R+X: Retrieval and Execution from Everyday Human Videos

RSS 2024

Project: robot-learning.uk/r-plus-x

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Reading Group | IRVL
31/1/25

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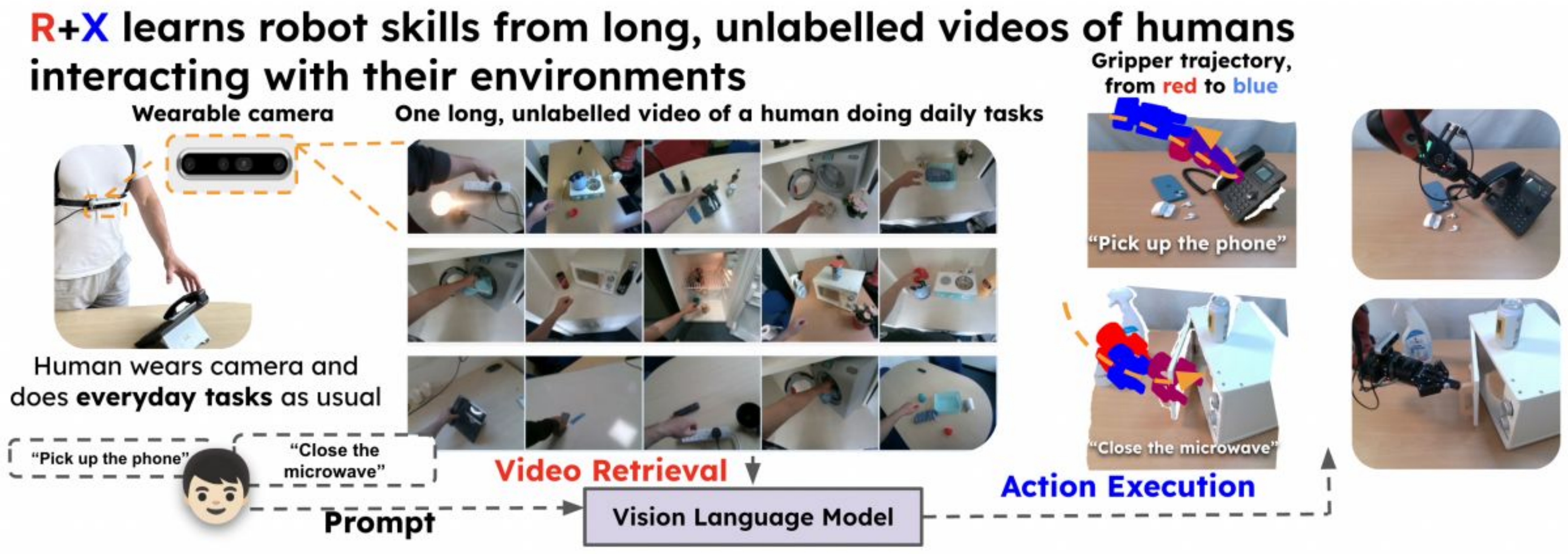
Problem



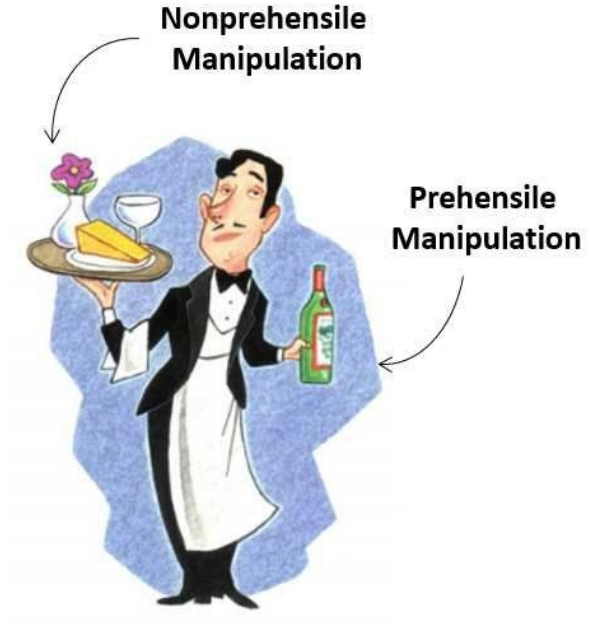
Leverage understanding of large models

- Via video retrieval and understanding
- No Finetuning

Few-Shot In-Context Imitation Learning

Related Works

	Multi task no label/align videos	No robot data	Non-prehensile tasks	New obj gener.	Distractors (both train & test)	No MoCap hardware
Vid2Robot	✗	✗	✓	✓	✓	✓
WHIRL	✗	✗	✓	✗	✓	✓
DITTO	✗	✓	✗	✗	✗	✓
ScrewMimic	✗	✗	✗	✓	✓	✓
Orion	✗	✓	✗	✗	✗	✓
DexCap	✗	✓	✓	✓	✓	✗
R+X	✓	✓	✓	✓	✓	✓



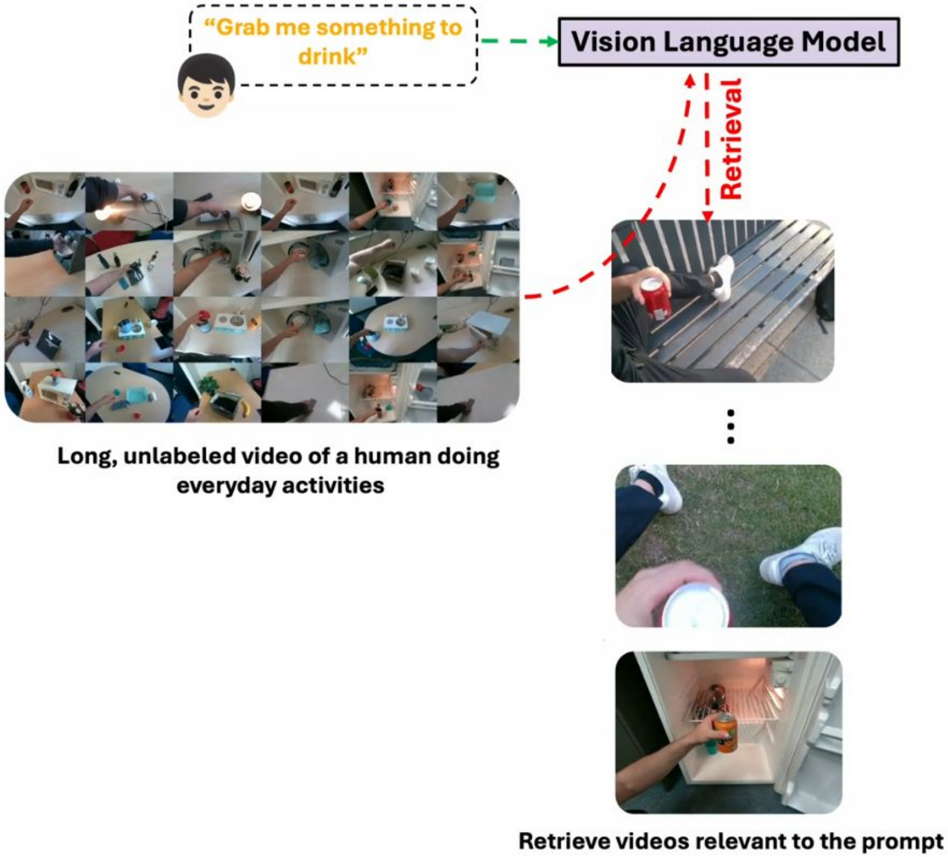
1. Get Videos: Record Anywhere, from Multiple Views

