The Concept Misalignment between Experts and AI

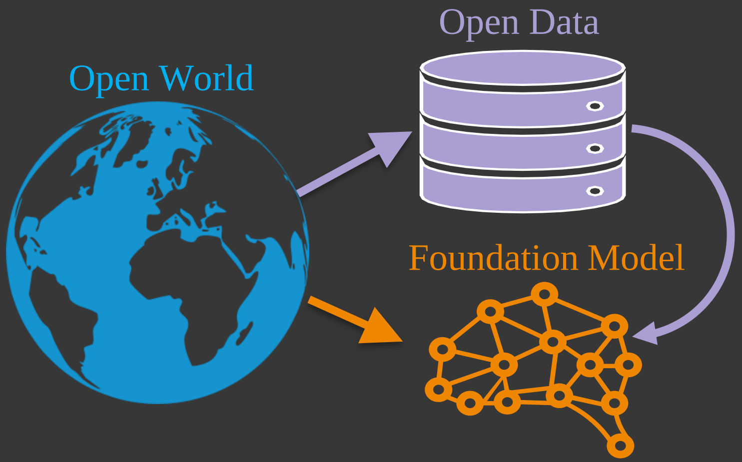
from Data Labeling to Data Versioning

Shu Kong

University of Macau

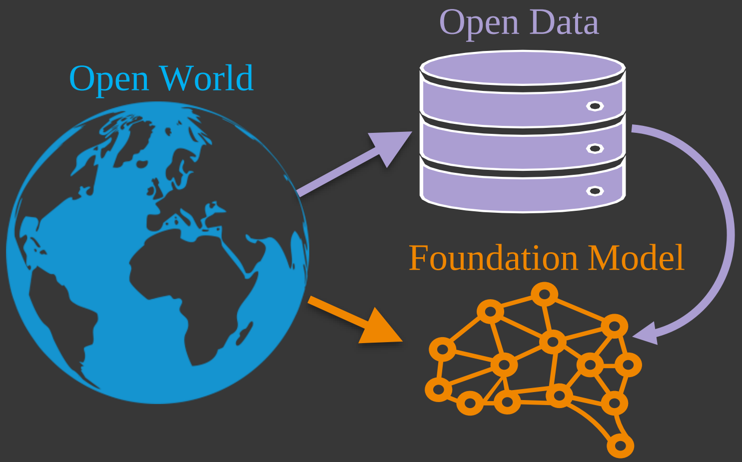
March 4, 2025

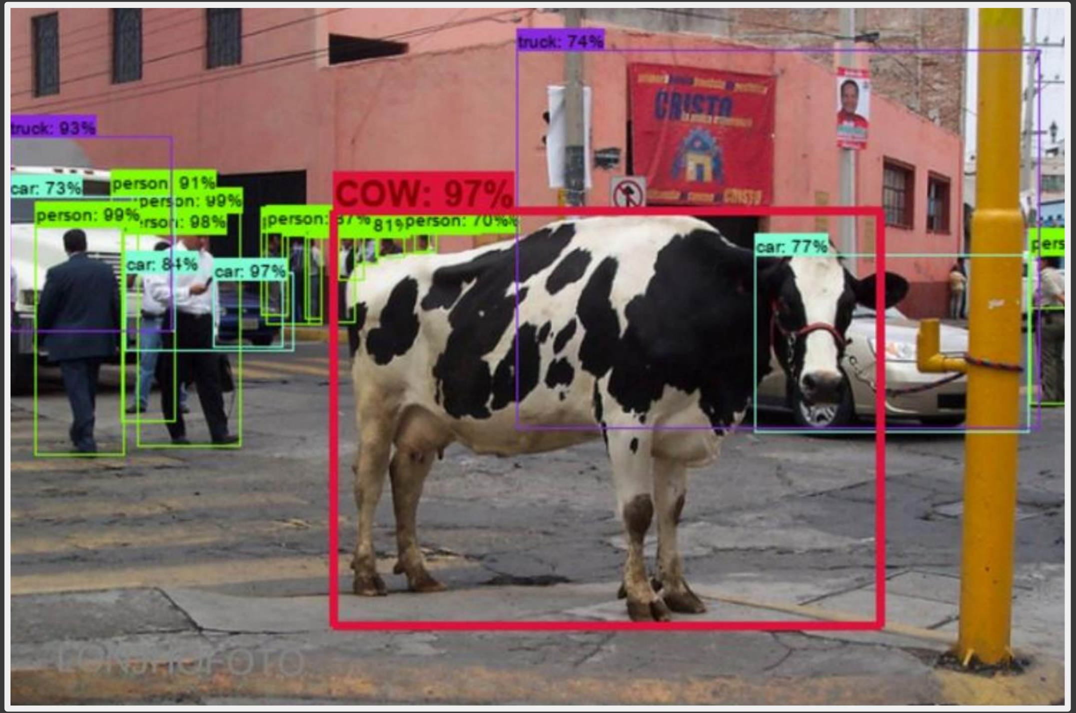
Representing the Open World: Foundation Model and Open Data



Foundation Model for Open-Vocabulary Detection

Cool!!!





Cheng, et al., "YOLO-World: Real-Time Open-Vocabulary Object Detection", CVPR, 2024
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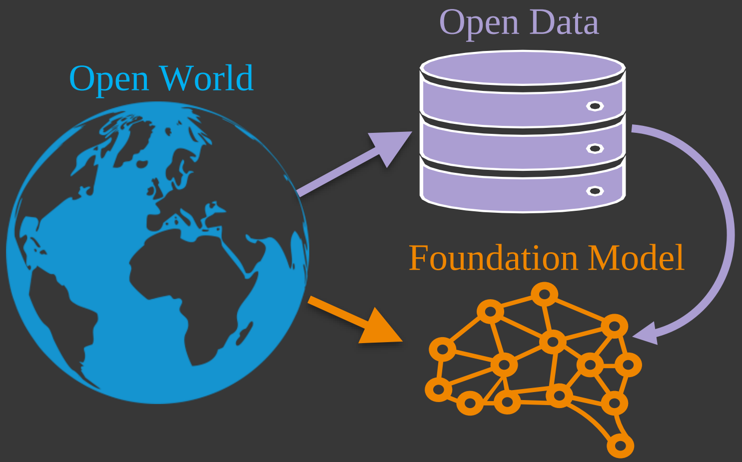

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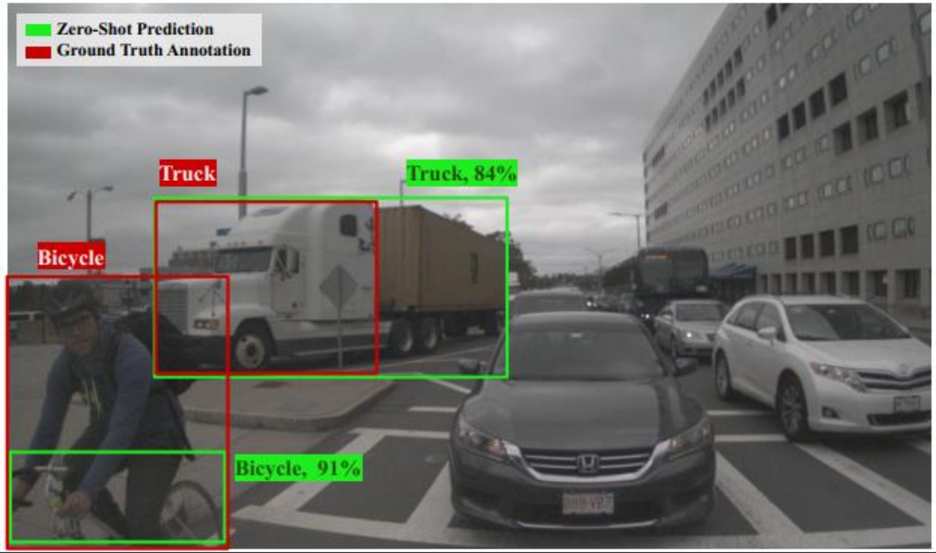
Data Labeling where a foundation model struggles!

nuImages dataset



Poor alignments between foundational detector and ground-truth annotations in nuImages dataset.
Why?

Liu, et al., "Grounding DINO: Marrying dino with grounded pre-training for open-set object detection", ECCV, 2024
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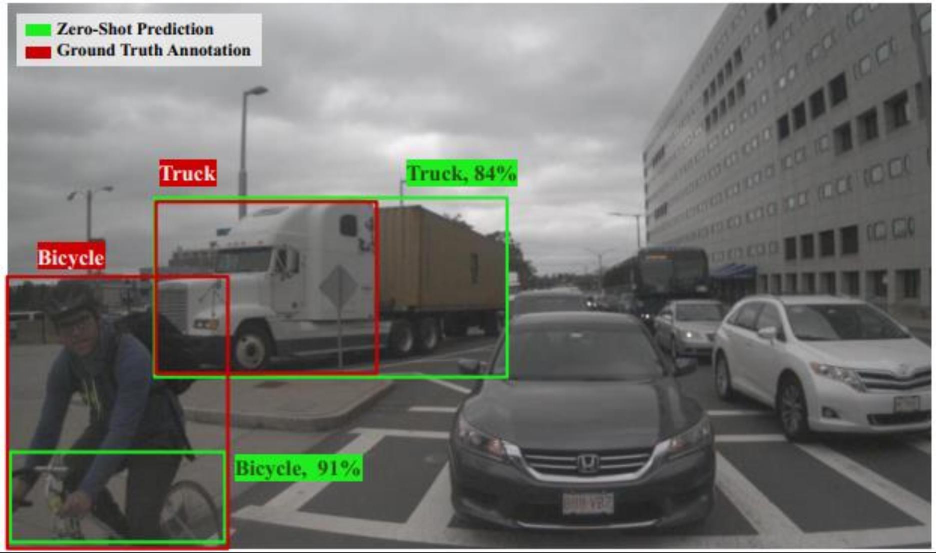

