

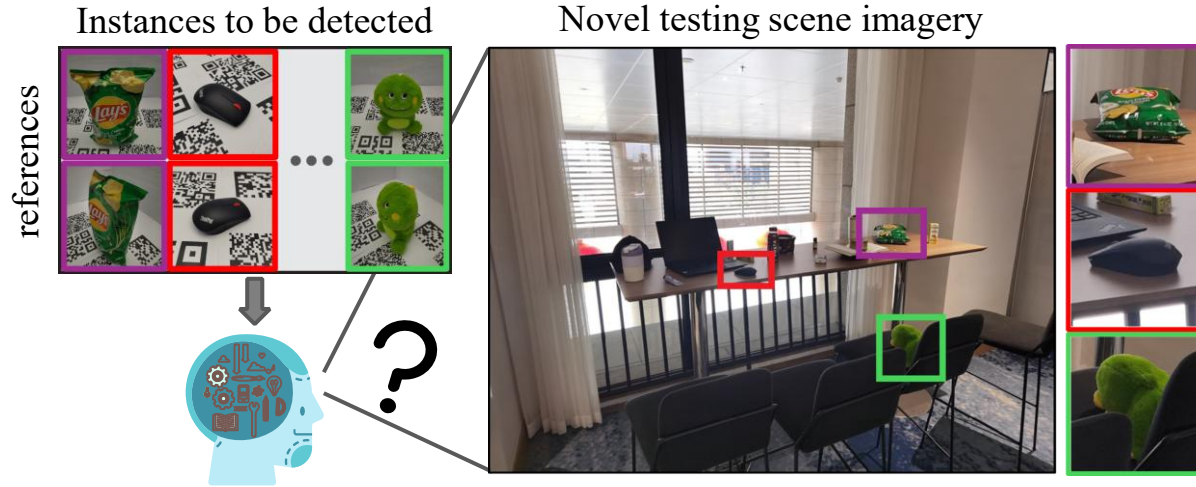
Solving **I**nstance **D**etection from an **O**pen-**W**orld Perspective

Qianqian Shen, Yunhan Zhao, Nahyun Kwon, Jeeun Kim, Yanan Li, Shu Kong



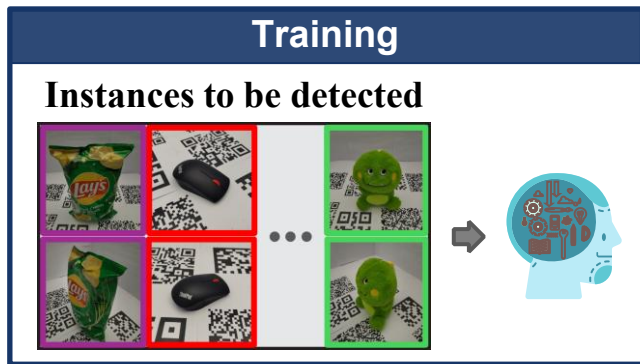
Project Page

Instance Detection (InsDet)



locating **specific** objects based on given **visual** references

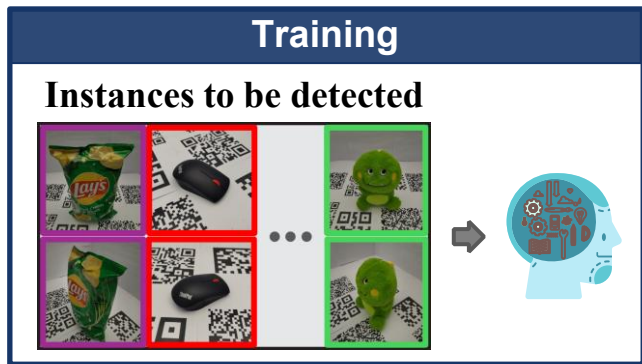
Two Settings: CID & NID



Conventional Instance Detection (CID)