Long, unlabeled video of a human doing everyday activities

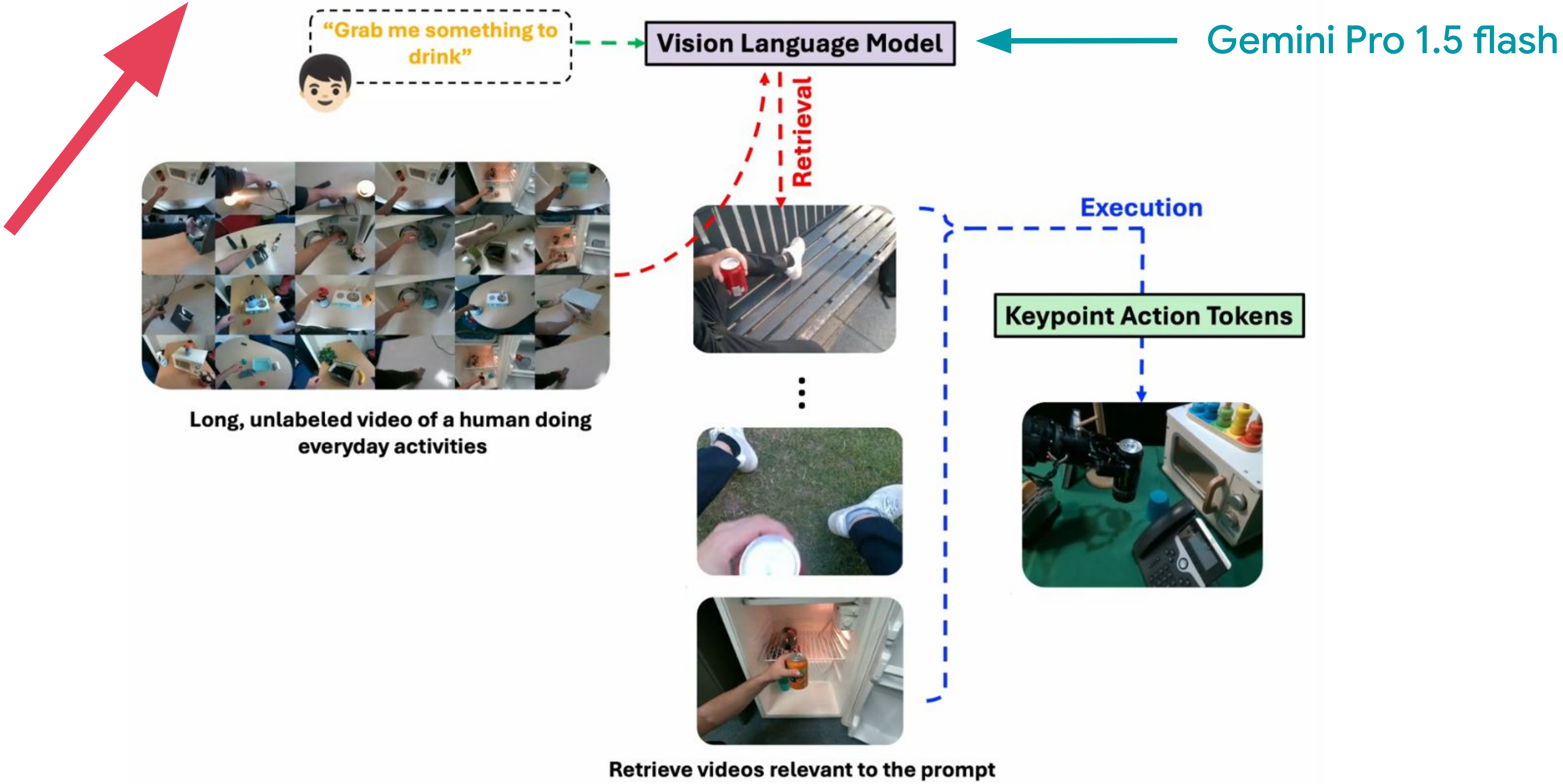
- Multiple rooms, multiple buildings, and even outside
- Chest camera, head camera or a third person camera

Single Unlabelled Video with less clutter/distractors

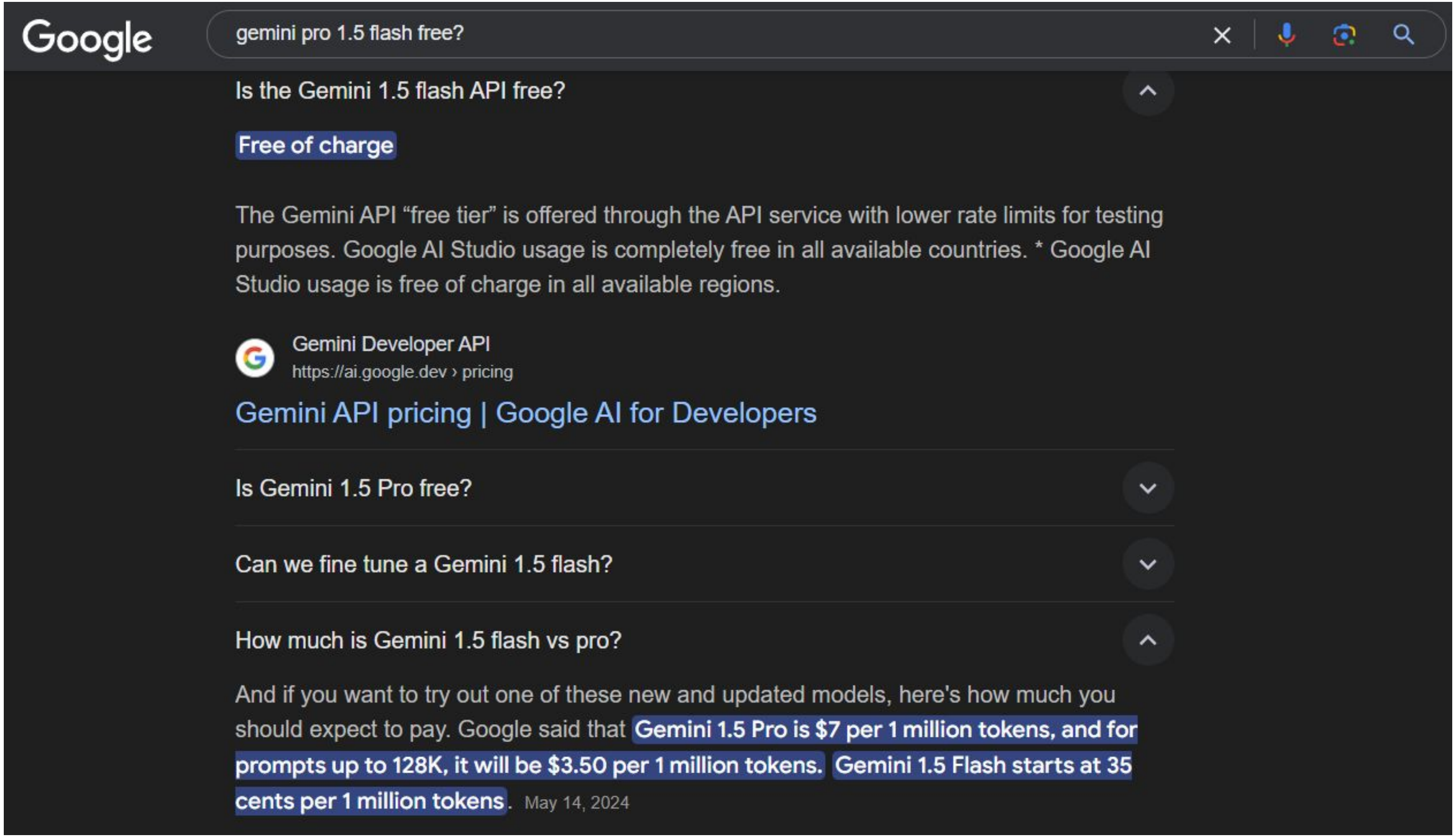
Long, unlabeled video of a human doing everyday activities


"Grab me something to drink"
Vision Language Model
Retrieval
Long, unlabeled video of a human doing everyday activities
Retrieve videos relevant to the prompt

R+X : Retrieval and Execution



Google Search as of 1/31/2025



gemini pro 1.5 flash free?

