



Video Understanding

Definitions...

Ego... a person's sense of self-esteem or self-importance



Definitions...

Ego... a person's sense of self-esteem or self-importance

Egocentric vision... the wearer serves as the central reference point in the study of interesting entities: objects, actions, interactions and intentions



360 vs Egocentric...



Ego

360

360 vs Egocentric...



In today's talk...



Motivation and Datasets in
Egocentric Video Understanding



Teaser: The Wizard of Oz
& Genie 3



Video Understanding
Out of the Frame



Outlook into the Future of
Egocentric Vision



→ Point Tracking

→ Object Tracking

→ Gaze Priming

→ Hand Tracking



Conclusion

In today's talk...



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Egocentric Vision



Point Tracking

Object Tracking

Gaze Priming

Hand Tracking

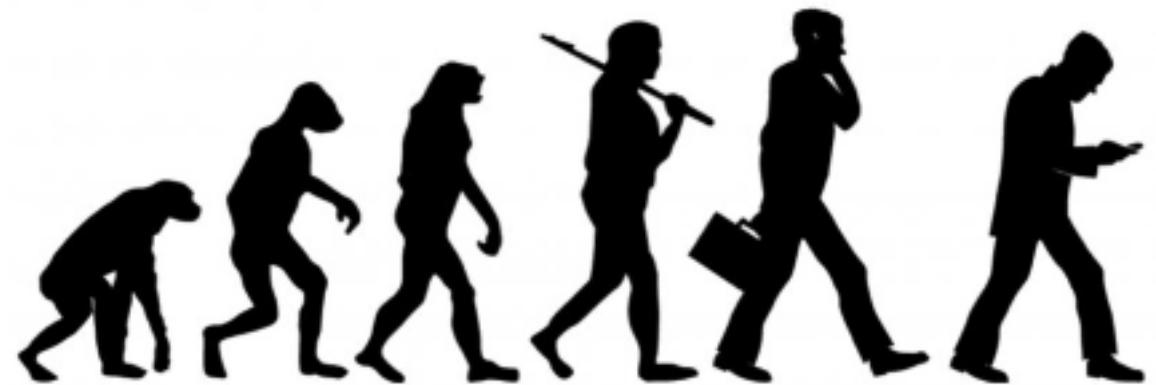


Conclusion

The present...



Photo *Illustration* by Pelle Cass



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Dima Damen
BinEgo-360 Workshop @ICCV2025

The future...

HoloLens 2
A new vision for computing

[See pricing and options >](#) [Watch the HoloLens 2 video](#)

[FACEBOOK](#) [Who We Are](#) [What We Build](#) [Our Actions](#) [Our Community](#) [Resources](#)

PROJECT ARIA GLASSES

The goal of Project Aria is learning in a safe and secure environment. Project Aria glasses will initially be made available to a limited group of Facebook employees and contractors that will be trained on when and where to use the device. We'll be asking people of diverse backgrounds to participate in the program to create an accurate and diverse view of the world.

Facebook Reality Lab
Facebook Reality Lab is a research and development organization focused on creating the next generation of virtual reality and augmented reality technologies. The lab is composed of several teams working on different aspects of VR and AR, including research, engineering, design, and product management. The goal of the lab is to push the boundaries of what's possible in VR and AR, and to develop technologies that can be used in a variety of applications, from gaming to education to healthcare.

RESEARCH

Samsung patent application reveals augmented reality headset design

It comes as the Gear VR slowly fades away



The future is here...



The future can be imagined...



Egocentric Videos?



In today's talk...



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Conclusion



EPIC-KITCHENS

EPIC Fields

with: V Tschernezki*, A Darkhalil*, Z Zhu*,
D Fouhey, I Laina, D Larlus, A Vedaldi