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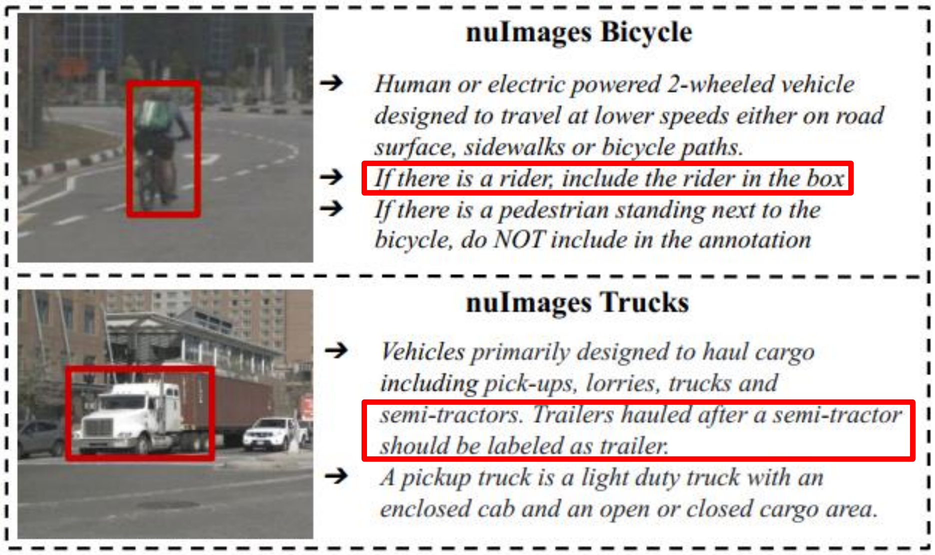
Why?

A snippet of annotation guidelines from nuImages



Annotation instructions designed by autonomous driving experts.
Due to practical considerations!

Liu, et al., "Grounding DINO: Marrying dino with grounded pre-training for open-set object detection", ECCV, 2024
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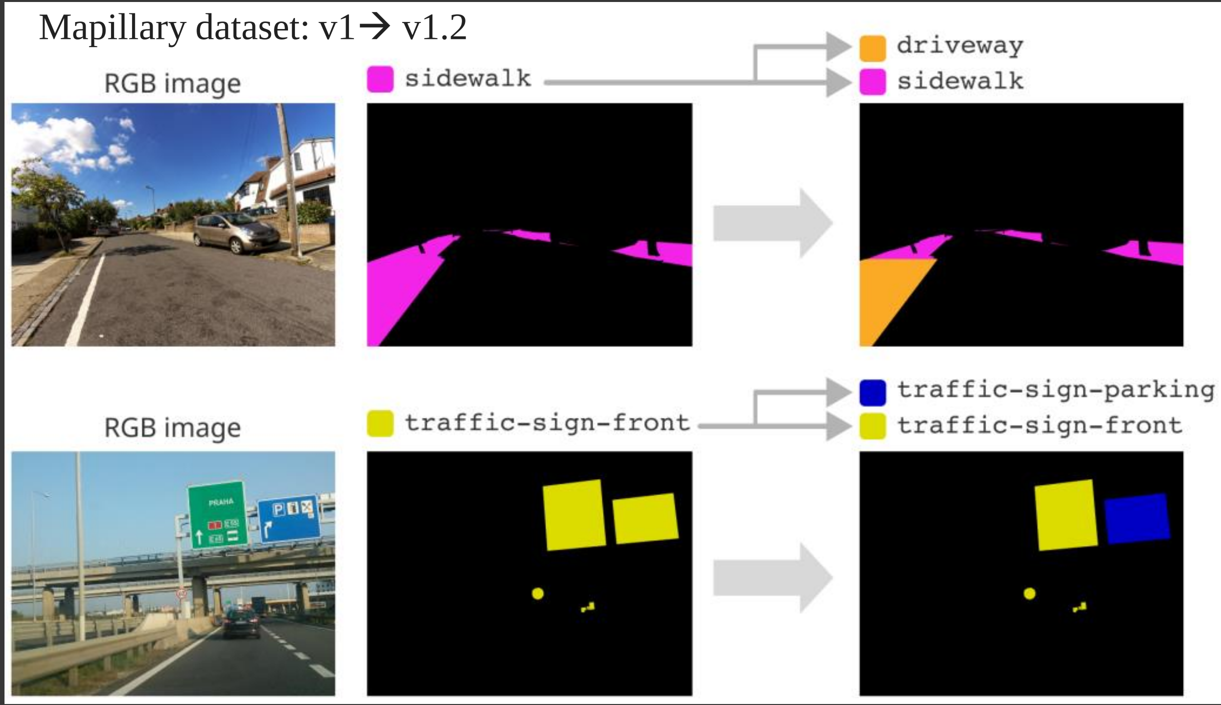
Data Versioning where a foundation model can continue to struggle!

Class ontologies evolve over time to meet needs in the open world.



Neuhold, et al. "The mapillary vistas dataset for semantic understanding of street scenes." ICCV, 2017.
Lin, et al. "Continual learning with evolving class ontologies", NeurIPS, 2022

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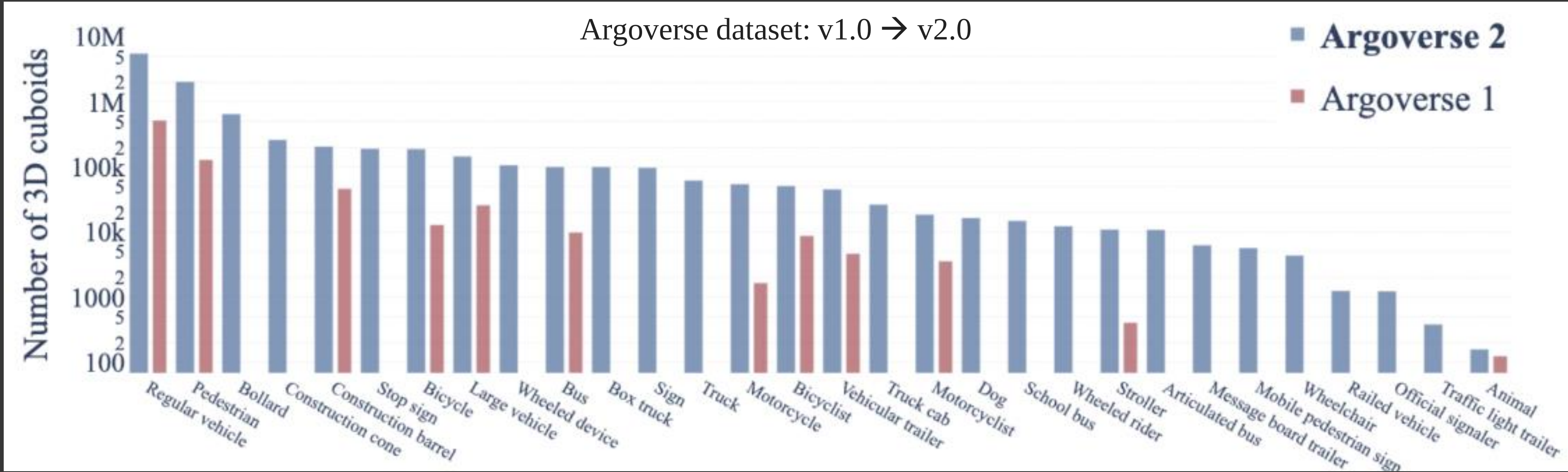


Chang, et al. "Argoverse: 3d tracking and forecasting with rich maps." CVPR, 2019.
Wilson, et al. "Argoverse 2: Next generation datasets for self-driving perception and forecasting." NeurIPS, 2021.
Lin, et al. "Continual learning with evolving class ontologies", NeurIPS, 2022

Let's formulate an interesting problem!

How to adapt foundation models to align with experts?

domain experts

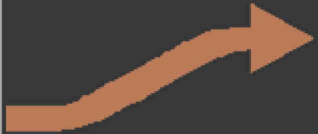
design

collect

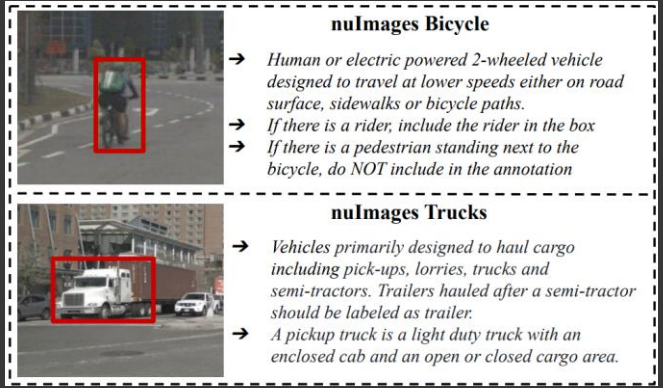
annotator instructions

data

sent to "annotators" for data annotation



Human annotator



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Foundation models

- Large Language Models (LLMs)
- Vision-Language Models (VLMs)
- Foundation Vision Models (FVMs)

nuImages Bicycle

→ *Human or electric powered 2-wheeled vehicle designed to travel at lower speeds either on road surface, sidewalks or bicycle paths.*
→ *If there is a rider, include the rider in the box*
→ *If there is a pedestrian standing next to the bicycle, do NOT include in the annotation*

nuImages Trucks

→ *Vehicles primarily designed to haul cargo including pick-ups, lorries, trucks and semi-tractors. Trailers hauled after a semi-tractor should be labeled as trailer.*
→ *A pickup truck is a light duty truck with an enclosed cab and an open or closed cargo area.*