Is the Gemini 1.5 flash API free?

Free of charge

The Gemini API "free tier" is offered through the API service with lower rate limits for testing purposes. Google AI Studio usage is completely free in all available countries. * Google AI Studio usage is free of charge in all available regions.

Gemini Developer API
https://ai.google.dev › pricing

Gemini API pricing | Google AI for Developers

Is Gemini 1.5 Pro free?

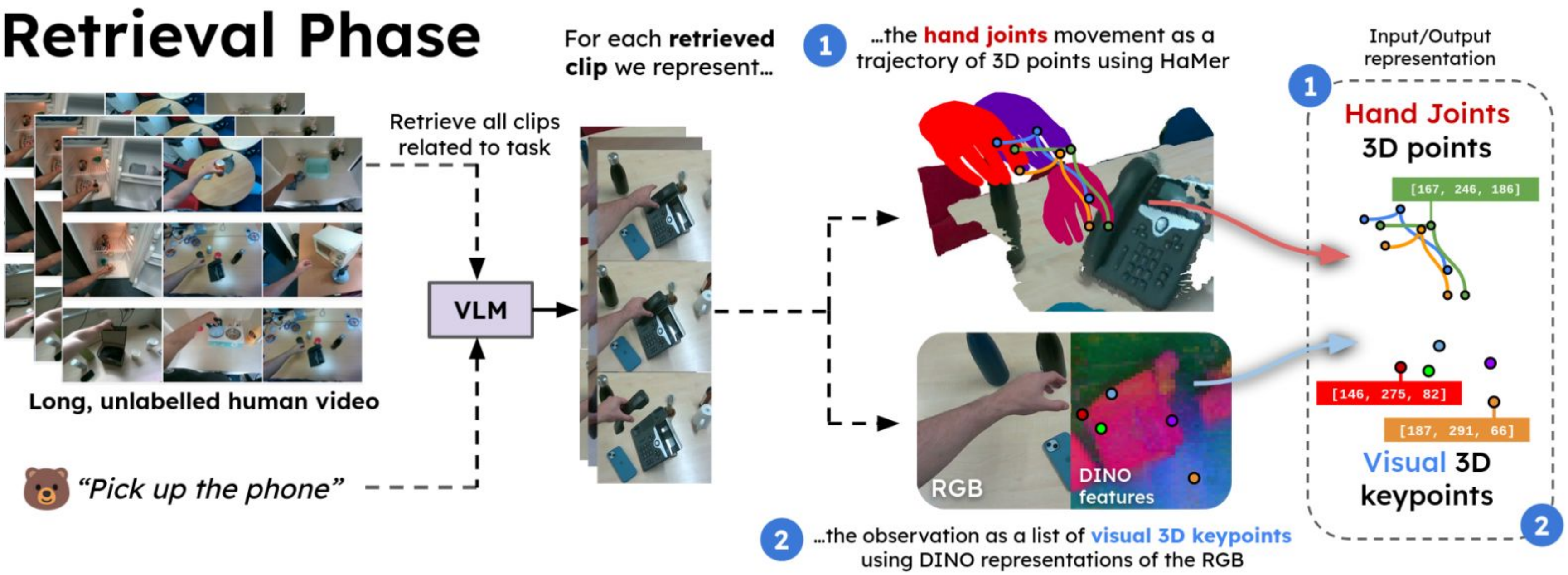
Can we fine tune a Gemini 1.5 flash?

How much is Gemini 1.5 flash vs pro?

And if you want to try out one of these new and updated models, here's how much you should expect to pay. Google said that **Gemini 1.5 Pro is $7 per 1 million tokens, and for prompts up to 128K, it will be $3.50 per 1 million tokens.** **Gemini 1.5 Flash starts at 35 cents per 1 million tokens**. May 14, 2024

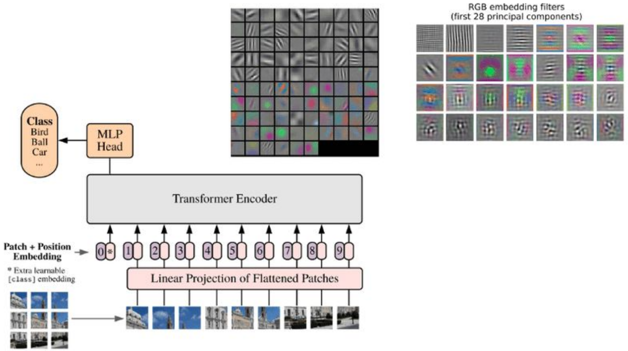
Deploy Immediately to Novel Environments and Objects

Skills learned from videos can generalize to novel environments, filled with distractors, and even unseen test objects.

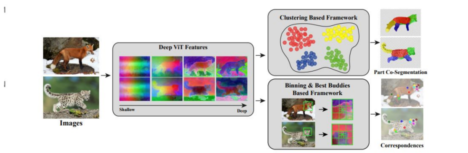


For Scene Semantics + Geometry
Only using first video frame

Visual Scene Keypoints



ViT



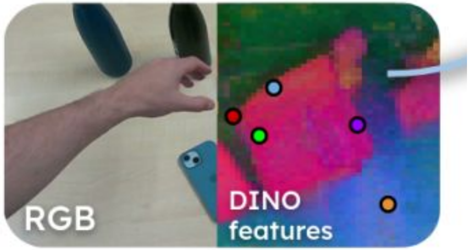
Deep ViT Features as Dense Visual Descriptors

Shir Amir[1], Yossi Gandelsman[2], Shai Bagon[1], and Tali Dekel[1]

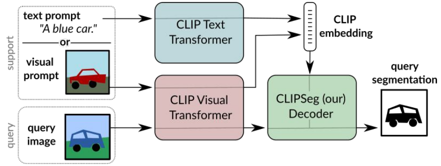
[1] Dept. of Computer Science and Applied Math, The Weizmann Inst. of Science
[2] Berkeley Artificial Intelligence Research (BAIR)