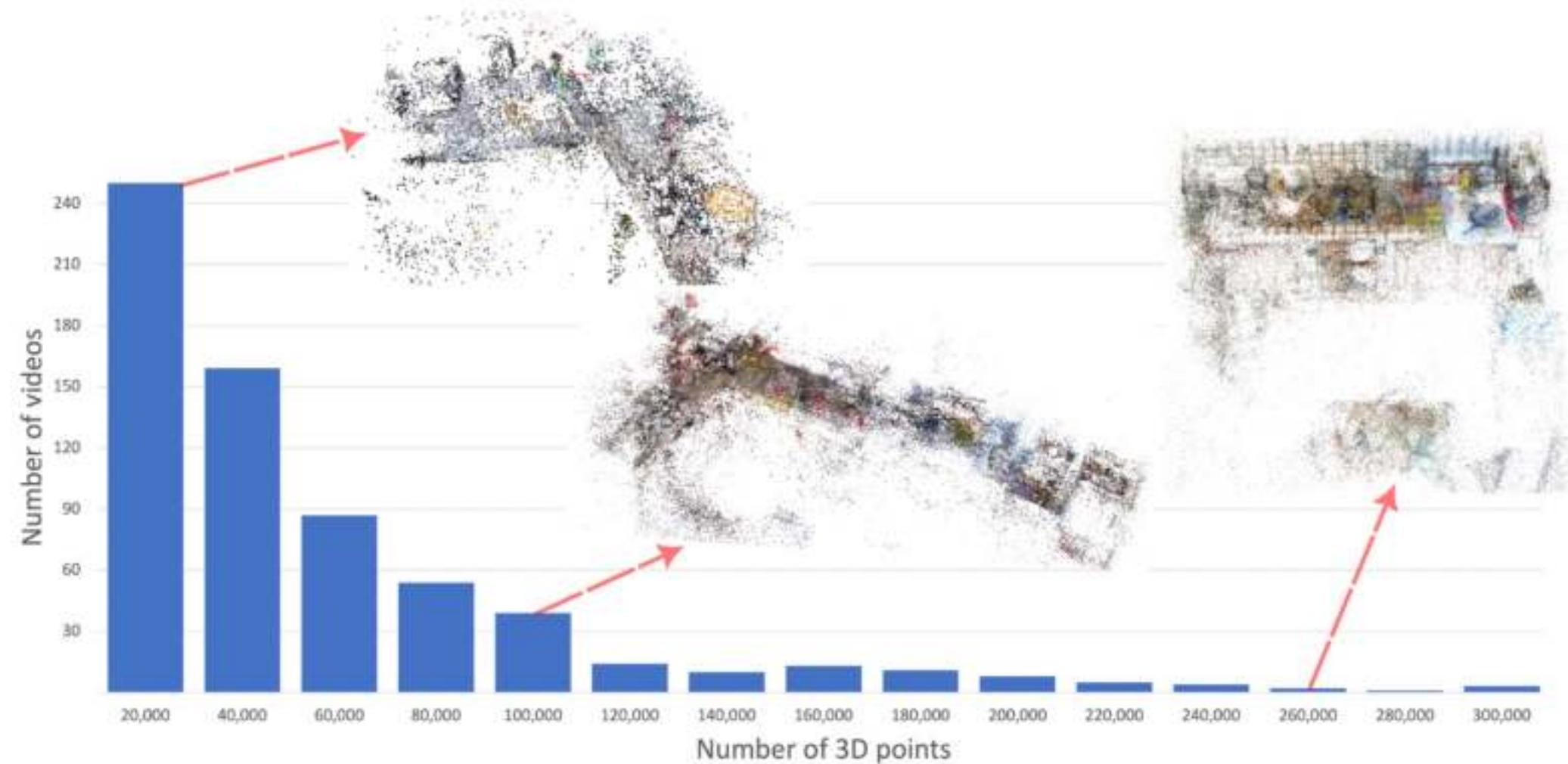


Figure 4: **Number of 3D points histogram.** The majority of our reconstructions generate less than 40,000 points that are enough to represent the kitchen. However, some reconstructions have more than 100,000, we include the point clouds for each points range showing the fine details covered by having more points

Table 1: Comparison of datasets commonly used in dynamic new-view synthesis.

Dataset	#Scenes	Seq. Length	Monocular	Semantics
Nerfies [37]	4	8–15 sec	-	-
D-NeRF [41]	8	1–3 sec	-	-
Plenoptic Video [22]	6	10-60 sec	-	-
NVIDIA Dynamic Scene Dataset [65]	12	1–5 sec	4 / 12	-
HyperNeRF [38]	16	8–15 sec	13 / 16	-
iPhone [13]	14	8–15 sec	7 / 14	-
SAFF [25]	8	1–5sec	-	✓
EPIC Fields (ours)	50	6–37 min (Avg 22)	50 / 50	✓

In today's talk...



Motivation and Datasets in
Egocentric Video Understanding



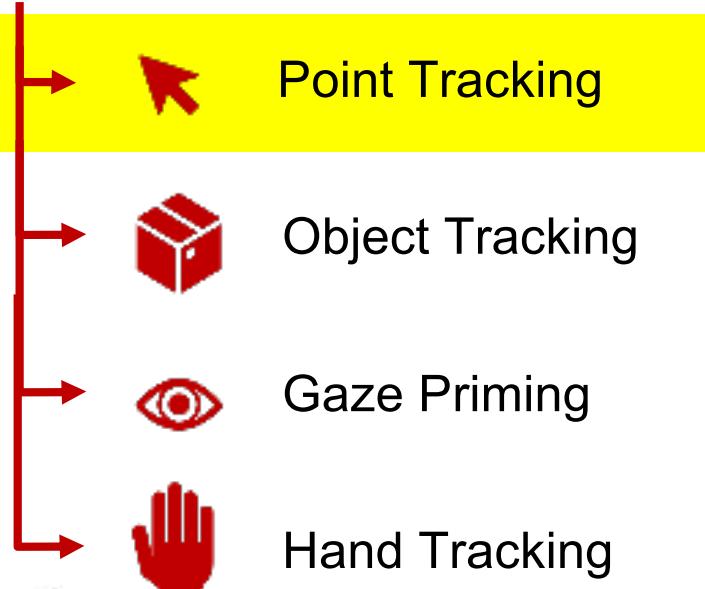
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Video Understanding
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Outlook into the Future of
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Conclusion



EgoPoints: Advancing Point Tracking for Egocentric Videos

Ahmad Darkhalil¹ Rhodri Guerrier¹ Adam W. Harley² Dima Damen¹

¹University of Bristol ²Stanford University

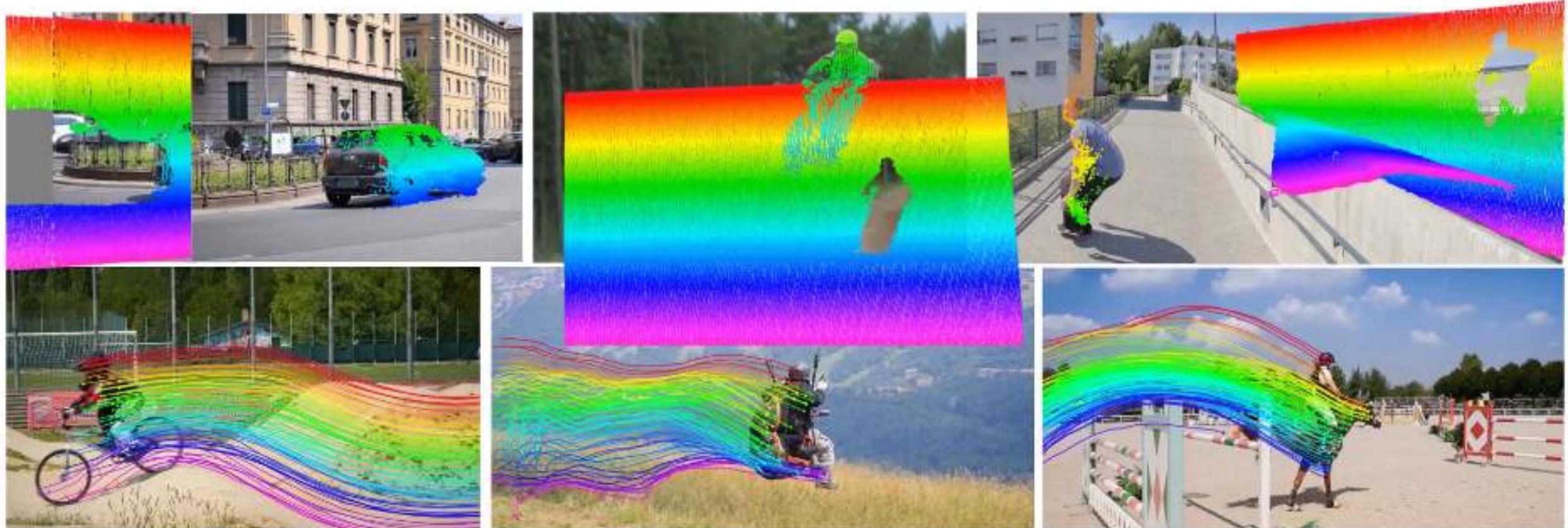


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What is point tracking?