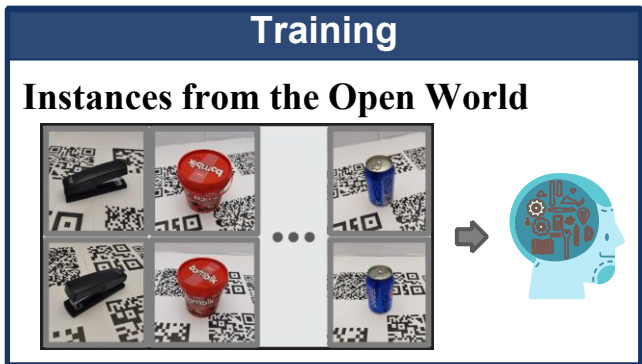
- Instances to be detected are **pre-defined during training**.
- The scene images are **unknown in testing**.

Two Settings: CID & NID



Conventional Instance Detection (CID)

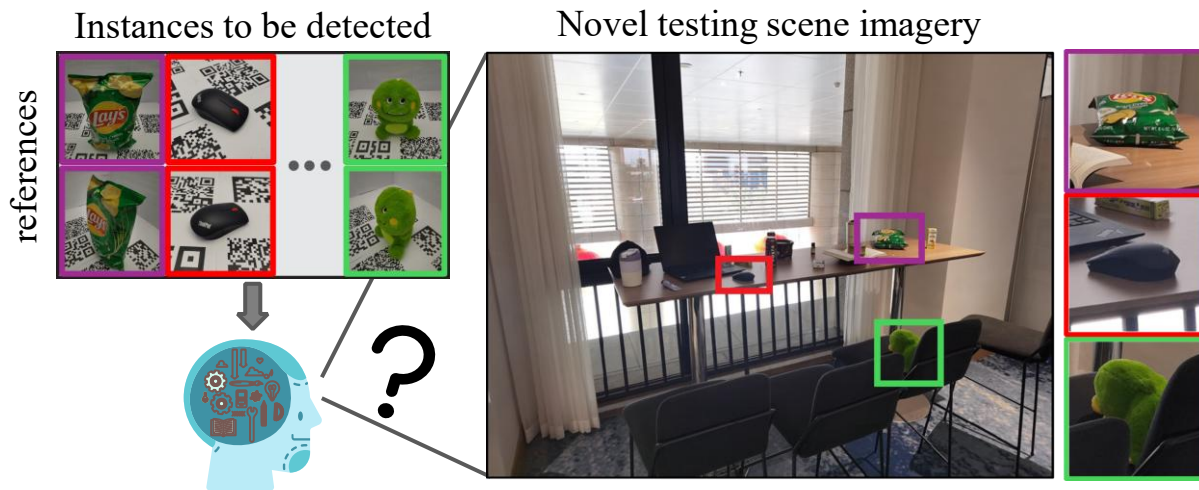
- Instances to be detected are **pre-defined during training**.
- The scene images are **unknown in testing**.



Novel Instance Detection (NID)

- Instances to be detected are **defined only in testing**.
- The trained models are **not** allowed to be **finetuned further during testing**.

Open-World Challenges of InsDet



- The testing imagery is **never-before-seen** and **unknown** to an instance detector.
- **Domain gaps** between visual references and detected proposals.
- **Robustness** and **generalization** are desperately needed to detect diverse instances.

Existing methods partially exploit the open-world information.

(a) Background Imagery



synthesize scene images for training,
e.g., Cut-Paste-Learn [ICCV2017]

↓
partially addressing **unknown**
testing scene distribution

Existing methods partially exploit the open-world information.