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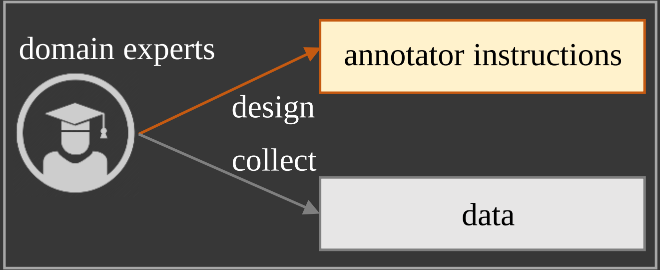
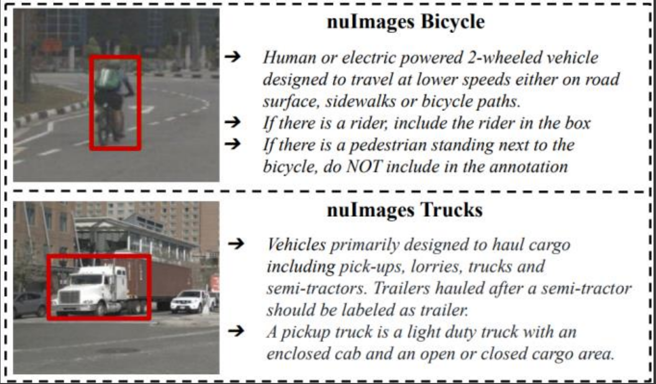
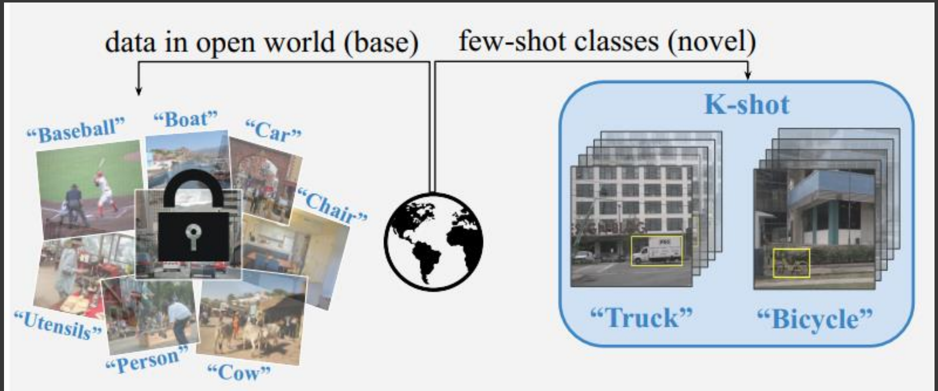
Can we adapt foundation models w.r.t annotation guidelines?
Technically, this is a multimodal few-shot learning problem.





The proposed multimodal few-shot learning setup



Realistically embracing the open world, leveraging foundation models to learn from few-shot visuals and texts

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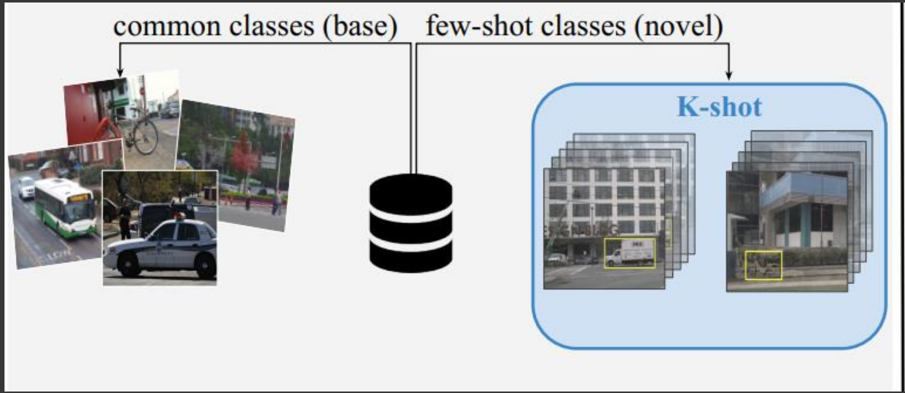
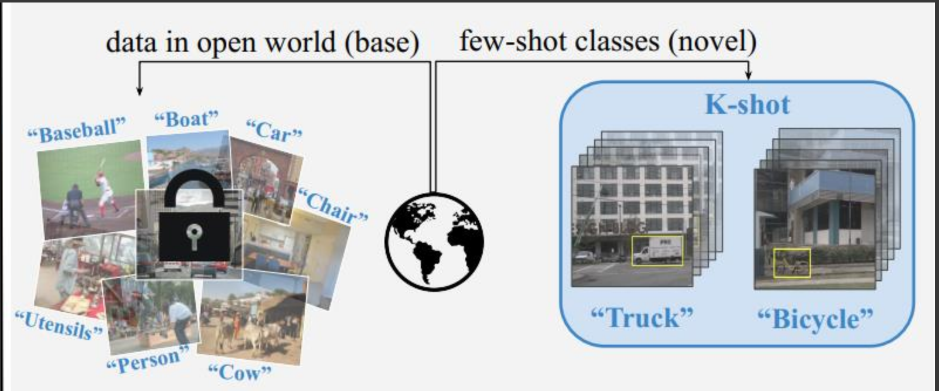
Existing few-shot learning setup



e.g., artificially splitting 80 classes of COCO into base set (60 classes) and novel set (20 classes)

The proposed multimodal few-shot learning setup



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Multimodal few-shot learning

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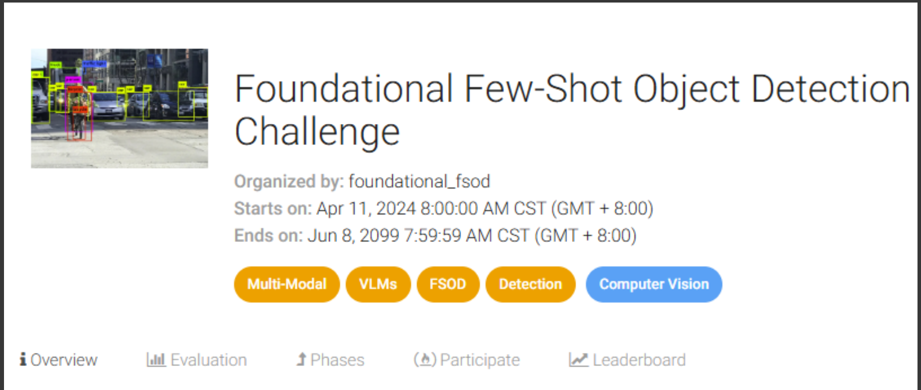
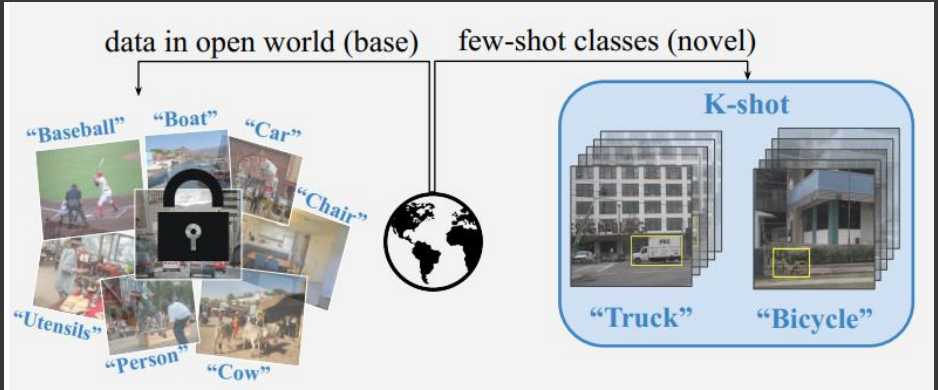
Challenge at CVPR'24 and CVPR'25



Validating various methods, collecting effective approaches, summarizing useful techniques

The proposed multimodal few-shot learning setup



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Approaches

Embracing the open world, esp. foundation models, we compare various approaches:

1. Prompt engineering
2. Standard finetuning
3. Language prompt tuning
4. Visual prompting
5. Multimodal prompting
6. Multimodal chat assistants

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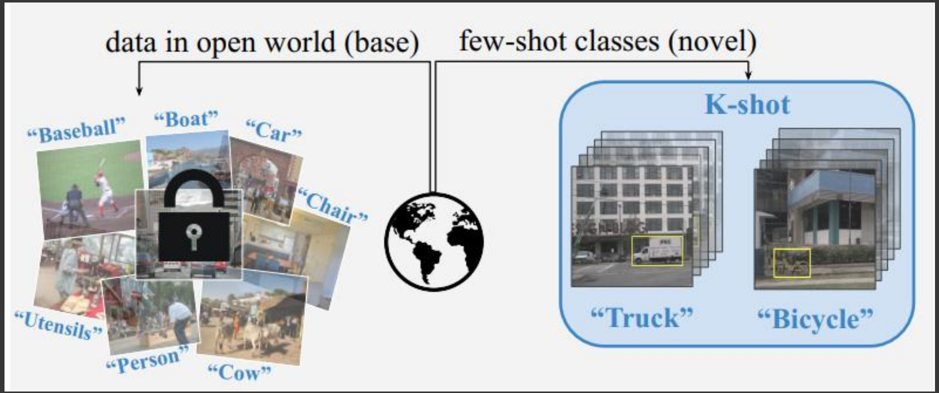