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley

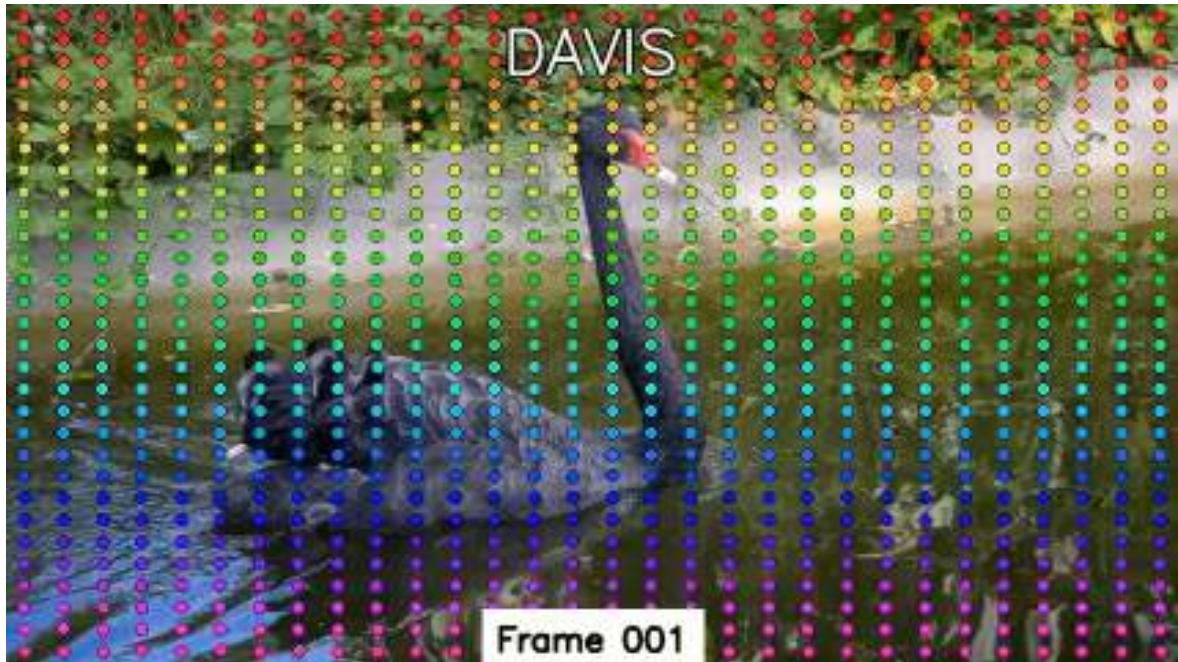
- Given: Query points in one frame
- Track these points throughout the video