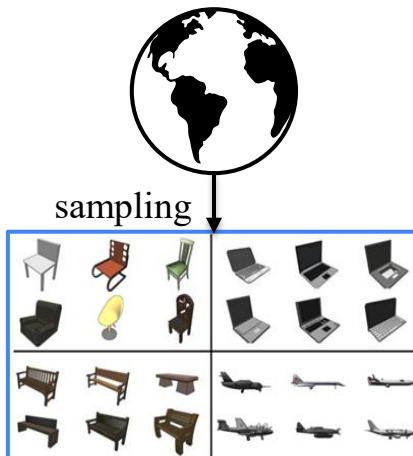
(a) Background Imagery



synthesize scene images for training,
e.g., Cut-Paste-Learn [ICCV2017]

partially addressing **unknown**
testing scene distribution

(b) Object Images



learn personalized representation,
e.g., VoxDet [NeurIPS2023]

partially addressing **domain gaps**
between proposals and references

Existing methods partially exploit the open-world information.

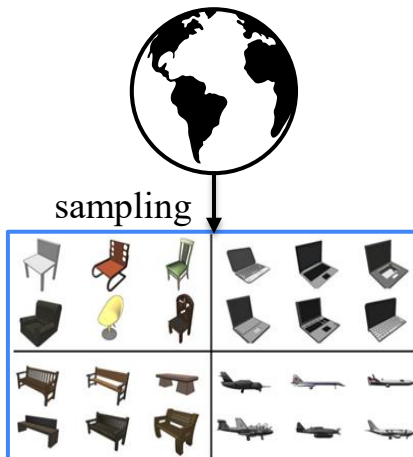
(a) Background Imagery



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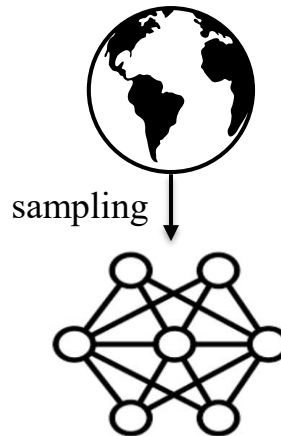
(b) Object Images



learn personalized representation,
e.g., VoxDet [NeurIPS2023]

partially addressing **domain gaps**
between proposals and references

(c) Foundation Models



leverage foundation models,
e.g., OTS-FM [NeurIPS2023]

improving proposal detectors
and feature representations

Dwibedi & Hebert, “Cut, paste and learn: Surprisingly easy synthesis for instance detection”, ICCV, 2017.

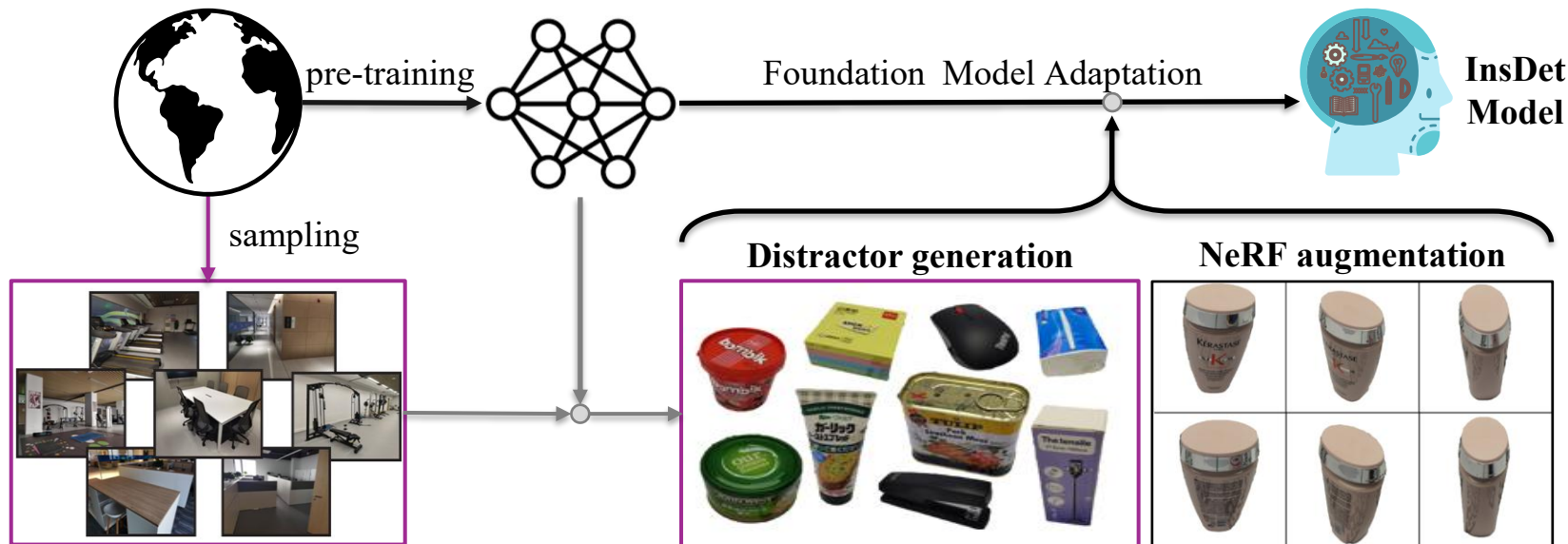
Li et al., “VoxDet: voxel learning for novel instance detection”, NeurIPS, 2023.