Patch2Pix
Keypoints
N_{patch}xD->Cluster->N_{Pix}xD

First Video Frame



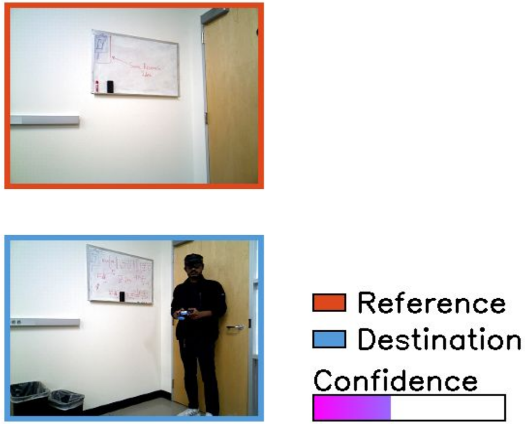
Get Keypoints in the remaining frames

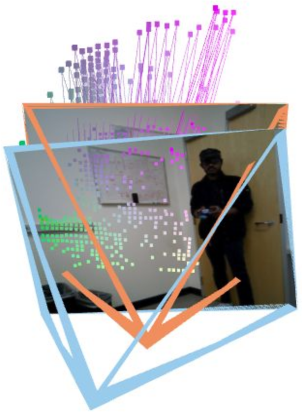


CLIPSeg

Only attend to static BG: Table, Wall, Floor + **Delete Arm, Person, Hand**

Rel Camera TF

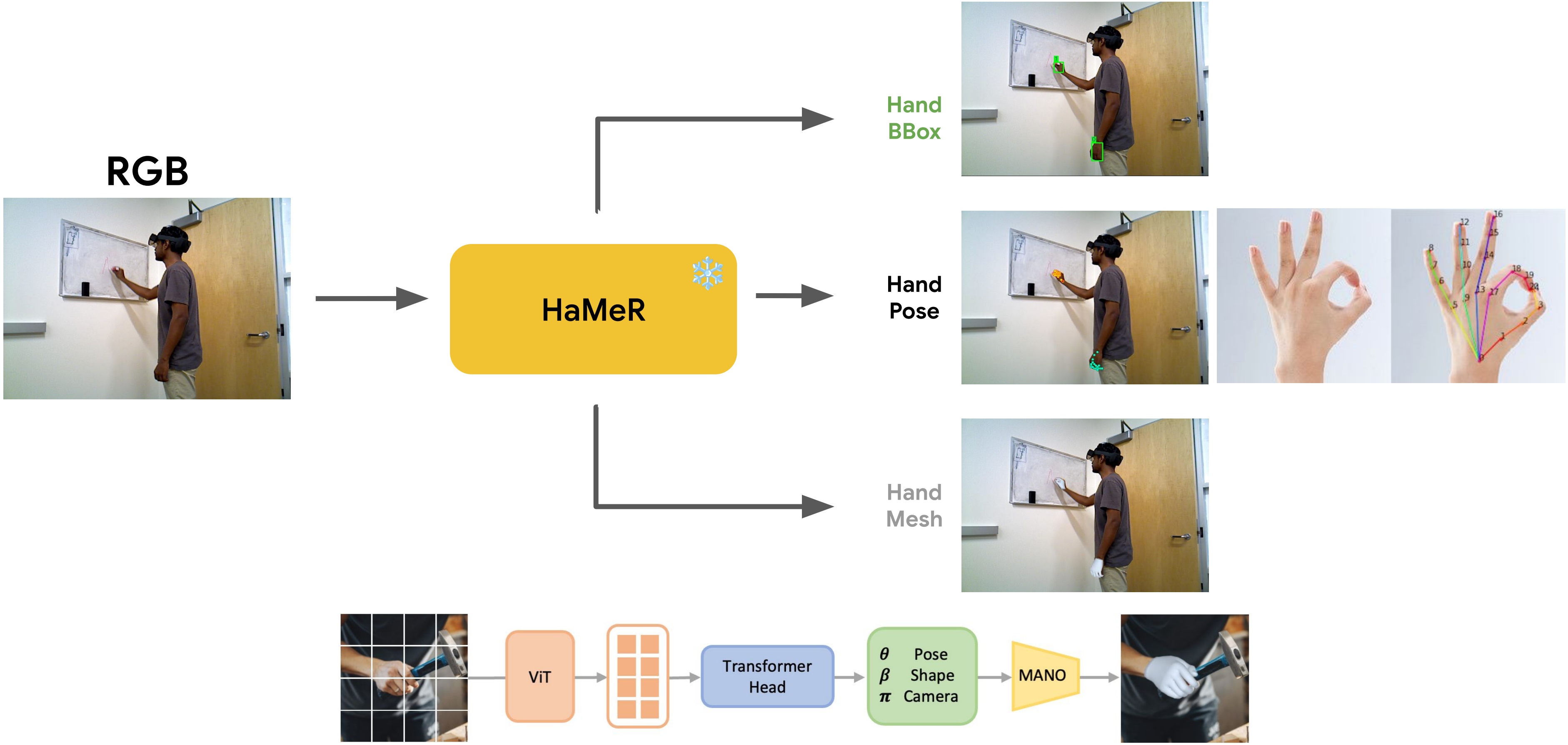




https://nianticlabs.github.io/mickey
[CVPR2024 Oral]

H-Demo: First Frame + Test Frame
Frame-1->Frame-2,........

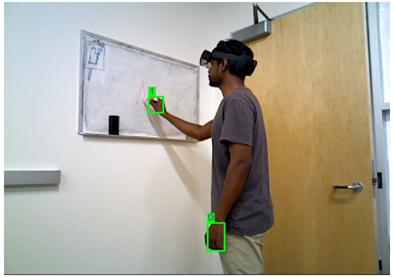
HaMeR

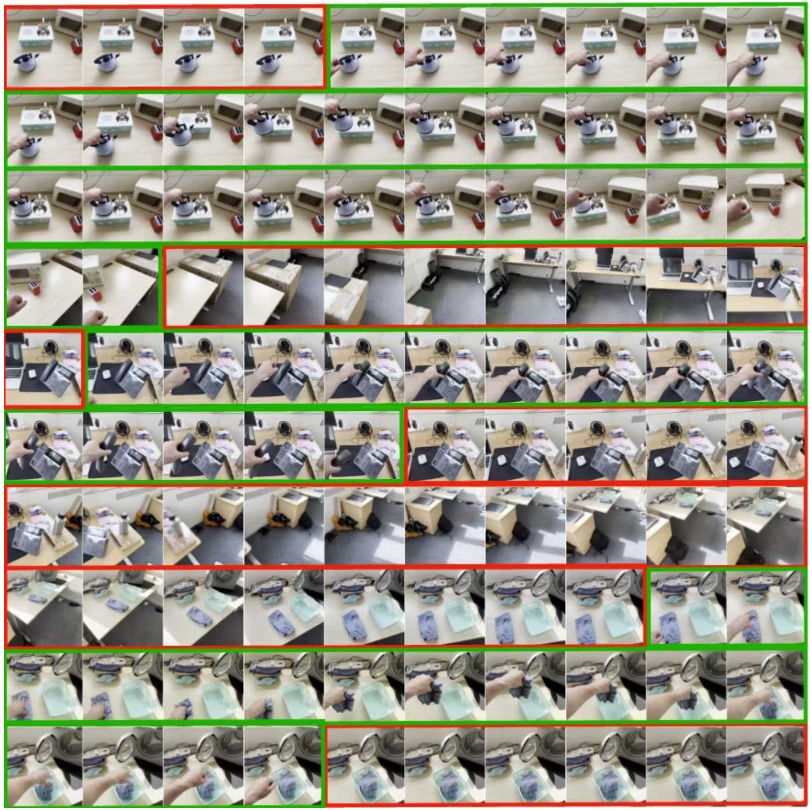


RGB
HaMeR
Hand BBox
Hand Pose
Hand Mesh
ViT
Transformer Head
θ Pose
β Shape
π Camera
MANO