SOTA on current benchmarks

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley

LocoTrack



CoTracker3

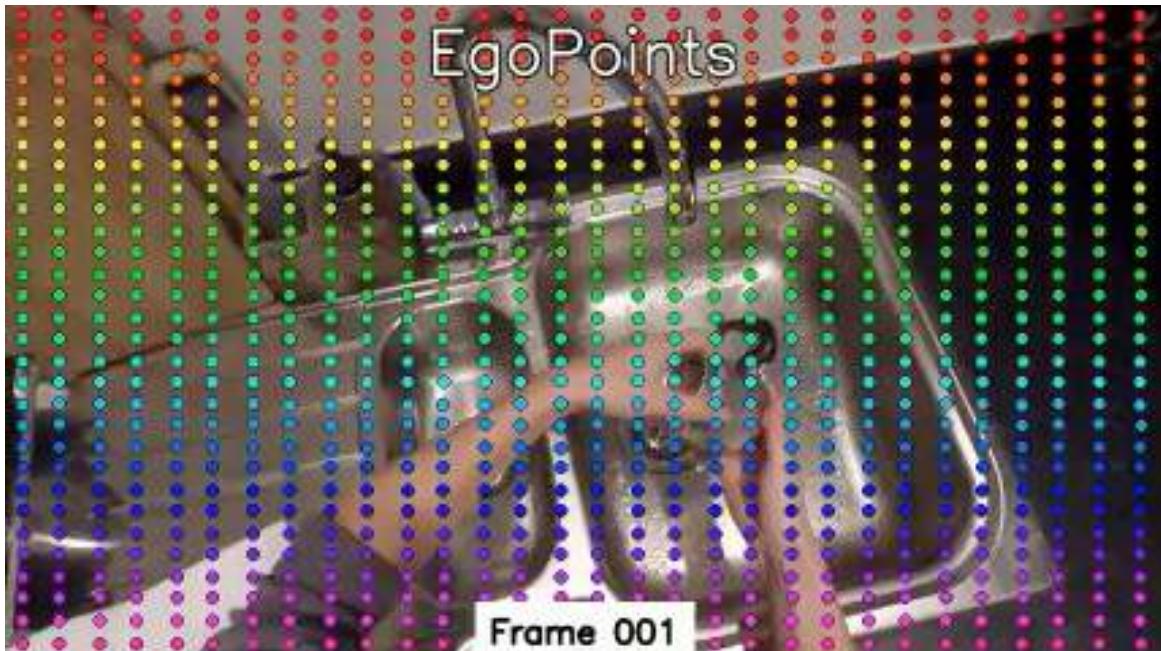


Current Models Struggle with Egocentric Videos

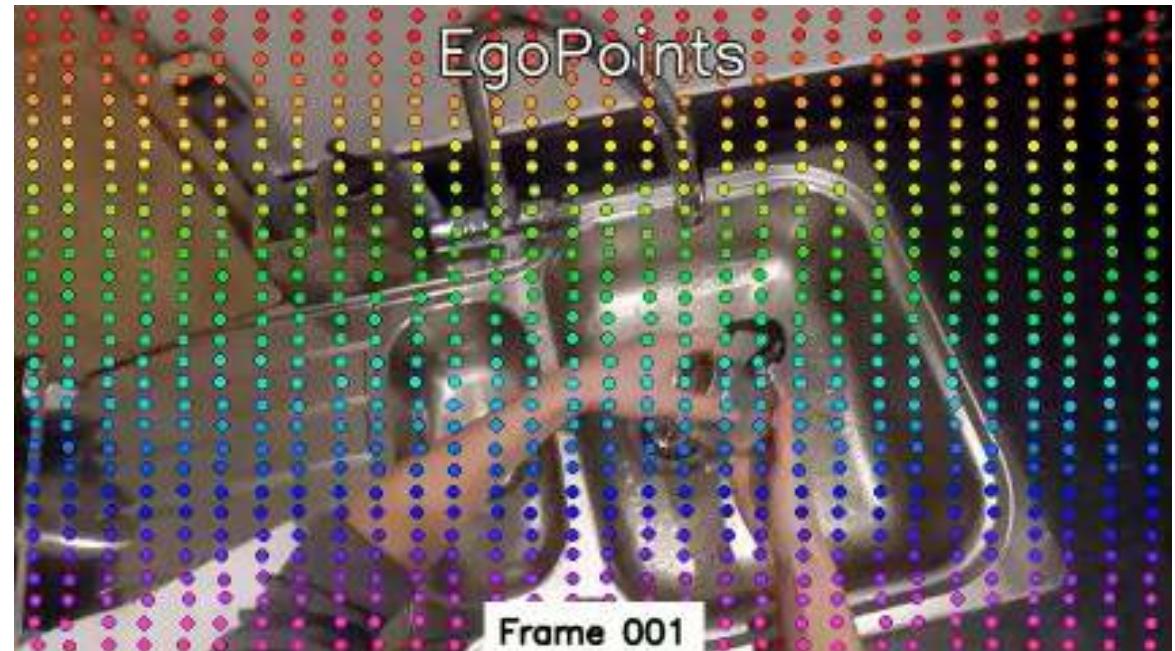
with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley

- Head motion and motion blur
- Frequent re-identification

LocoTrack



CoTracker3



Main Contributions

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley

- Identify challenges that point trackers face in egocentric videos.
- Propose a new benchmark (EgoPoints) and new metrics to showcase these challenges
- Propose K-EPIC, a pipeline to generate semi-real training data

EgoPoints Annotation interface

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley



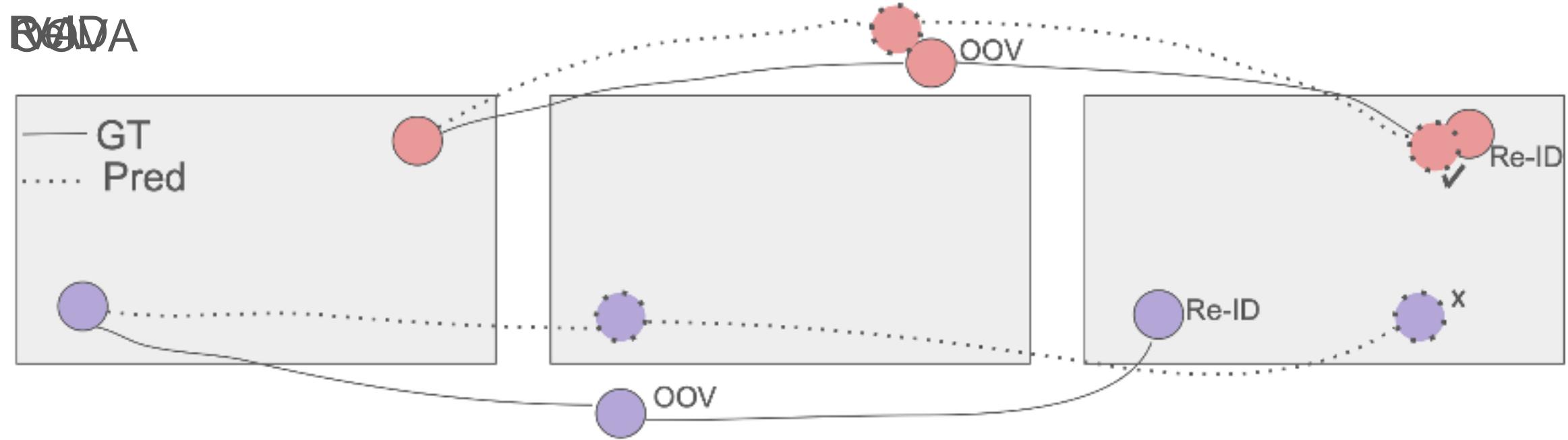
EgoPoints Benchmark

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley



Proposed Metrics

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley



EgoPoints Benchmark

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley

Dataset	Total Tracks	OOV Tracks	ReID Tracks	Avg. Video Length	Avg. Points/Frame
TAP-Vid-DAVIS	650	94	10	66.6	21.7
EgoPoints	4703	875	593	511.0	8.5

Comparisons of our annotated sequences, EgoPoints, and the commonly used TAP-Vid-DAVIS [7] point tracking benchmarks