Shen et al., “A high-resolution dataset for instance detection with multi-view object capture”, NeurIPS, 2023.

Our Philosophy: Addressing InsDet in the Open World (IDOW)

Thoughts:

- A foundational detector yields high recall, i.e., SAM detecting all instances of interest. Let's focus on **instance matching**.
- Using features of DINOv2 for matching is promising but far from perfect. Let's **finetune** it.
- Data examples in the open world are diverse. Let's sample both **synthetic and real data**.



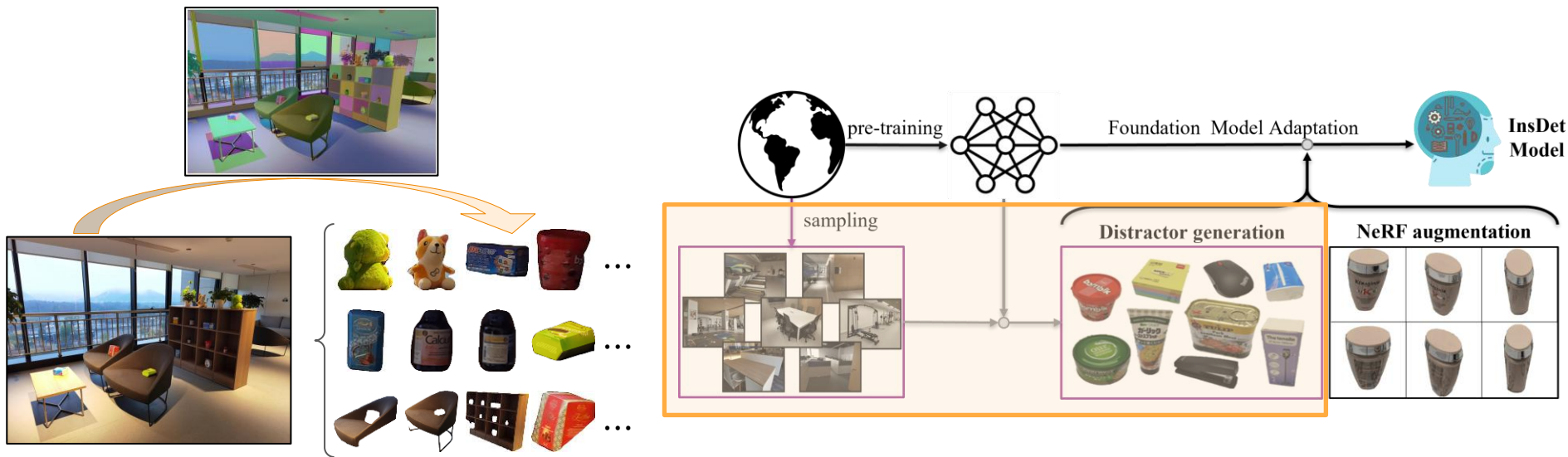
Kirillov et al, "Segment Anything", ICCV, 2023.

