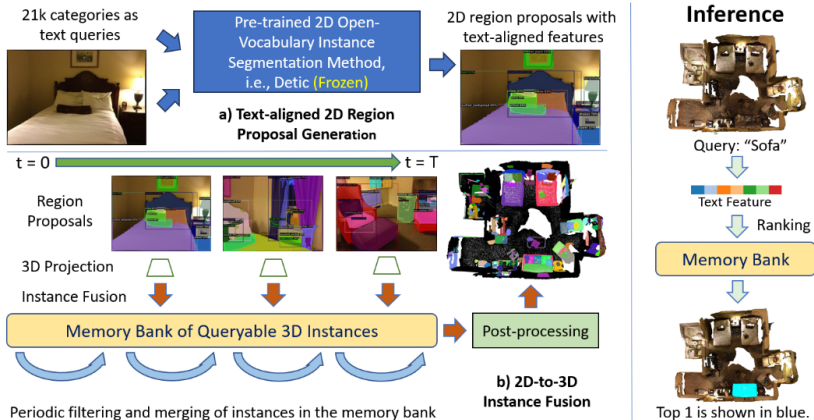


Figure 2: Pipeline of the proposed method.

Takeaways

1. A good semantic segmentation model
2. Encorporating human interaction like Prompting can give more possiblities
3. An existing experiment pattern can achieve great result when combined with new emerging techniques