HaMeR: Automatic non-hand frame elimination

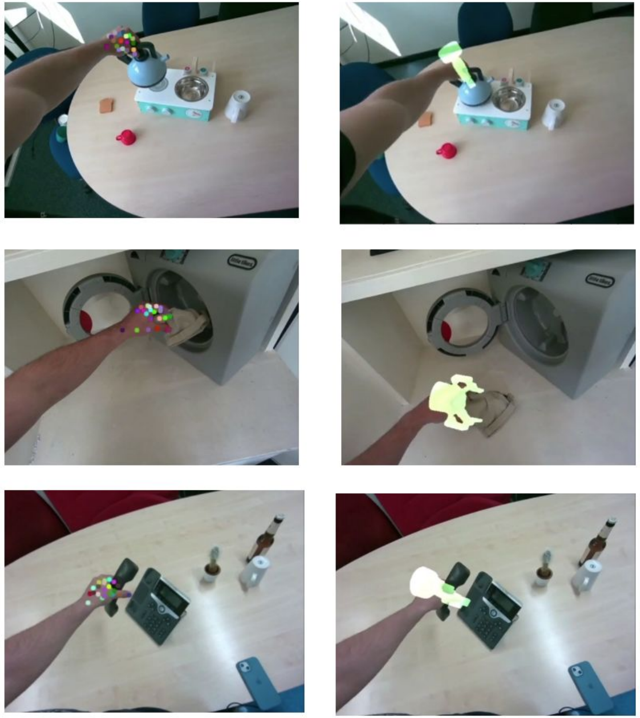
Long, unlabeled video of a human doing everyday activities

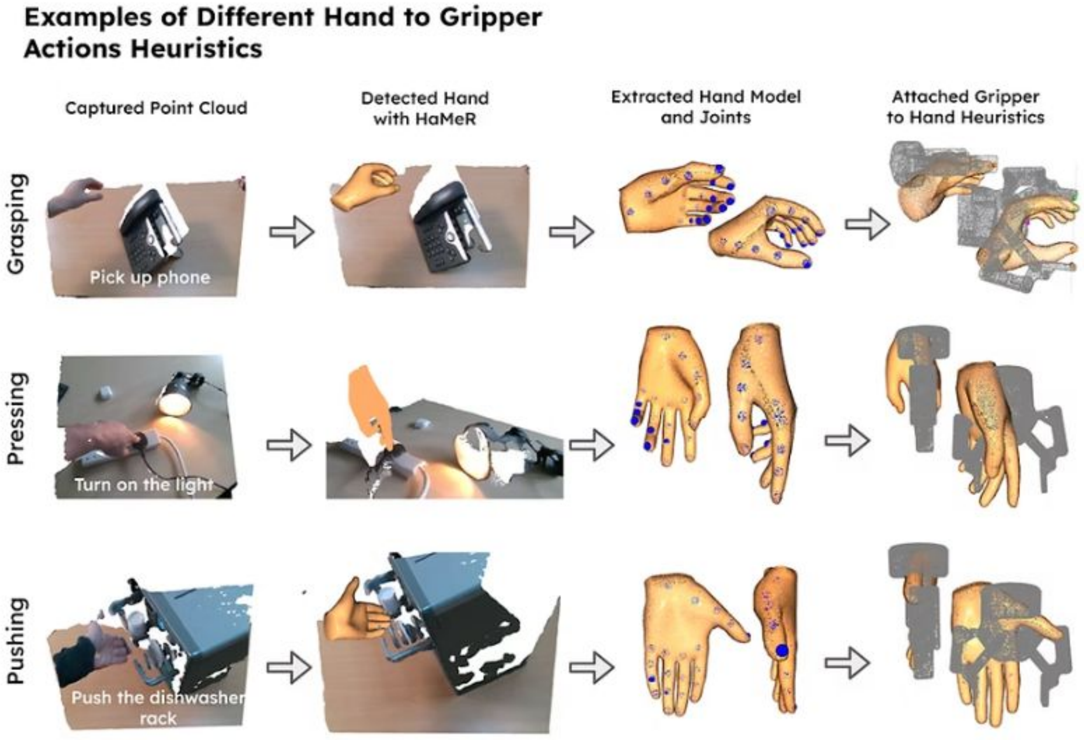




HaMeR: Automatic non-hand frame elimination

Human Hand -> Gripper





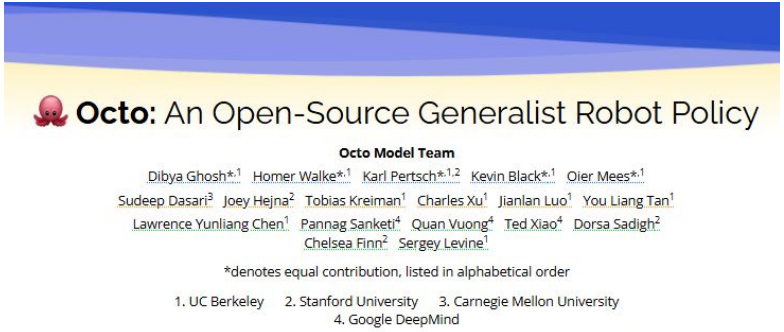
Chest Camera Movement & Scene as a fixed point cloud

Point Cloud before Stabilisation

Point Cloud **after** Stabilisation

Gripper's trajectory before Stabilisation

Gripper's trajectory **after** Stabilisation


🐙 Octo: An Open-Source Generalist Robot Policy

Octo Model Team
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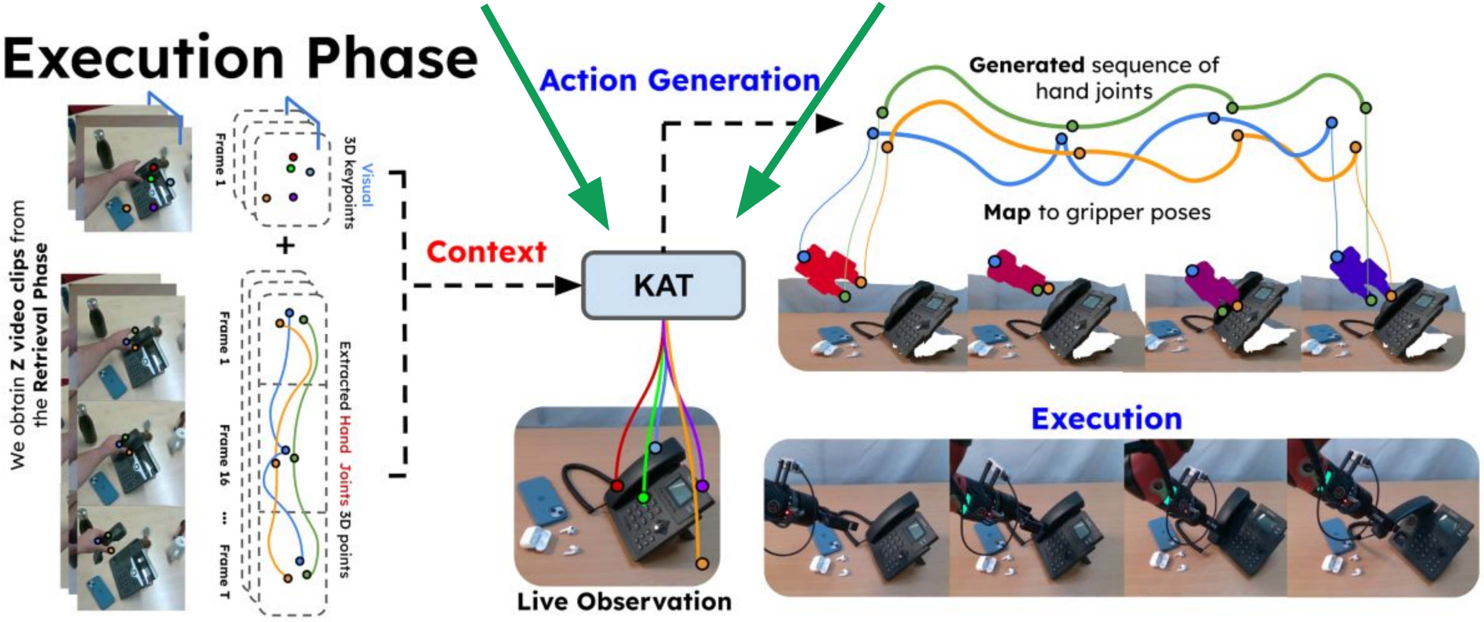
*denotes equal contribution, listed in alphabetical order