Liu et al, "GroundingDINO: Marrying DINO with Grounded Pre-training for Open-Set Object Detection", ECCV, 2024.

Ben et al., "NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis". ECCV, 2020.

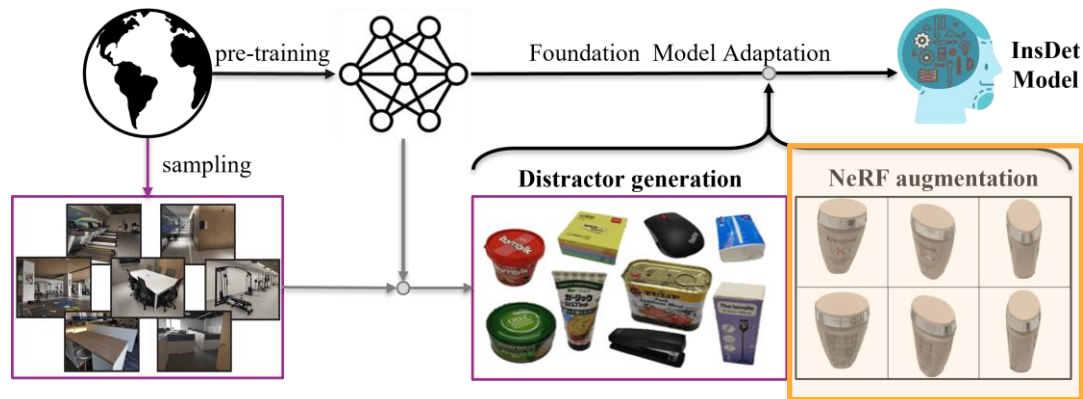
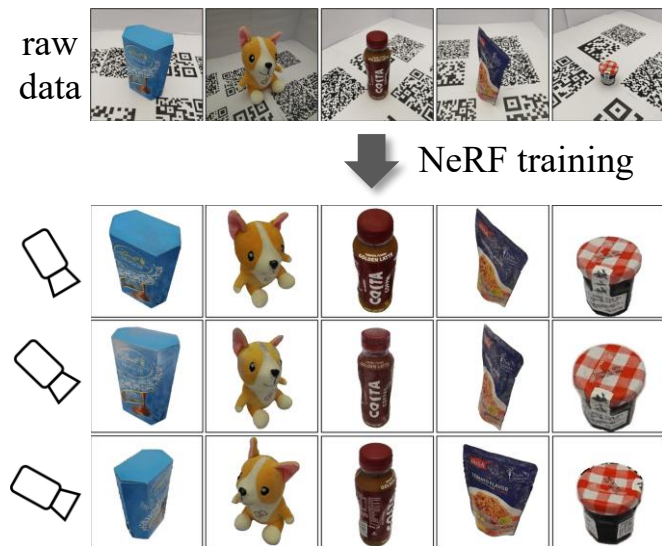
Oquab et al, "DINOv2: Learning Robust Visual Features without Supervision", Arxiv, 2023.