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Approach	Backbone	Pre-Train Data	Average Precision (AP) All	Many	Med	Few
Zero-Shot Detection						
RegionCLIP [64]	RN50	CC3M	2.50	3.20	3.80	0.40
Detic [67]	SWIN-B	LVIS, COCO, IN-21K	14.40	25.83	16.59	2.32
GroundingDINO [33]	SWIN-T	Objects365, GoldG, Cap4M	12.05	17.29	15.45	3.72
GLIP [30]	SWIN-L	FourODs,GoldG,Cap24M	17.01	23.36	19.86	8.40
MQ-GLIP-Text [59]	SWIN-L	Objects365, FourODs, GoldG, Cap24M	17.01	23.36	19.85	8.41
Prompt Engineering						
Detic [67]	SWIN-B	LVIS, COCO, IN-21K	14.92	26.48	17.29	2.53
GLIP [30]	SWIN-L	FourODs, GoldG, Cap24M	17.15	23.82	19.36	9.02
Standard Fine-Tuning						
RegionCLIP [64]	RN50	CC3M	3.86	6.08	5.13	0.54
Detic [67]	SWIN-B	LVIS, COCO, IN-21K	16.09	25.46	20	3.73
Federated Fine-Tuning (Ours)						
Detic [67]	SWIN-B	LVIS, COCO, IN-21K	17.24	28.07	20.71	4.18
Detic [67] w/ Prompt Engineering	SWIN-B	LVIS, COCO, IN-21K	17.71	28.46	21.14	4.75
Language Prompt Tuning						
GLIP [30]	SWIN-L	FourODs,GoldG,Cap24M	19.41	22.18	**25.16**	**10.39**
Visual Prompting						
MQ-GLIP-Image [59]	SWIN-L	Objects365,FourODs,GoldG,Cap24M	14.07	24.39	15.89	3.34
Multi-Modal Prompting						
MQ-GLIP [59]	SWIN-L	Objects365,FourODs,GoldG,Cap24M	21.42	32.19	23.29	10.26
Multi-Modal Chat Assistants						
GPT-4o Zero-Shot Classification [1]	*Private*	*Private*	9.95	16.81	12.11	1.71
MQ-GLIP Iterative Prompting	*Private*	*Private*	**22.03**	**33.42**	24.72	9.41
CVPR 2024 Competition Results						
NJUST KMG	SWIN-L	Objects365V2, OpenImageV6, GoldG, V3Det, COCO2014, COCO2017, LVISV1, GRIT, RefCOCO, RefCOCO+, RefCOCOg, gRef-COCO	32.56	50.21	34.87	15.16
zjyd_cxy_vision	SWIN-L	Objects365V2, COCO2017, LVIS, GoldG, VG, OpenImagesV6, V3Det, PhraseCut, RefCOCO, RefCOCO+, RefCOCOg, gRef-COCO	31.57	46.59	33.32	17.03

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Approaches

It's cool to embrace foundation models!

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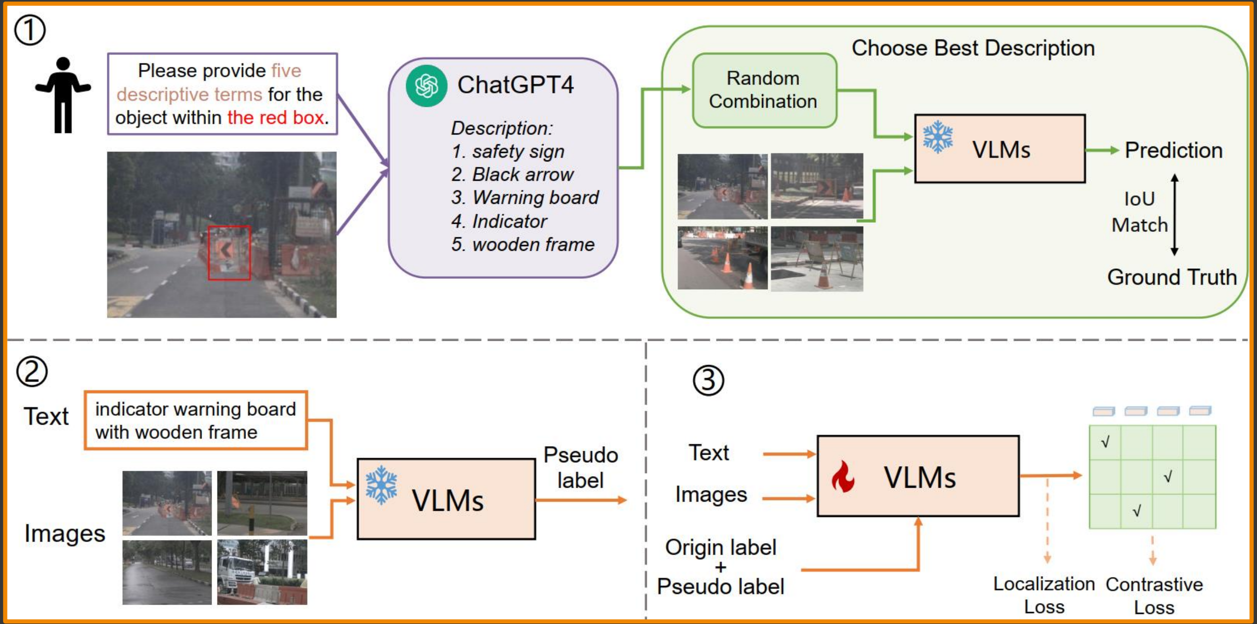

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Approaches

It's cool to embrace foundation models! Really?

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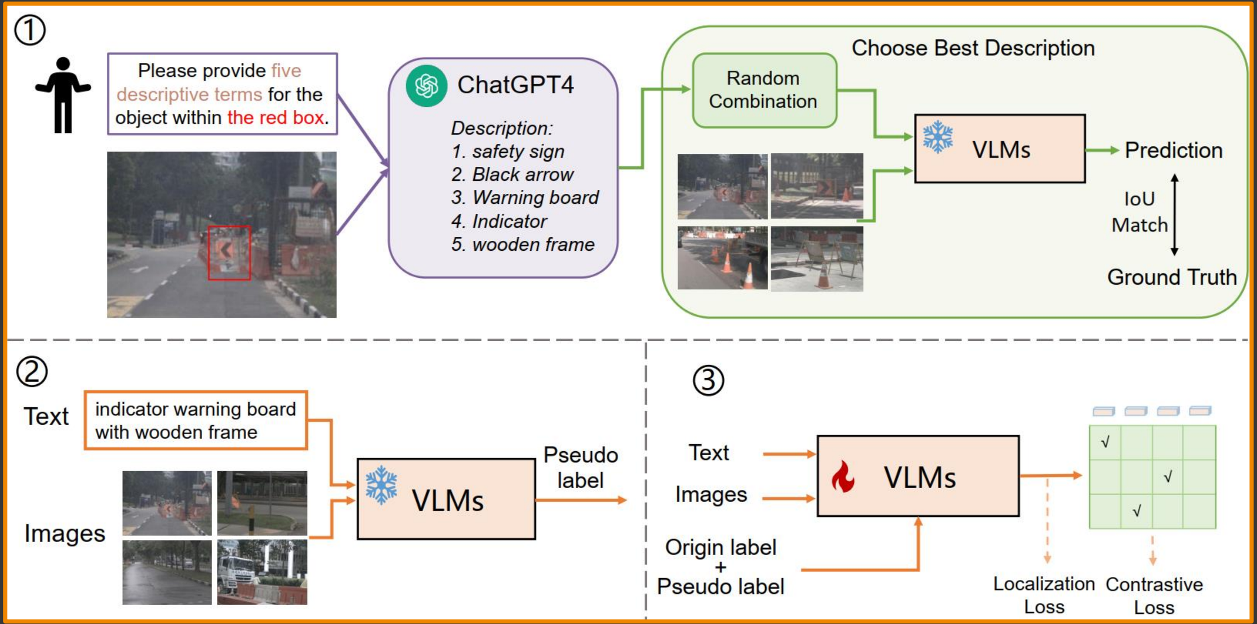

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Chat assistant can fail too!