1. UC Berkeley 2. Stanford University 3. Carnegie Mellon University
4. Google DeepMind

3D Trajectory = KAT(3D Visual Keypoints)

3D Traj for gripper movement

No Finetuning
Use off the shelf LLMs' in context learning (few-shot) ability



Hardware

IV. EXPERIMENTS

Human Video. We collect the human video $\mathcal{H}$ using an Intel RealSense 455, worn by a human on their chest as shown in Figure 1. To reduce downstream computational time, we filter out each frame in which human hands are not visible right after recording. As our robot is single-armed, we limit ourselves to single hand tasks. However, our method could identically be applied to bimanual settings and dexterous manipulators. The video is collected in many different rooms and buildings.

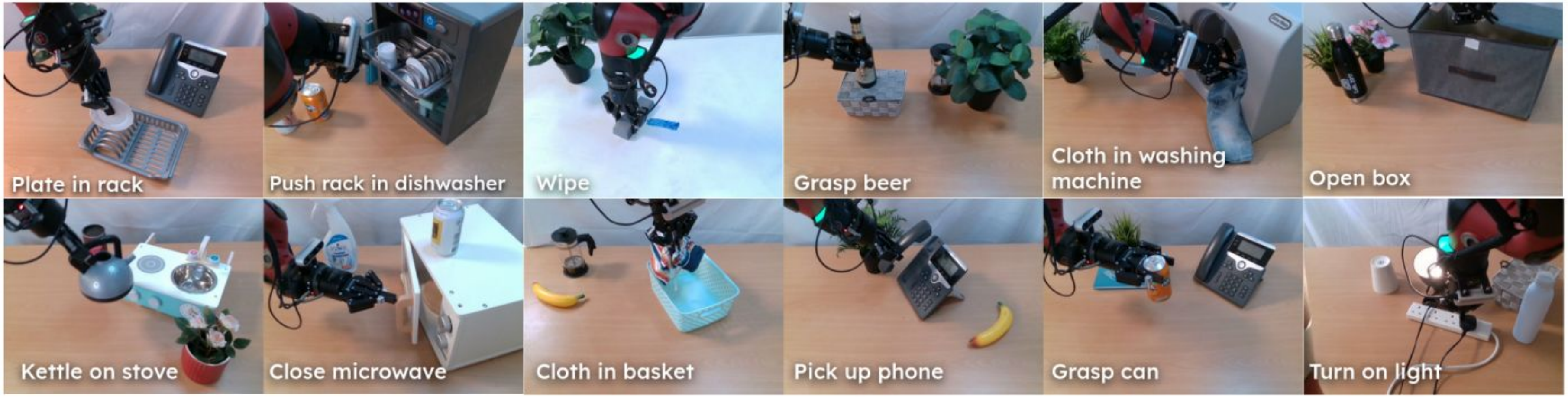
Robot Setup. At execution, we use a Sawyer robot equipped with a RealSense 415 head-camera. The robot is equipped with a two-fingered parallel gripper, the Robotiq 2F-85. As the robot is not mobile, we setup different scenes in front of it with variations of the tasks recorded by the human, placing several different distractors for each task, while the human video was recorded in many different

Human 455

Sawyer Robot with fixed base

WristCam 415; not used in the work

Tasks



12 Everyday Tasks

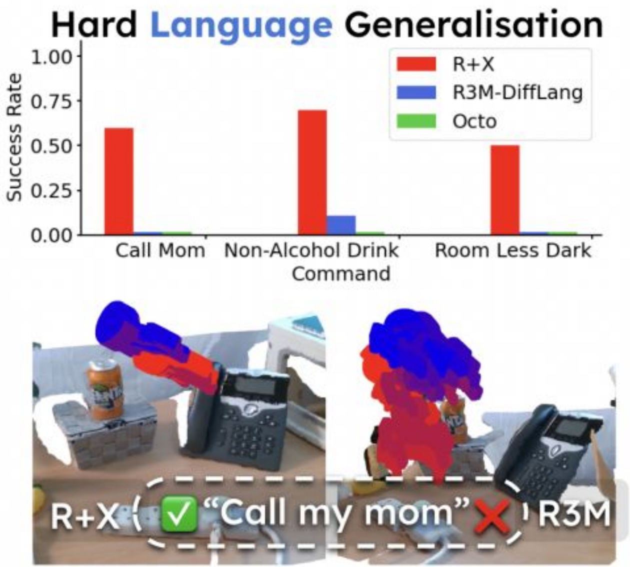
Baselines

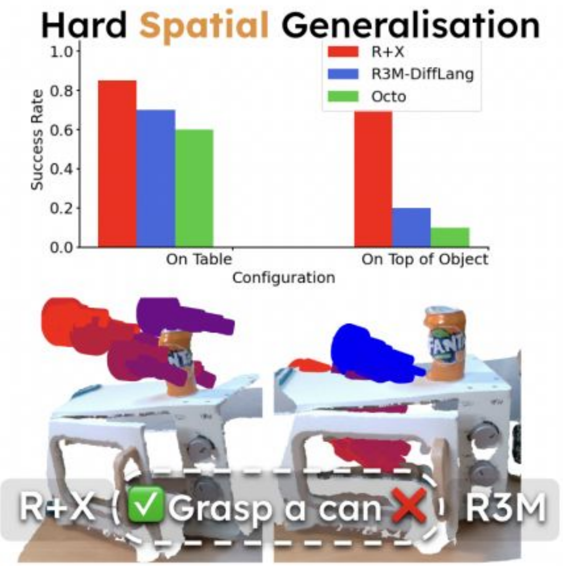
Baselines. We compare R+X, and its retrieval and execution design, to training a single, language-conditioned policy. To obtain language captions from the human video, we use Gemini to autonomously caption snippets of the video, obtaining a *(observation, actions, language)* dataset. We finetune R3M (ResNet-50 version [28]) [29] and Octo [30] on this data. We extend R3M to also encode language via SentenceBERT and use a Diffusion Policy [31] head to predict actions from intermediate representations. We denote this version as R3M-DiffLang.