Sampling Distractor Instance from Real Imagery



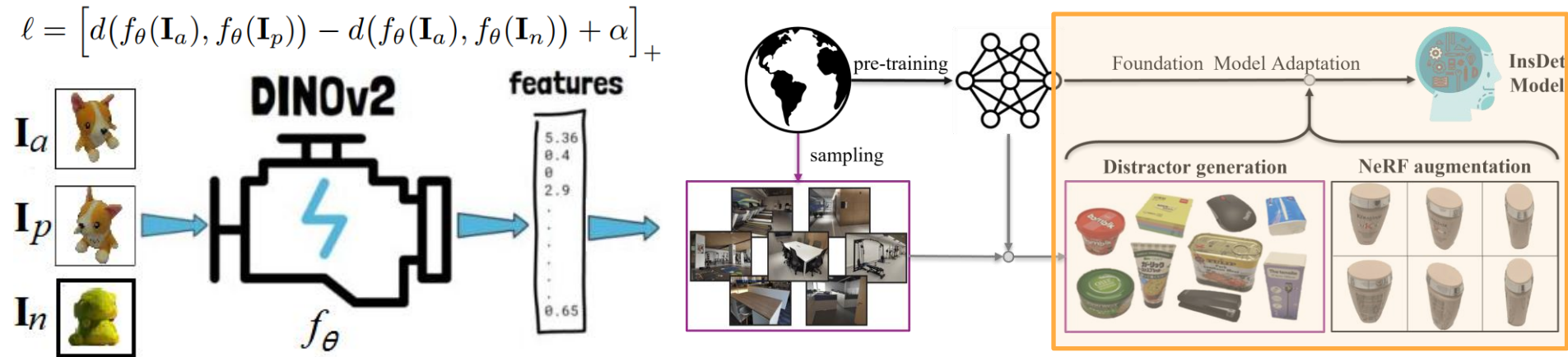
sample distractors from diverse images in the open world by SAM

Sampling More Positive Instances



synthesize novel-view images by using NeRF on the given visual references

Adapting DINOv2 using Metric Learning



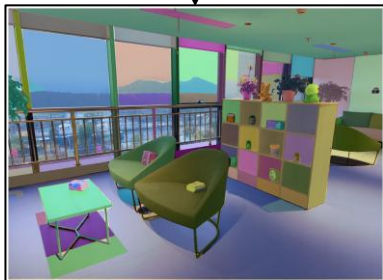
finetune foundation models (e.g., DINOv2) with metric learning

IDOW: Solving InsDet from an Open-World Perspective

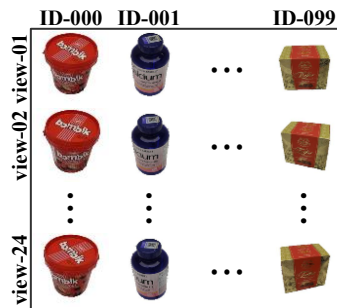
Proposal Detection



OW-detector



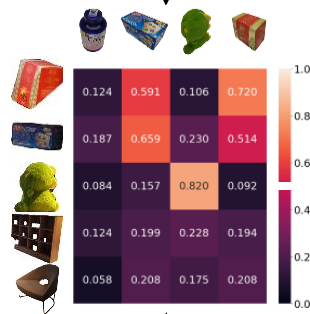
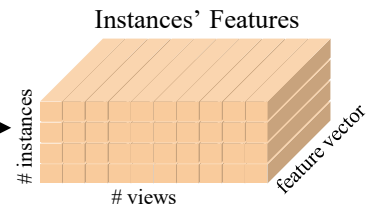
Feature Extraction