ImageNet

```
59: 'vine snake',
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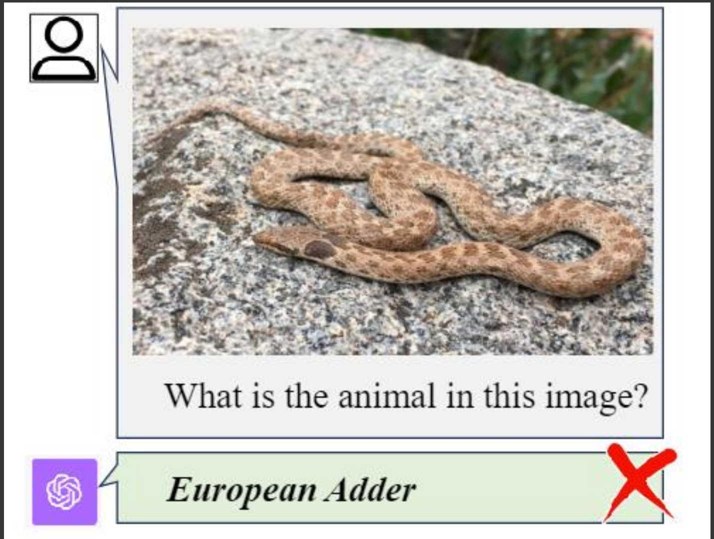
GPT-4 misclassifies “*night snake*” as “*European Adder*”



Parashar, et al., “Prompting Scientific Names for Zero-Shot Species Recognition”, EMNLP, 2023
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It has seen the whole internet data, right?

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The neglected long tails in VLMs

Hypothesis: certain concepts are insufficiently presented in the open world.

"night snake" is one of rare concepts in the open world

Parashar, et al., "The Neglected Tails of Vision-Language Models", CVPR, 2024

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Justification: We *count* the occurrence of pretraining texts related to the concept of interest.

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Schuhmann, et al. "Laion-400m: Open dataset of clip-filtered 400 million image-text pairs." arXiv:2111.02114, 2021
Schuhmann, et al. "Laion-5b: An open large-scale dataset for training next generation image-text models", NeurIPS 2022
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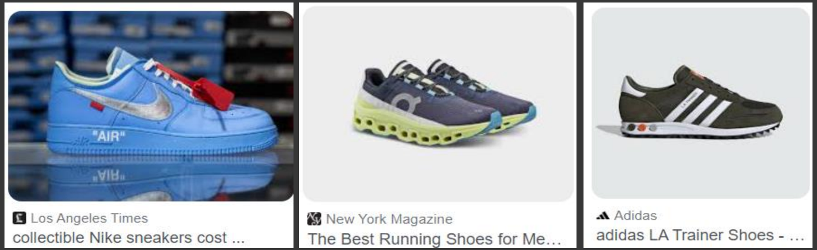

Lexical variation, e.g., synonyms

Linguistic ambiguity

Schuhmann, et al. “Laion-400m: Open dataset of clip-filtered 400 million image-text pairs”, arXiv, 2021
Gadre, et al. “Datacomp: In search of the next generation of multimodal datasets”, NeurIPS, 2024

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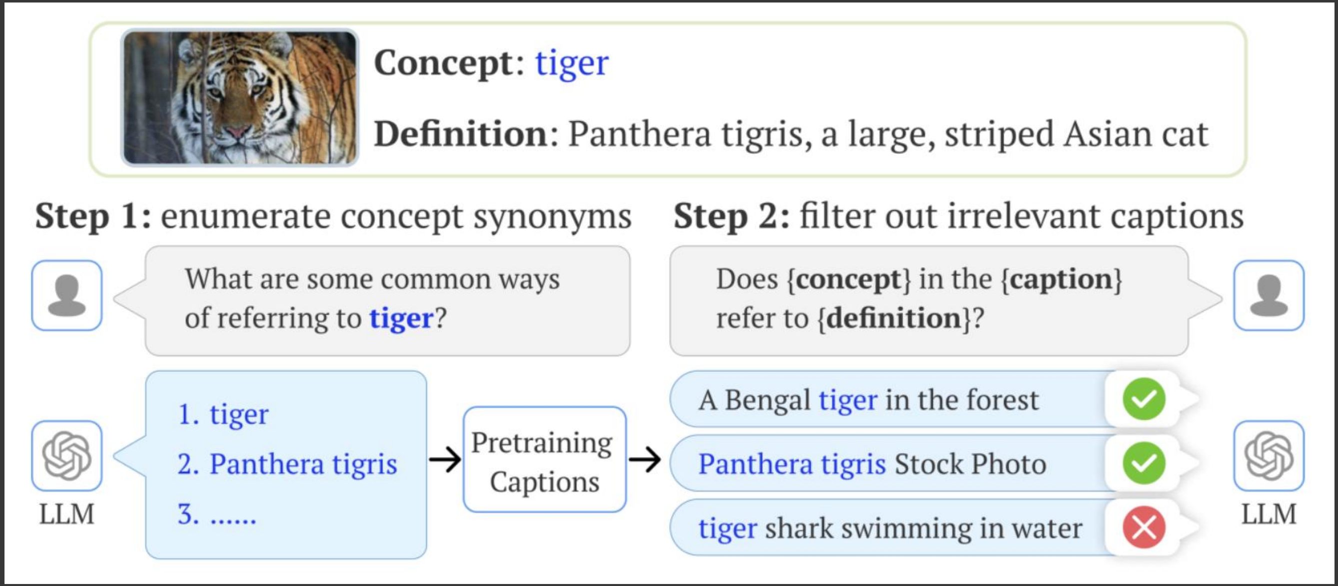

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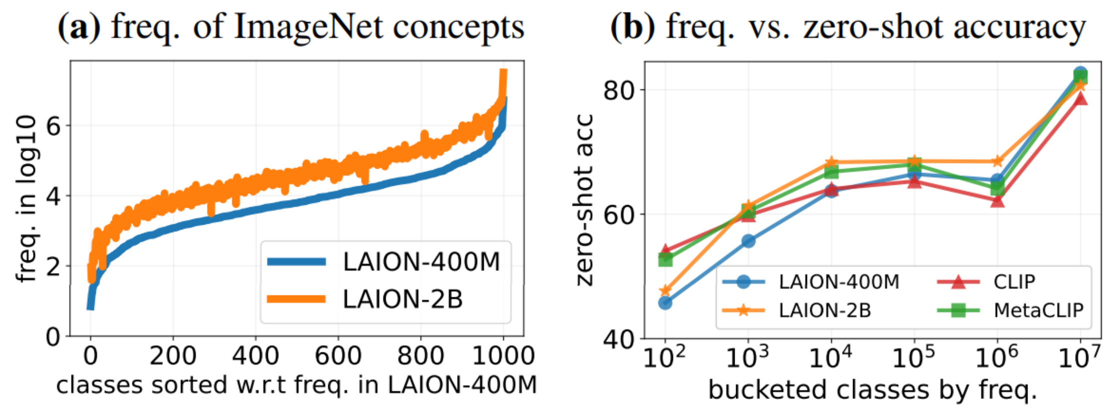