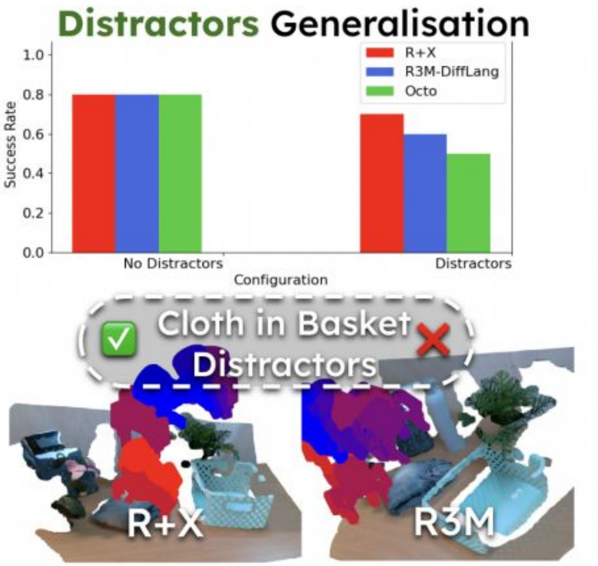
Method / Task	Plate	Push	Wipe	Beer	Wash	Box	Kettle	Micro.	Basket	Phone	Can	Light	**Avg.**
R3M-DiffLang	0.5	0.7	0.4	0.7	0.5	0.5	0.4	0.8	0.7	0.4	0.7	0.3	0.55
Octo	0.5	0.8	0.5	0.6	0.5	0.5	0.4	0.7	0.6	0.4	0.6	0.3	0.53
R+X	**0.6**	0.8	**0.7**	**0.8**	**0.6**	**0.7**	**0.6**	0.8	0.7	**0.7**	**0.8**	**0.6**	**0.7**

10 episodes (runs)

Spatial, Language and Distractors generalisation
Gripper trajectories move from red to blue.





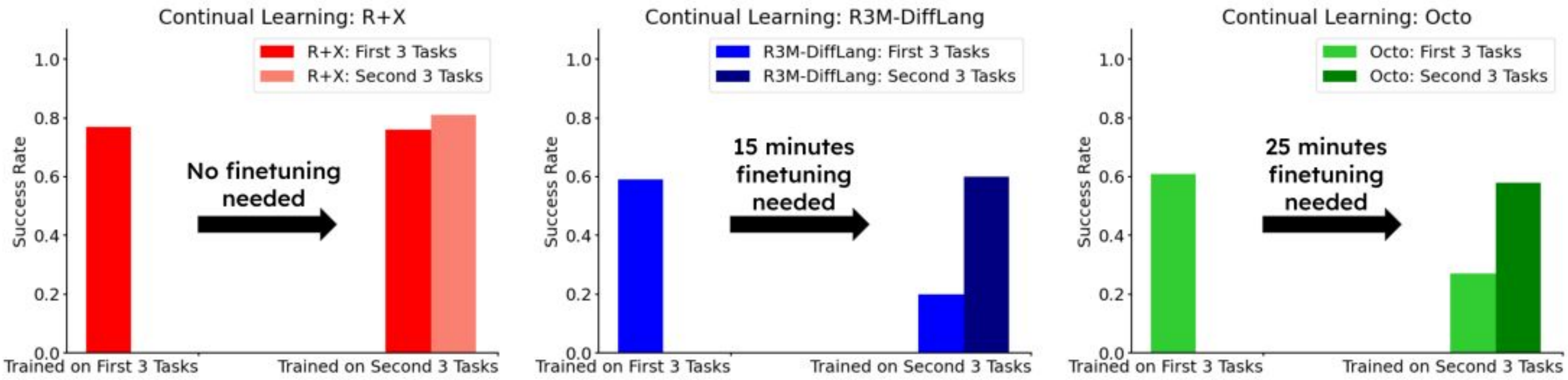


5 episodes (runs)

5 episodes (runs)

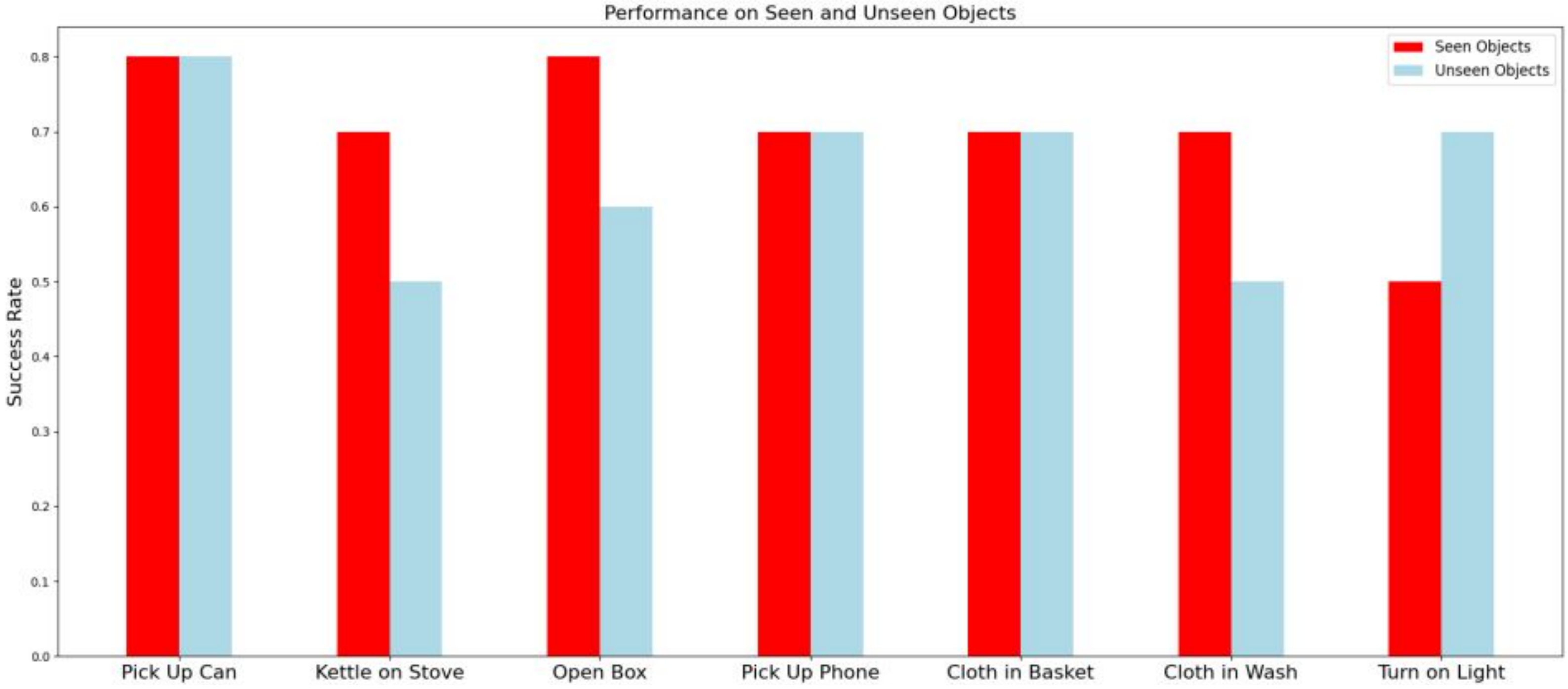
10 episodes (runs)