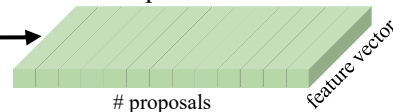
Finetuned
DINOv2



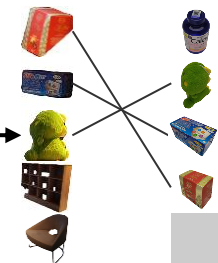
Proposal Matching & Selection



Proposals' Features

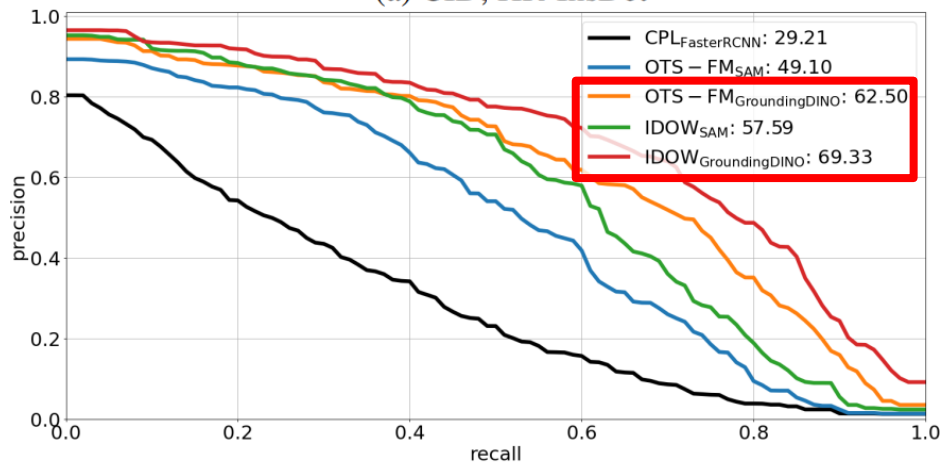


Stable Matching

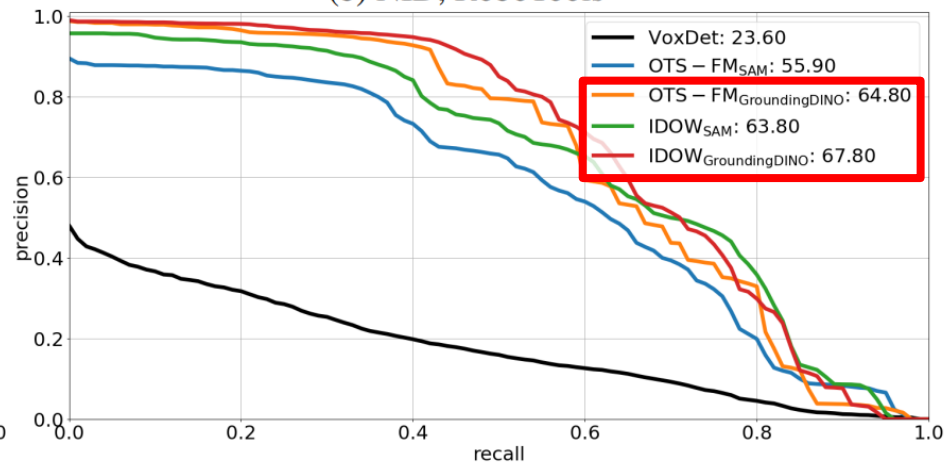


Benchmarking results

(a) CID, HR-InsDet



(b) NID, RoboTools



- Our **IDOW** significantly outperforms the compared methods in both CID and NID settings.
- Using **stronger open-world detector** improves InsDet performance, cf. GroundingDINO vs. SAM.
- Using **stronger features** improves InsDet performance, cf. finetuned DINOv2 vs. OTS-FM.