Justification: We *count* the occurrence of pretraining texts related to the concept of interest.
Evidence: a strong correlation between concept frequency and per-concept accuracy.

"night snake" is one of rare concepts in the open world



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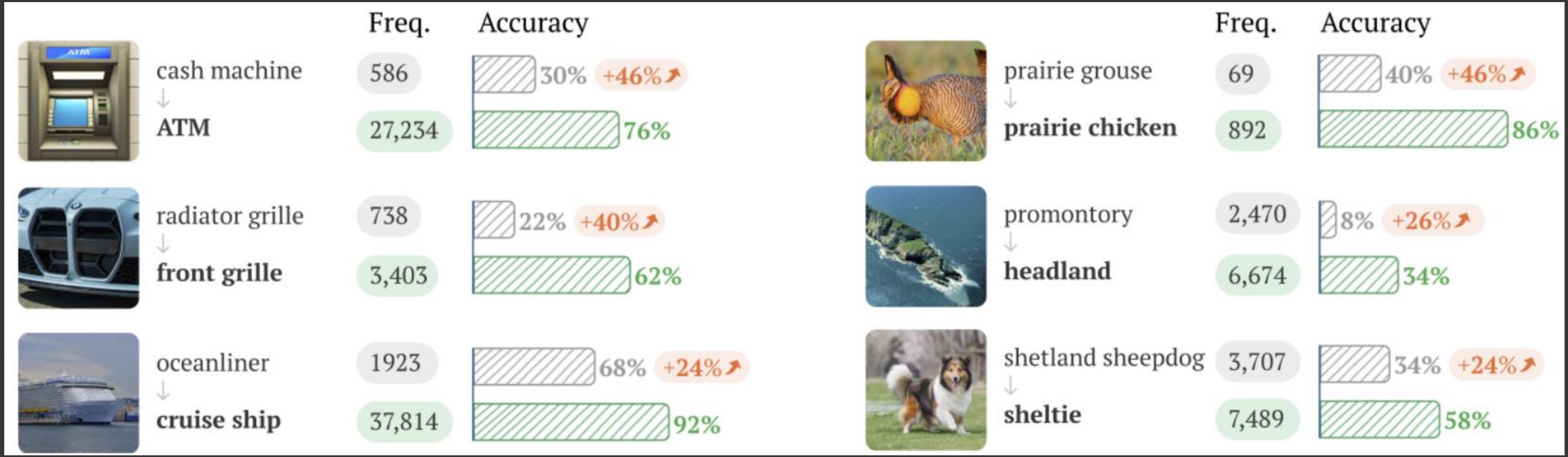
Insight 1: prompt VLM using the most frequent synonym

This simple change significantly boosts zero-shot accuracy!



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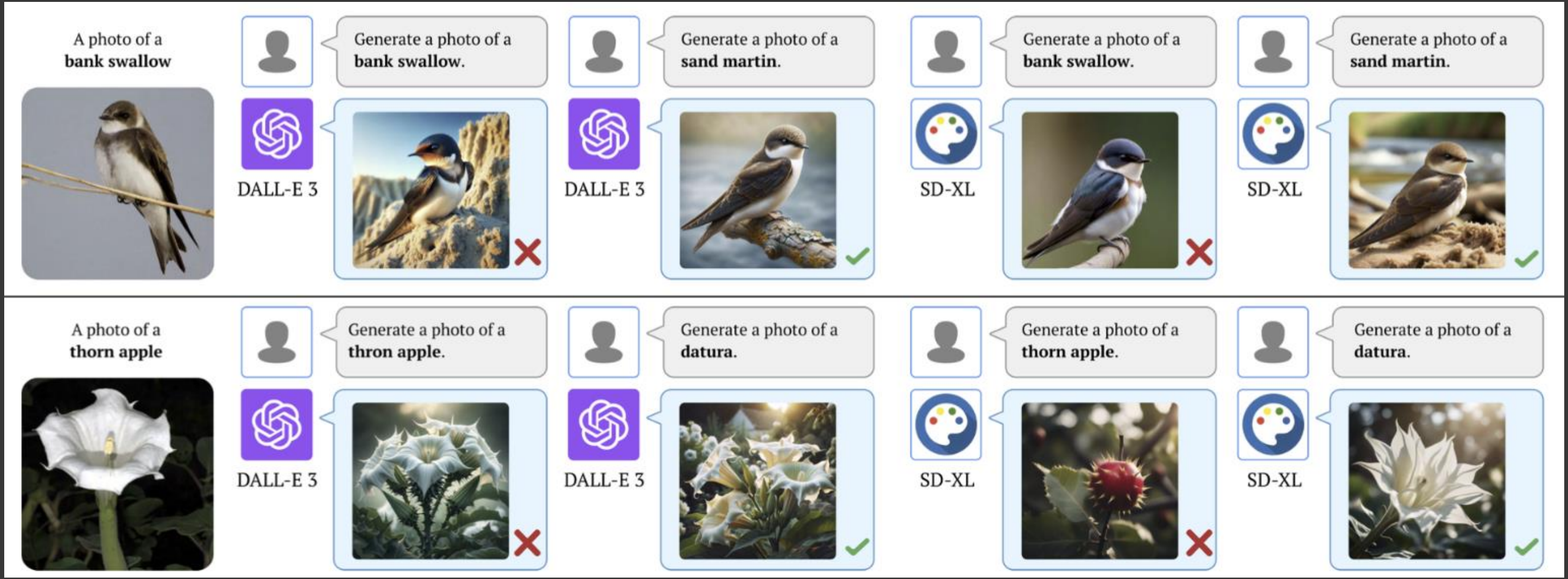
Insight 2: use the most frequent synonym in image generation

replace the original query with its most frequent synonym in prompts



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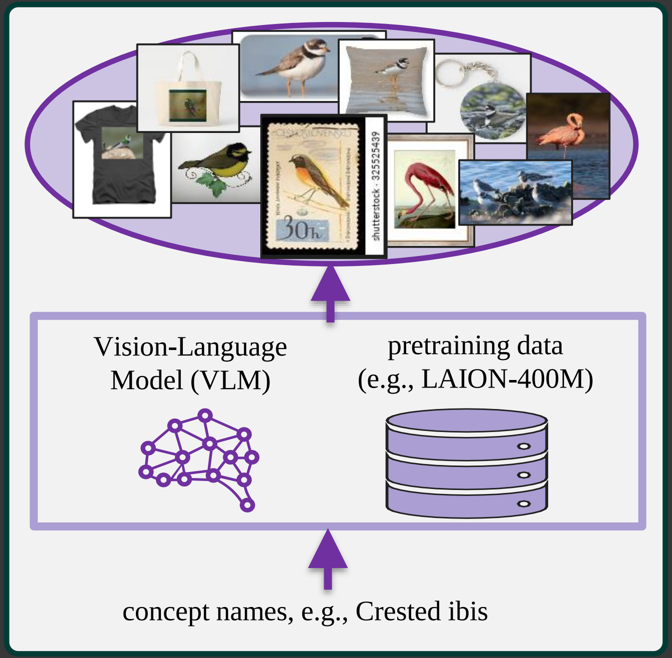
Insight 3: use all synonyms for Retrieval Augmented Learning (RAL)

[REACT] is the state-of-the-art RAL method for zero-shot recognition



[REACT] Liu, et al., "Learning customized visual models with retrieval-augmented knowledge", CVPR, 2023

Insight 3: use all synonyms for Retrieval Augmented Learning (RAL)

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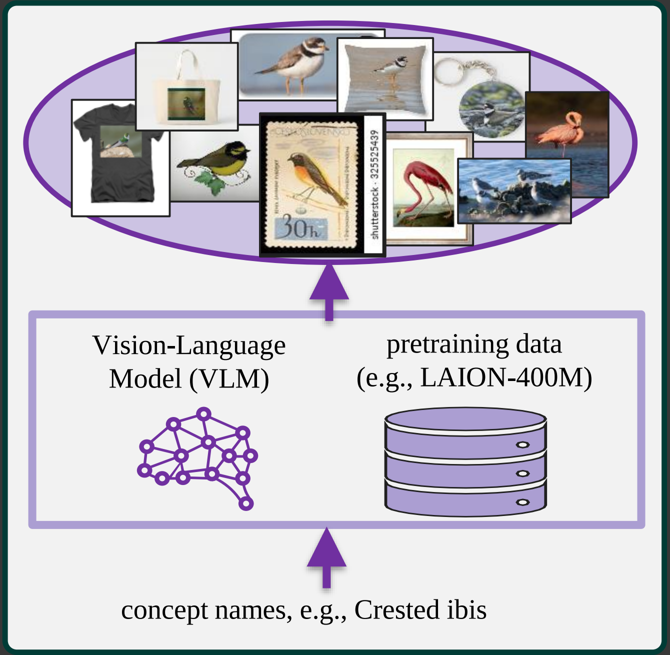
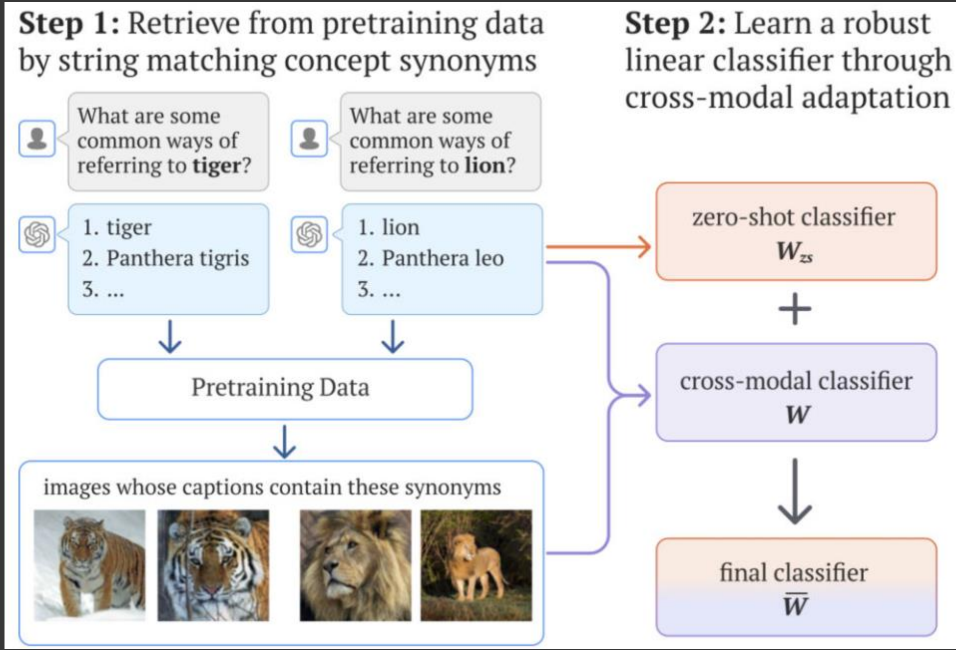
[Ours] exploits all synonyms to retrieve data using string matching





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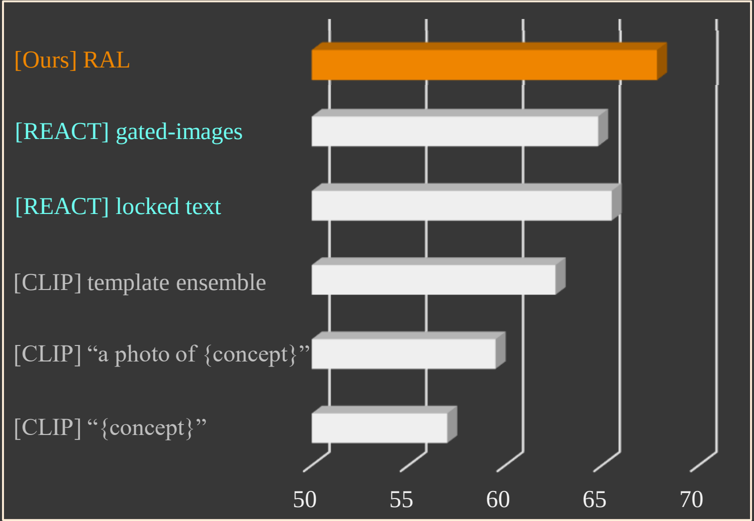
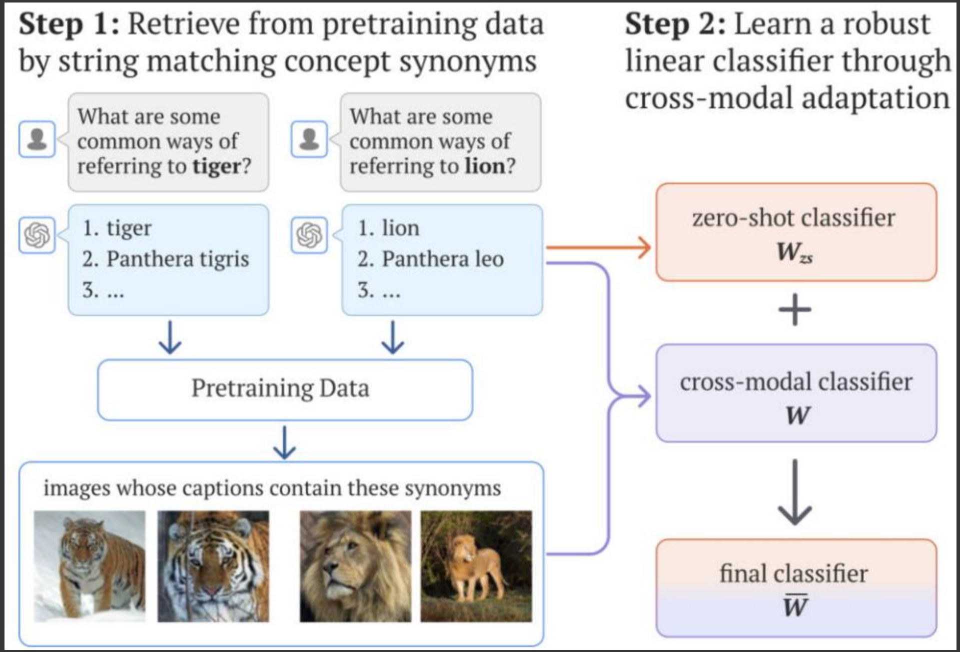
Accuracy averaged over eight datasets such as ImageNet, Food…





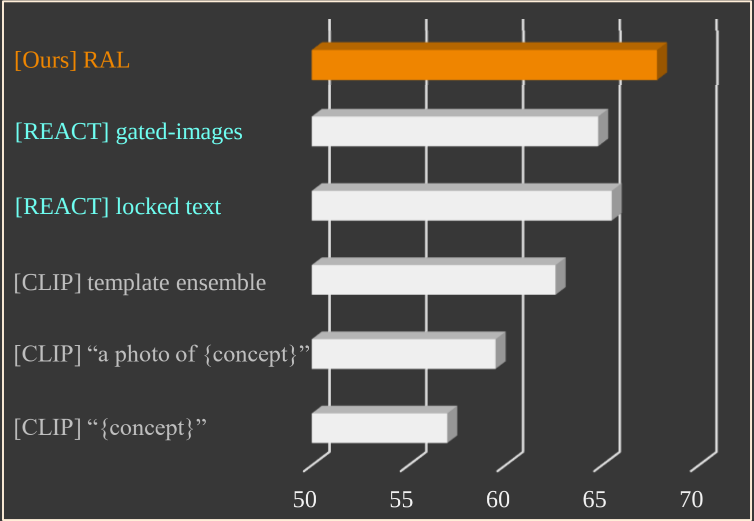
[REACT] Liu, et al., "Learning customized visual models with retrieval-augmented knowledge", CVPR, 2023
[Ours] Parashar, et al., "The Neglected Tails of Vision-Language Models", CVPR, 2024