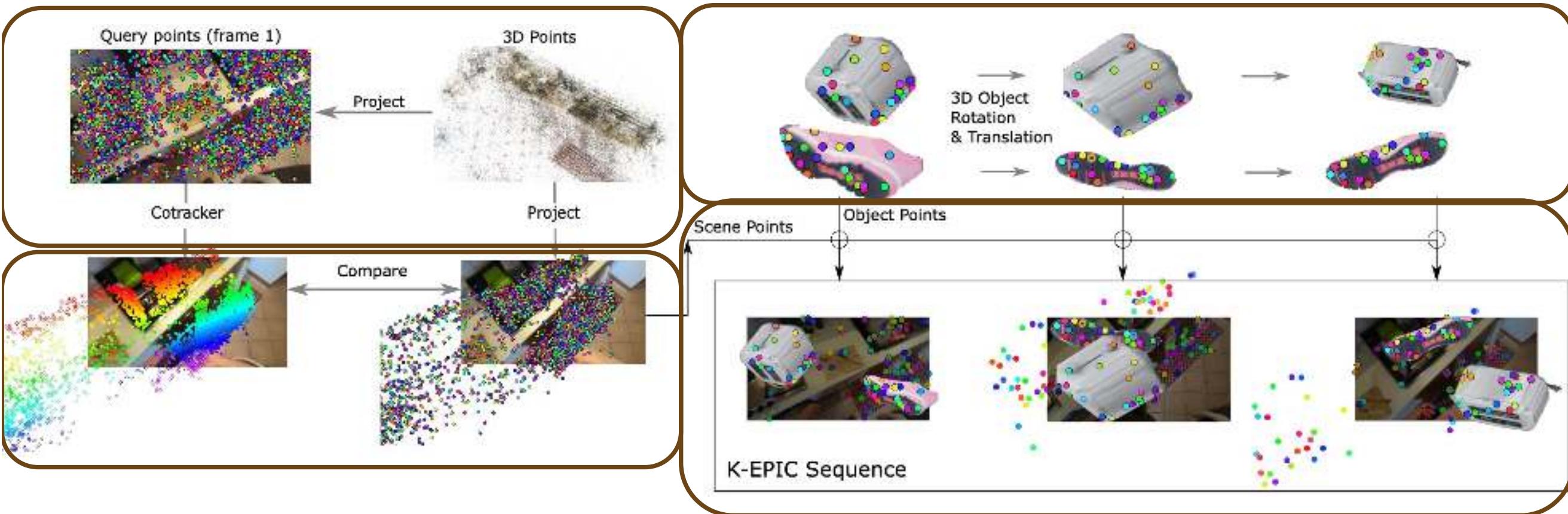
SOTA Models Struggle on EgoPoints

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley

Model	TAP-Vid-DAVIS		EgoPoints			
	$\delta_{\text{avg}} \uparrow$	$\delta_{\text{avg}} \uparrow$	ReID	$\delta_{\text{avg}} \uparrow$	OOVA↑	IVA↑
PIPs++ [42]	64.0	36.9		14.6	50.4	89.2
CoTracker [22]	74.7	38.5		4.8	81.4	73.4
BootsTAPIR Online [8]	65.2	39.6		0.0	0.0	100.0
LocoTrack [4]	75.3	59.4		0.1	0.2	99.9
CoTracker v3 [21]	77.2	50.0		15.0	31.8	99.3

Pipeline of K-EPIC

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley



Examples from K-EPIC

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley



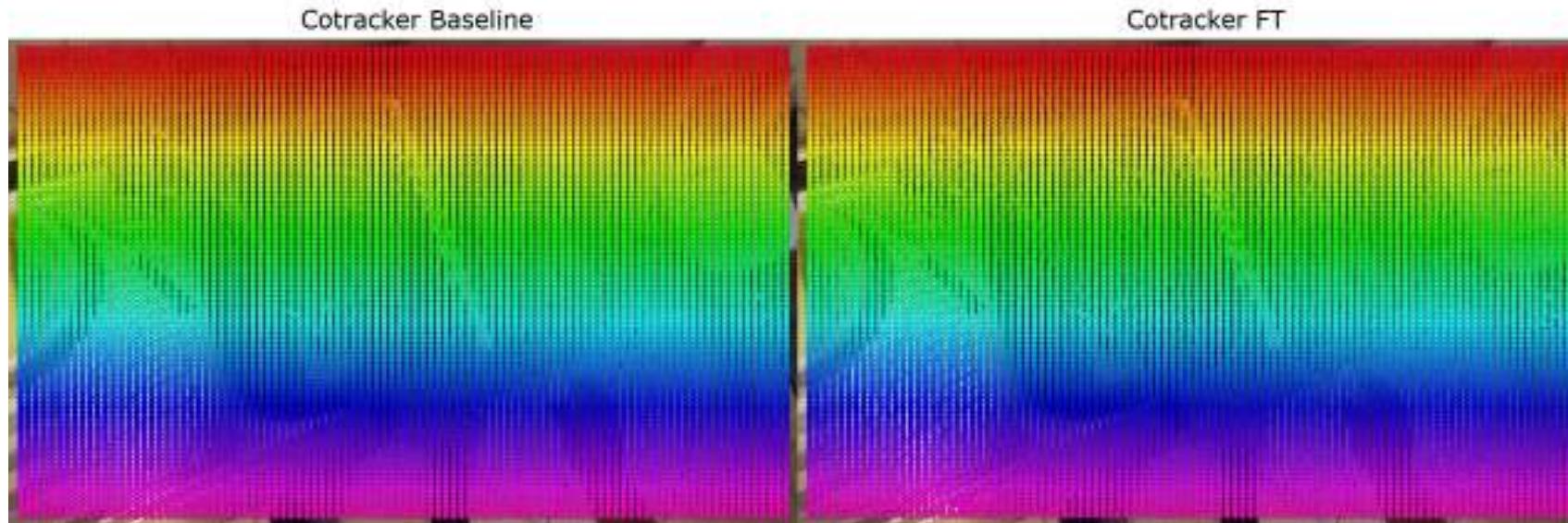
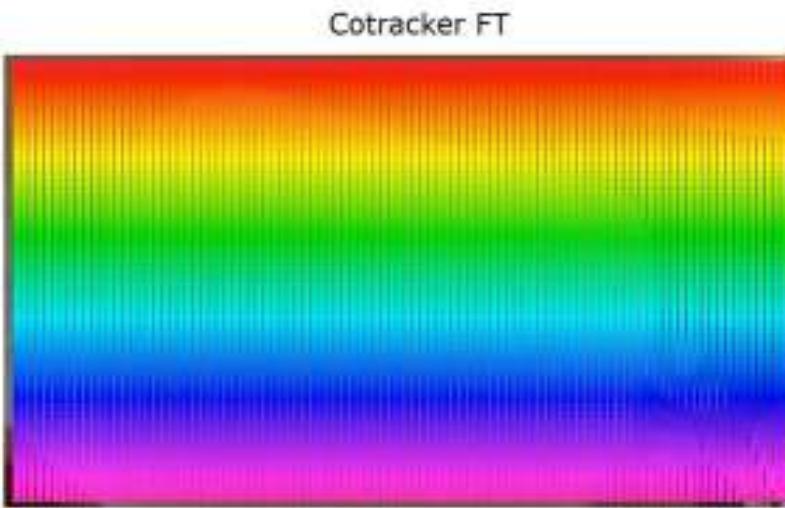
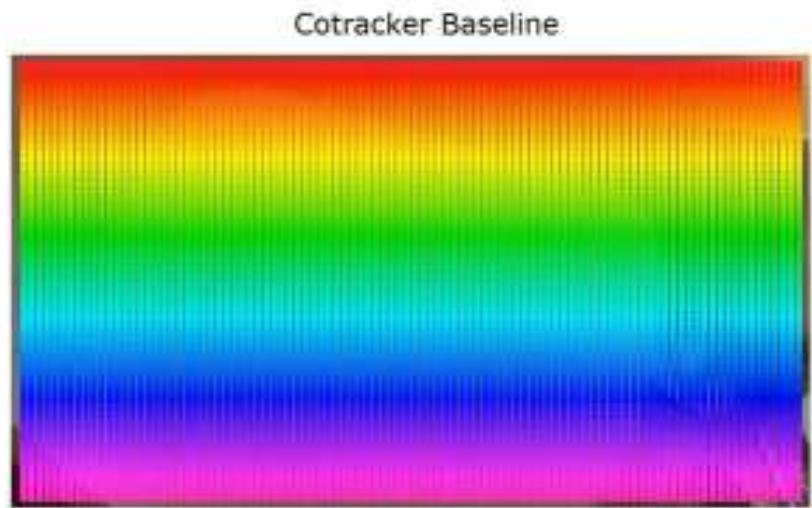
Improvements After Fine-Tuning on K-EPIC