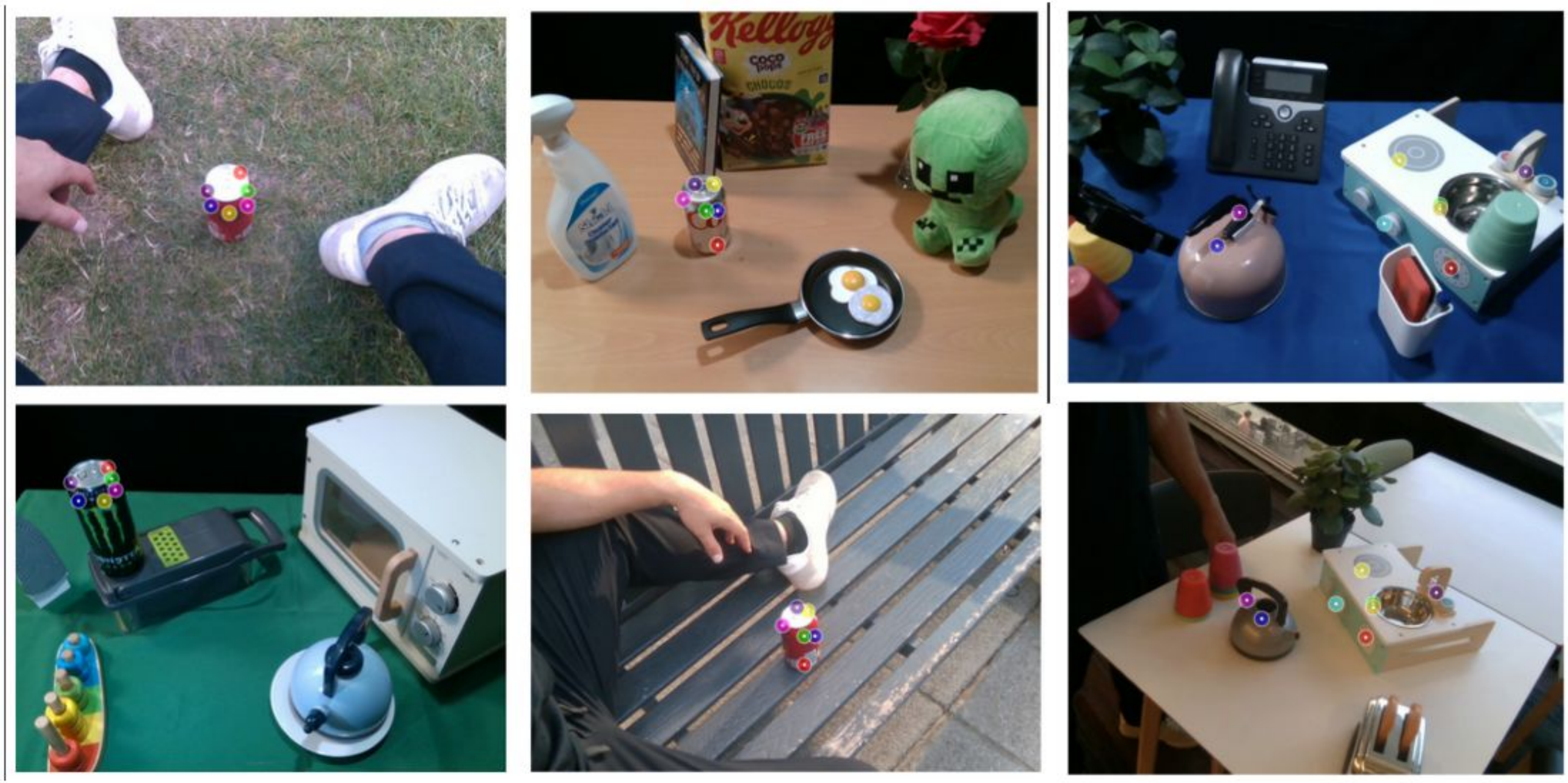
Can R+X learn task sequentially over time?



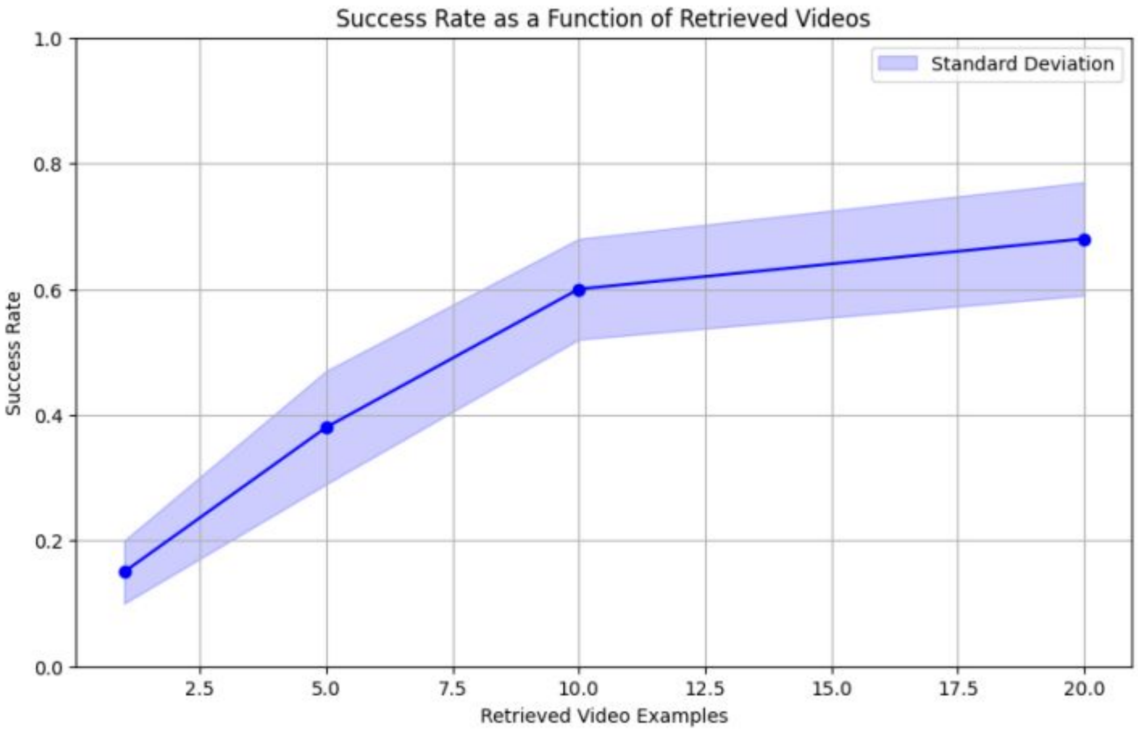
10 demos for 3 new tasks

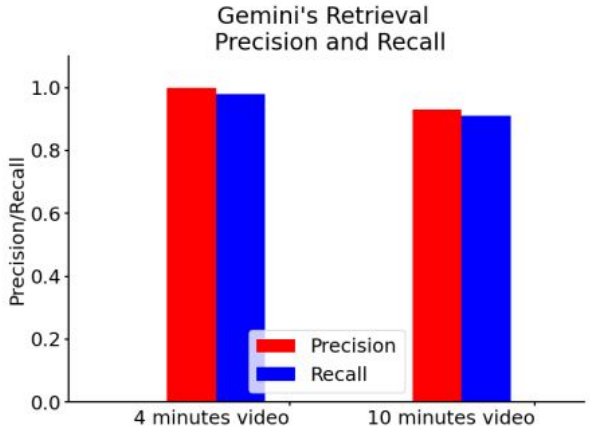
Success rate on Seen & Unseen Objects





Examples of keypoints extracted for the same tasks, but with different views, settings, and target objects


Success Rate as a Function of Retrieved Videos
Standard Deviation
Success Rate
Retrieved Video Examples
1.0
0.8
0.6
0.4
0.2
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0


Gemini's Retrieval
Precision and Recall
Precision/Recall
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
4 minutes video
10 minutes video

Gemini

Takeaways

High time to use the reasoning capability of Large Multi Modal Models (LMMs)

Leverage LMMs' few-shot in context learning ability for generalization purposes

Latent plan pre-training benefits multi-task learning. [MimicPlay, LAPA]

Similarly, nuanced inputs like Keypoints are good for generalization instead of direct RGBD or text

Questions?