[CLIP] Radford, et al. "Learning transferable visual models from natural language supervision." ICML, 2021

Insight 3: use all synonyms for Retrieval Augmented Learning (RAL)

[REACT] is the state-of-the-art RAL method for zero-shot recognition

[Ours] exploits all synonyms to retrieve data using string matching

Accuracy averaged over eight datasets such as ImageNet, Food…



Stage	Resource	REACT	[Our] RAL	Relative Cost
Retrieval	retrieved examples	400M	0.5M	0.1%
	time	200 hrs	6 hrs	3%
	storage	10 TB	25 GB	0.25%
Learning	training images	10M	0.5M	5%
	time	256 hrs	2 mins	0.01%
	# of learned parameters	87M	0.5M	0.6%
	GPU memory	256 GB	2 GB	0.8%

[REACT] Liu, et al., "Learning customized visual models with retrieval-augmented knowledge", CVPR, 2023
[Our] Parashar, et al., "The Neglected Tails of Vision-Language Models", CVPR, 2024
[CLIP] Radford, et al. "Learning transferable visual models from natural language supervision." ICML, 2021

Exploit the open world for auto-annotation

We study few-shot recognition by adapting a Vision-Language Model (VLM)

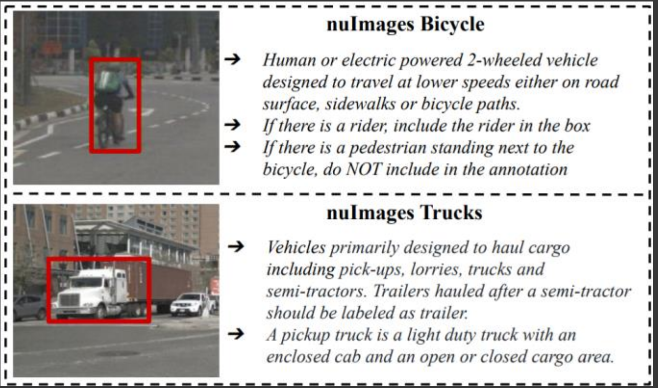
domain experts

design

collect

annotator instructions

data



sent to "annotators"
for data annotation

Human annotator

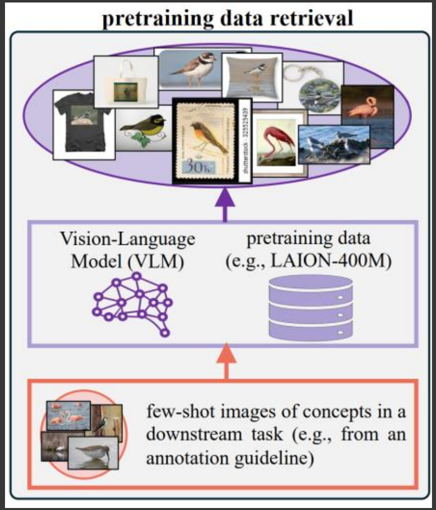
Foundation models

- Large Language Models (LLMs)
- Vision-Language Models (VLMs)
- Foundation Vision Models (FVMs)

Madan et al., "Revisiting Few-Shot Object Detection with Vision-Language Models", NeurIPS, 2024

Exploit the open world for auto-annotation

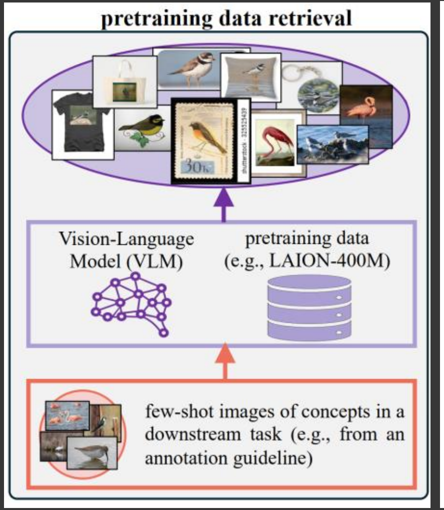
- Retrieve data

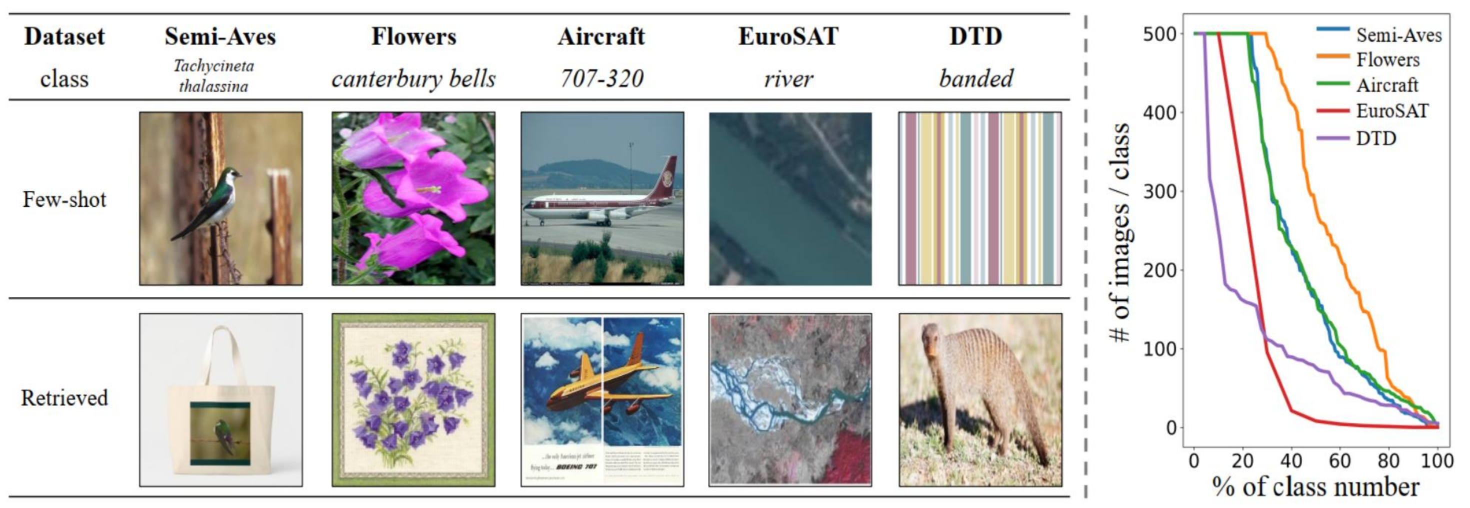


Liu, et al., "Few-Shot Recognition via Stage-Wise Augmented Finetuning", CVPR, 2025