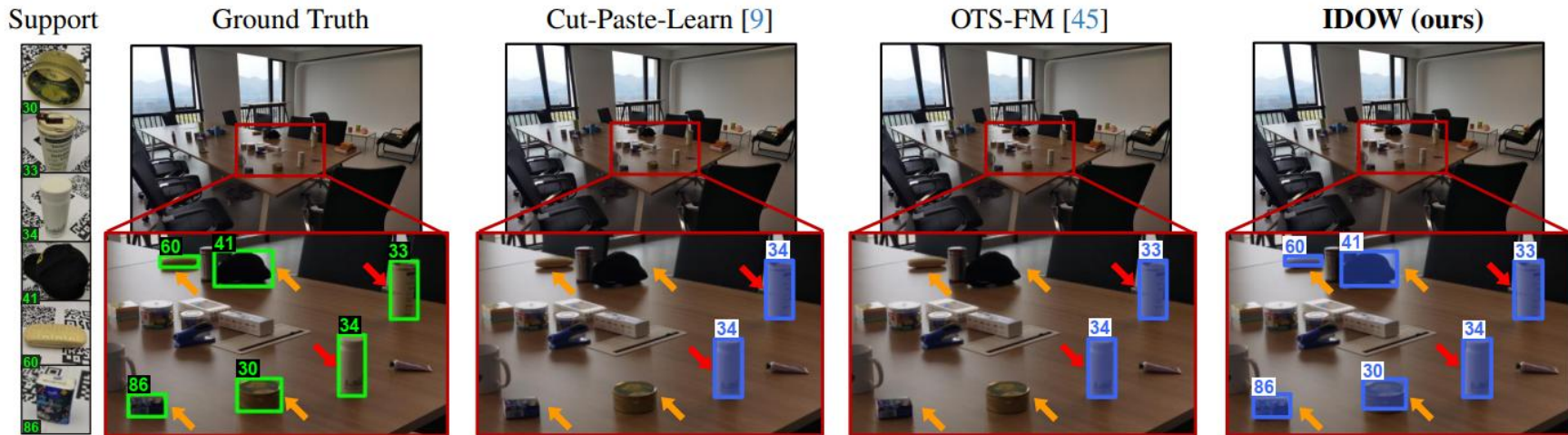
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Shen et al. “A High-Resolution Dataset for Instance Detection with Multi-View Instance Capture”, NeurIPS, 2023.

Qualitative evaluations

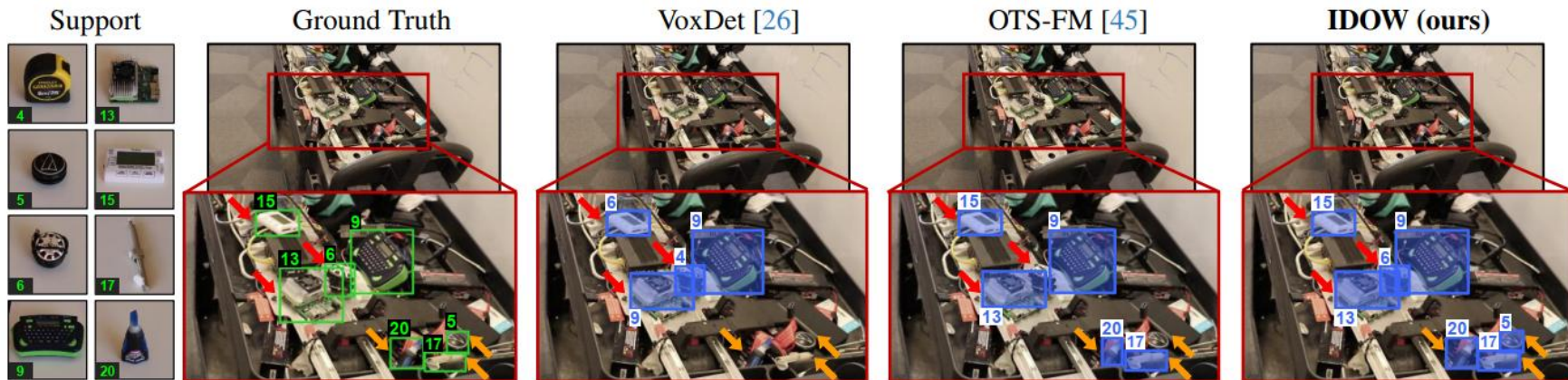
HR-InsDet in the CID setting



Our **IDOW** significantly outperforms the compared methods in both CID and NID settings.

Qualitative evaluations

RoboTools in the NID setting



Our **IDOW** significantly outperforms the compared methods in both CID and NID settings.

Li et al. “VoxDet: Voxel Learning for Novel Instance Detection”, NeurIPS, 2023.

Shen et al. “A High-Resolution Dataset for Instance Detection with Multi-View Instance Capture”, NeurIPS, 2023.

Thank You!



ExHall D Poster #431

<https://shenqq377.github.io/IDOW>