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley

Model	δ Metrics			Accuracy Metrics			Error
	$\delta_{\text{avg}} \uparrow$	$\delta_{\text{avg}}^* \uparrow$	ReID $\delta_{\text{avg}} \uparrow$	IVA \uparrow	OOVA \uparrow	OA \uparrow	MTE \downarrow
PIPs++ [42]	36.9	57.8	14.0	89.2	50.4	–	22.9
PIPs++ w. K-EPIC FT (scene points only)	36.3	57.8	13.0	90.1	53.0	–	22.9
PIPs++ w. K-EPIC FT (scene and object points)	36.6	58.1	16.8	89.9	52.0	–	22.2
CoTracker [22]	38.5	54.8	4.8	73.4	81.4	81.0	52.1
CoTracker w. K-EPIC FT (scene points only)	38.9	56.0	6.3	74.8	85.4	80.7	51.3
CoTracker w. K-EPIC FT (scene and object points)	39.6	57.5	7.2	78.1	82.0	81.8	40.5

Qualitative Examples of CoTracker

with: Ahmad Darkhalil
Rhodri Guerrier
Adam W Harley



AllTracker – newest work

Table 1. Comparison against recent point trackers and optical flow models, across nine datasets. We evaluate δ_{avg} (higher is better), using an input resolution of 384×512 . The benchmarks are BADJA [3], CroHD [46], TAPVid-DAVIS [11], DriveTrack [1], EgoPoints [10], Horse10 [33], TAPVid-Kinetics [11], RGB-Stacking [28], and RoboTAP [52].

Method	Params.	Training	Bad.	Cro.	Dav.	Dri.	Ego.	Hor.	Kin.	Rgb.	Rob.	Avg.
RAFT [47]	5.26	Flow mix	23.7	29.3	48.5	44.8	41.0	27.8	64.3	82.8	72.2	48.3
SEA-RAFT [54]	19.66	Flow mix	23.9	21.9	48.7	49.4	44.0	33.1	64.3	85.7	67.6	48.7
AccFlow [55]	11.76	Flow mix	10.3	22.2	23.5	26.4	4.0	12.1	38.8	63.2	57.9	28.7
PIPs++ [59]	17.57	PointOdyssey	34.1	27.5	62.5	51.3	38.5	21.4	64.2	70.4	73.4	49.3
LocoTrack [6]	11.52	Kubric	41.4	43.1	68.0	66.5	58.4	48.9	70.0	80.3	76.9	61.5
BootsTAPIR [13]	54.70	Kubric+15M	42.7	34.9	67.9	66.9	56.8	48.8	70.6	81.0	78.2	60.9
DELTA [37]	59.17	Kubric	44.6	42.9	75.3	67.8	40.3	41.8	66.5	83.0	74.8	59.7
CoTracker2 [23]	45.43	Kubric	40.0	31.7	70.9	67.8	43.2	33.9	65.8	73.4	73	55.5
CoTracker3-Kub [25]	25.39	Kubric	47.5	48.9	77.4	69.8	58.0	47.5	70.6	83.4	77.2	64.5
CoTracker3 [25]	25.39	Kubric+15k	48.3	44.5	77.1	69.8	60.4	47.1	71.8	84.2	81.6	65.0
AllTracker-Tiny-Kub	6.29	Kubric	45.4	39.6	73.7	65.1	55.9	45.2	70.6	86.1	79.3	62.3
AllTracker-Tiny	6.29	Kubric+mix	47.5	39.8	74.3	63.9	58.3	45.5	71.5	88.1	80.7	63.3
AllTracker-Kub	16.48	Kubric	46.4	42.3	75.2	66.1	60.3	49.0	71.3	90.1	82.2	64.8
AllTracker	16.48	Kubric+mix	51.5	44.0	76.3	65.8	62.5	49.0	72.3	90.0	83.4	66.1

In today's talk...



Motivation and Datasets in
Egocentric Video Understanding



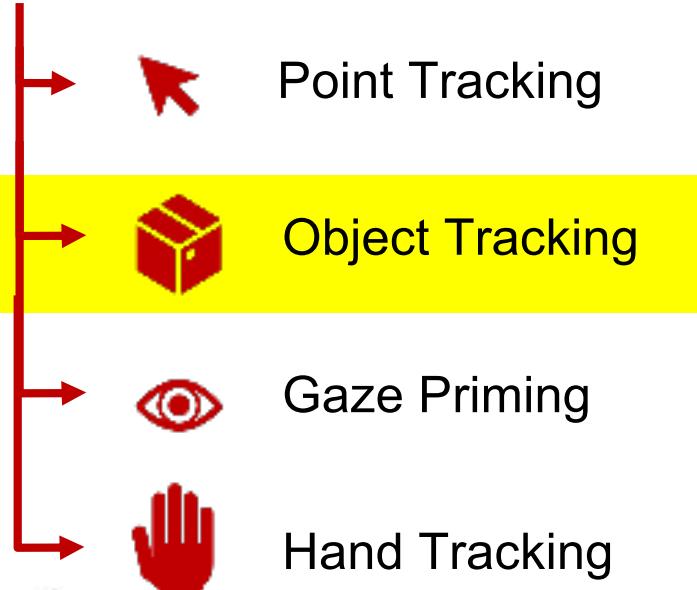
Teaser: The Wizard of Oz
& Genie 3



Video Understanding
Out of the Frame



Outlook into the Future of
Egocentric Vision



Conclusion

Out of Sight, not Out of Mind

with: Chiara Plizzari
Toby Perrett

Shubham Goel
Angjoo Kanazawa

Spatial Cognition from Egocentric Video: Out of Sight, Not Out of Mind

Chiara Plizzari

Shubham Goel

Toby Perrett

Jacob Chalk

Angjoo Kanazawa

Dima Damen

<http://dimadamen.github.io/OSNOM>



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Plizzari et al (2025). Spatial Cognition from Egocentric Video: Out of Sight, Not Out of Mind. 3DV