Exploit the open world for auto-annotation

- Retrieve data, which has (1) domain gaps, and (2) imbalanced distributions.

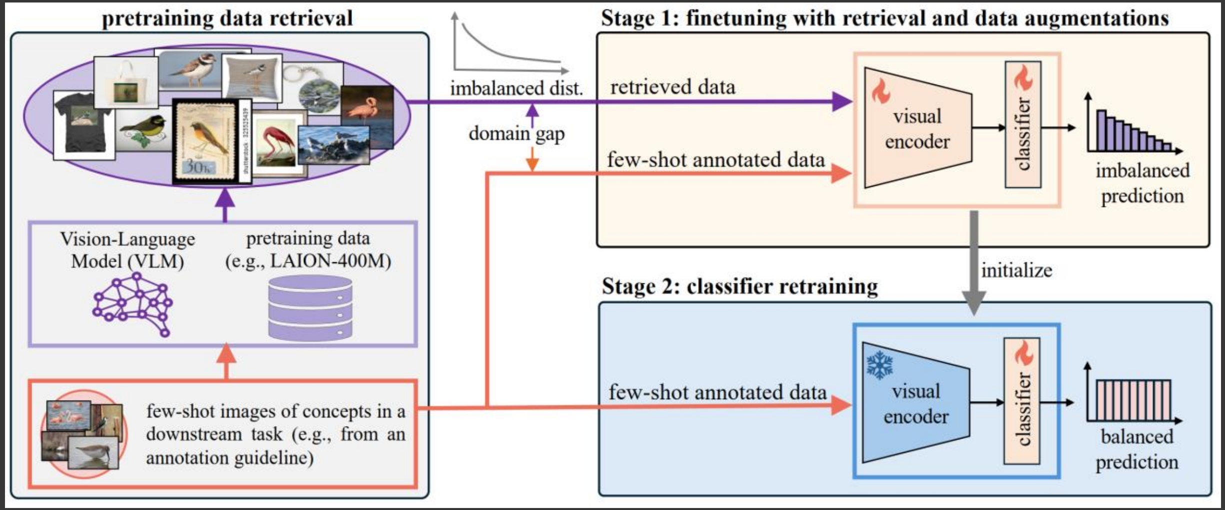




Liu, et al., “Few-Shot Recognition via Stage-Wise Augmented Finetuning”, CVPR, 2025

Exploit the open world for auto-annotation

- Retrieve data, which has (1) domain gaps, and (2) imbalanced distributions.
- We solve the above issues via Stage-Wise retrieval Augmented fine-Tuning (SWAT), cf. decoupled feature and classifier for long-tailed recognition, and transfer learning for domain adaptation.



Liu, et al., "Few-Shot Recognition via Stage-Wise Augmented Finetuning", CVPR, 2025

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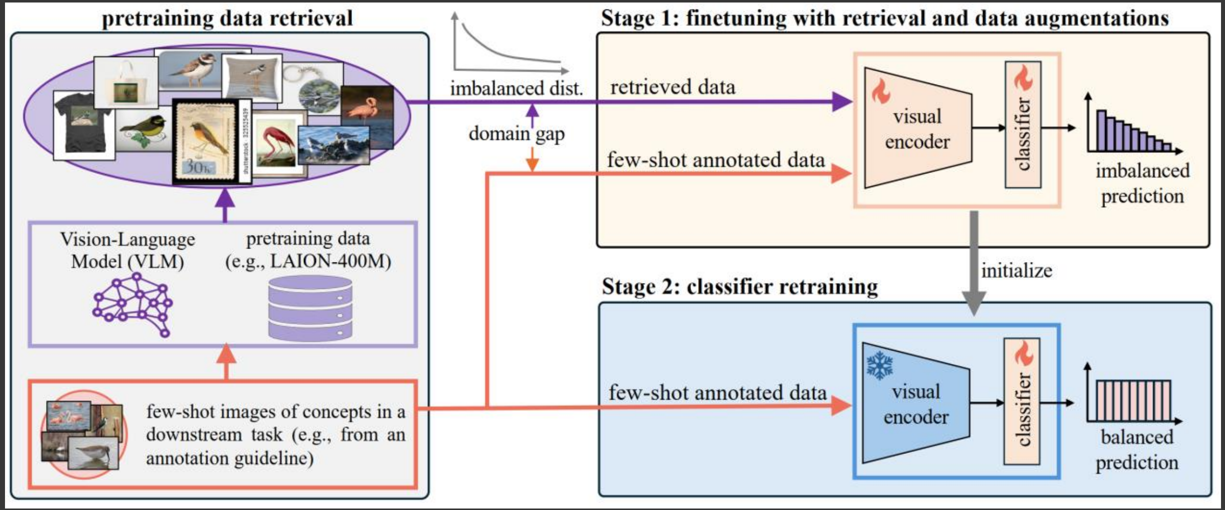

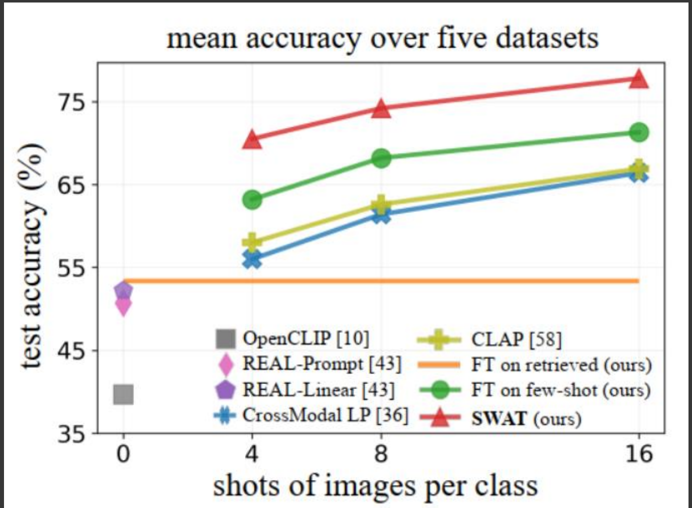

Liu, et al., "Few-Shot Recognition via Stage-Wise Augmented Finetuning", CVPR, 2025

Exploit the open world for auto-annotation

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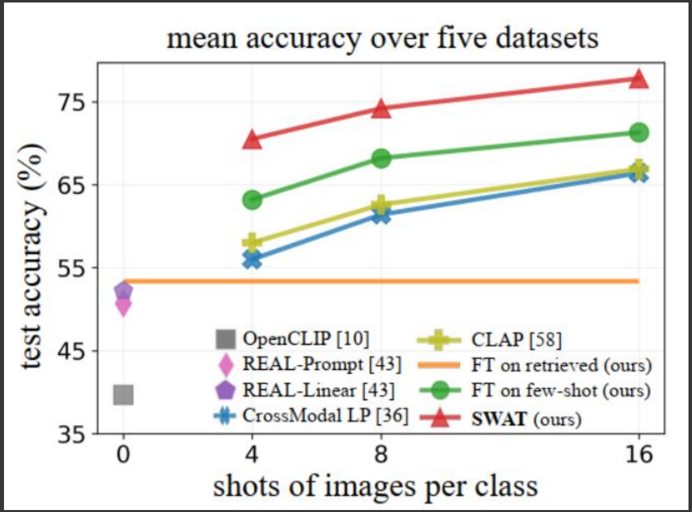
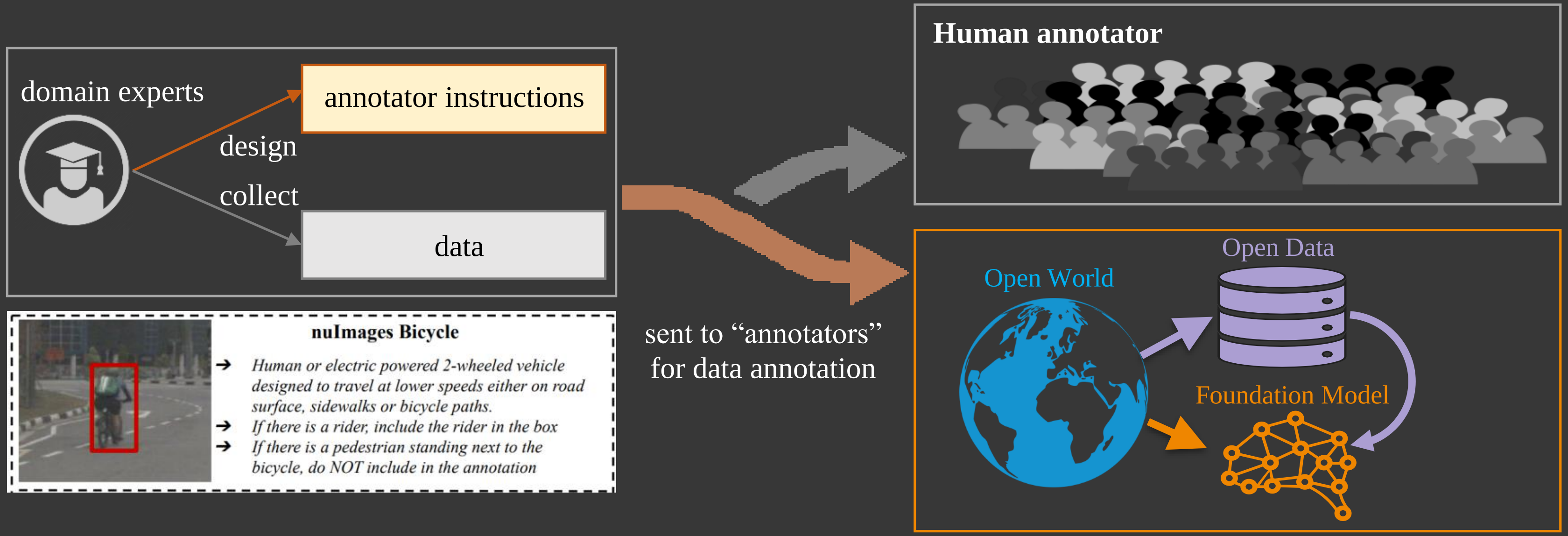
- SWAT performs the best.
- Few-shot finetuning outperforms existing few-shot learning methods!
- Finetuning on retrieved data underperforms zero-shot method (REAL-Linear) due to domain gaps & imbalanced distributions.



Parashar, et al., “The Neglected Tails of Vision-Language Models”, CVPR, 2024
Liu, et al., “Few-Shot Recognition via Stage-Wise Augmented Finetuning”, CVPR, 2025

Conclusions

- Embrace the open world – the foundation models and open data!
- Watch out for misalignment between AI and experts (like you)!
- Be aware of the imbalance of the open world!



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