Dima Damen
BinEgo-360 Workshop @ICCV2025

Out of Sight, not Out of Mind

with: Chiara Plizzari
Toby Perrett

Shubham Goel
Angjoo Kanazawa



All active/moved objects in this video are represented by neon balls.
Their initial positions are shown at the start of the video

3D Scene
Mesh →

← Egocentric Image

↑ 3D Ego
view w/
in-view
objects

Ego
Camera
in 3D

All active/moved objects in this video are represented by neon balls.
Their initial positions are shown at the start of the video

Out of Sight, not Out of Mind

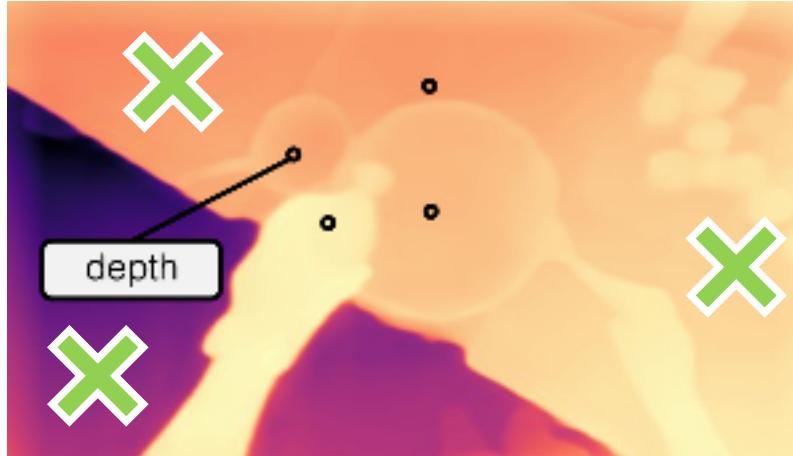
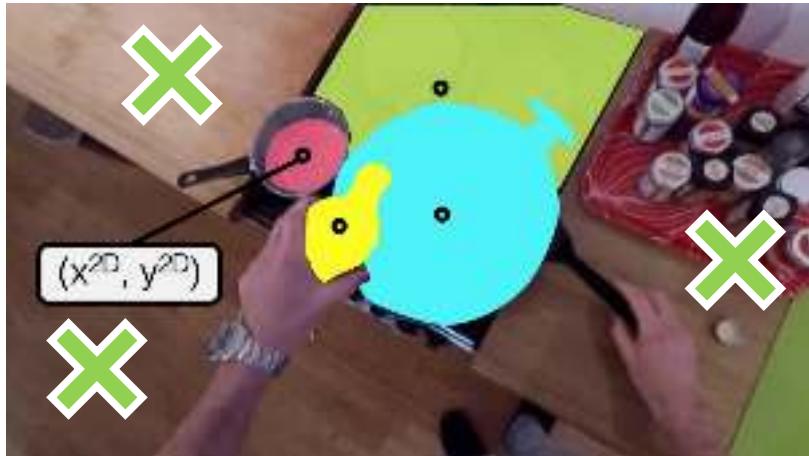
with: Chiara Plizzari
Toby Perrett

Shubham Goel
Angjoo Kanazawa

Lift

Match

Keep



0.0 ... 1.0

0.3m ... 1.8m

Out of Sight, not Out of Mind

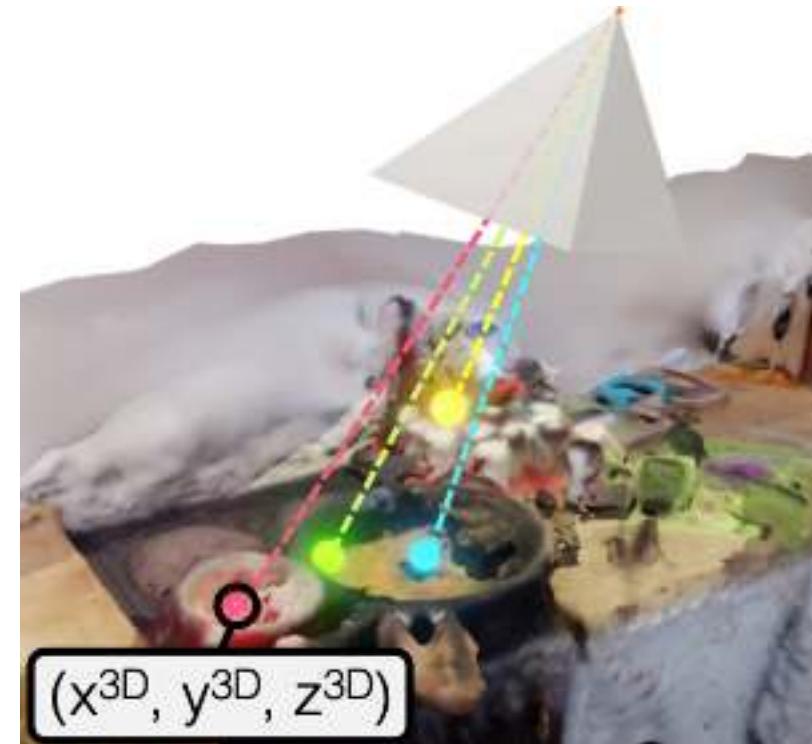
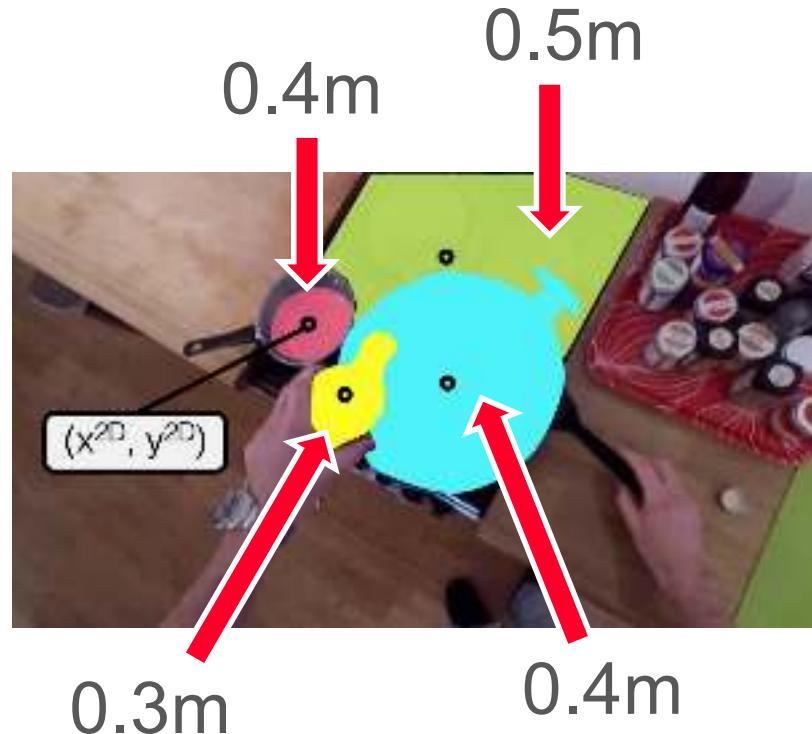
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Lift

Match

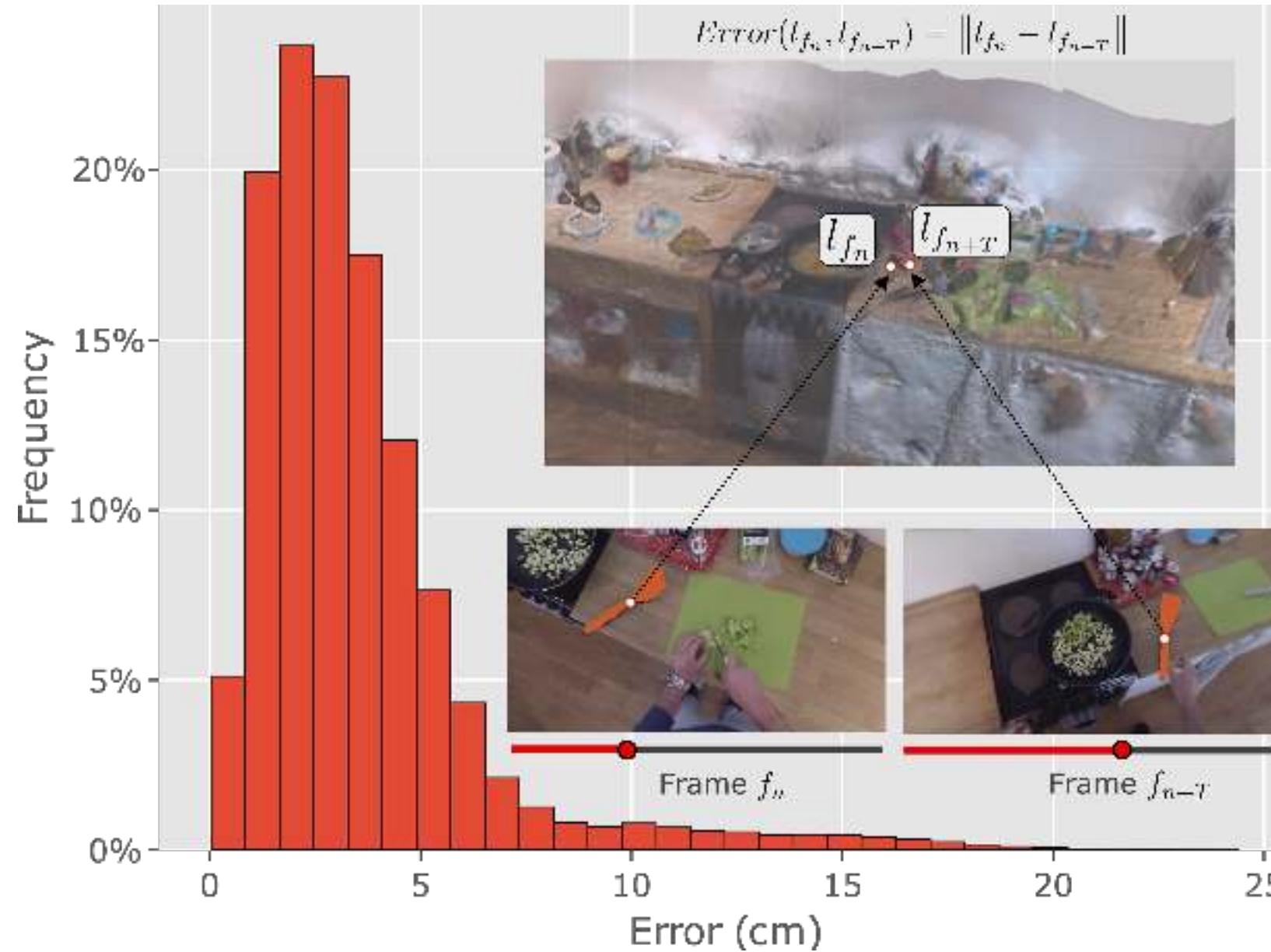
Keep



Out of Sight, not Out of Mind

with: Chiara Plizzari
Toby Perrett

Shubham Goel
Angjoo Kanazawa



Out of Sight, not Out of Mind

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Shubham Goel
Angjoo Kanazawa



Instead of tracking in 2D, we track in 3D, using combination of appearance and location distances

Out of Sight, not Out of Mind

with: Chiara Plizzari
Toby Perrett

Shubham Goel
Angjoo Kanazawa

After we Lift, Match and Keep (LMK), we can reason about an object's visibility and position

- In-View vs Out-of-View
- In-Sight vs Out-of-Sight (Occluded)
- Within-Reach vs Out-of-Reach (defining the camera wearer's near space)



Out of Sight, not Out of Mind

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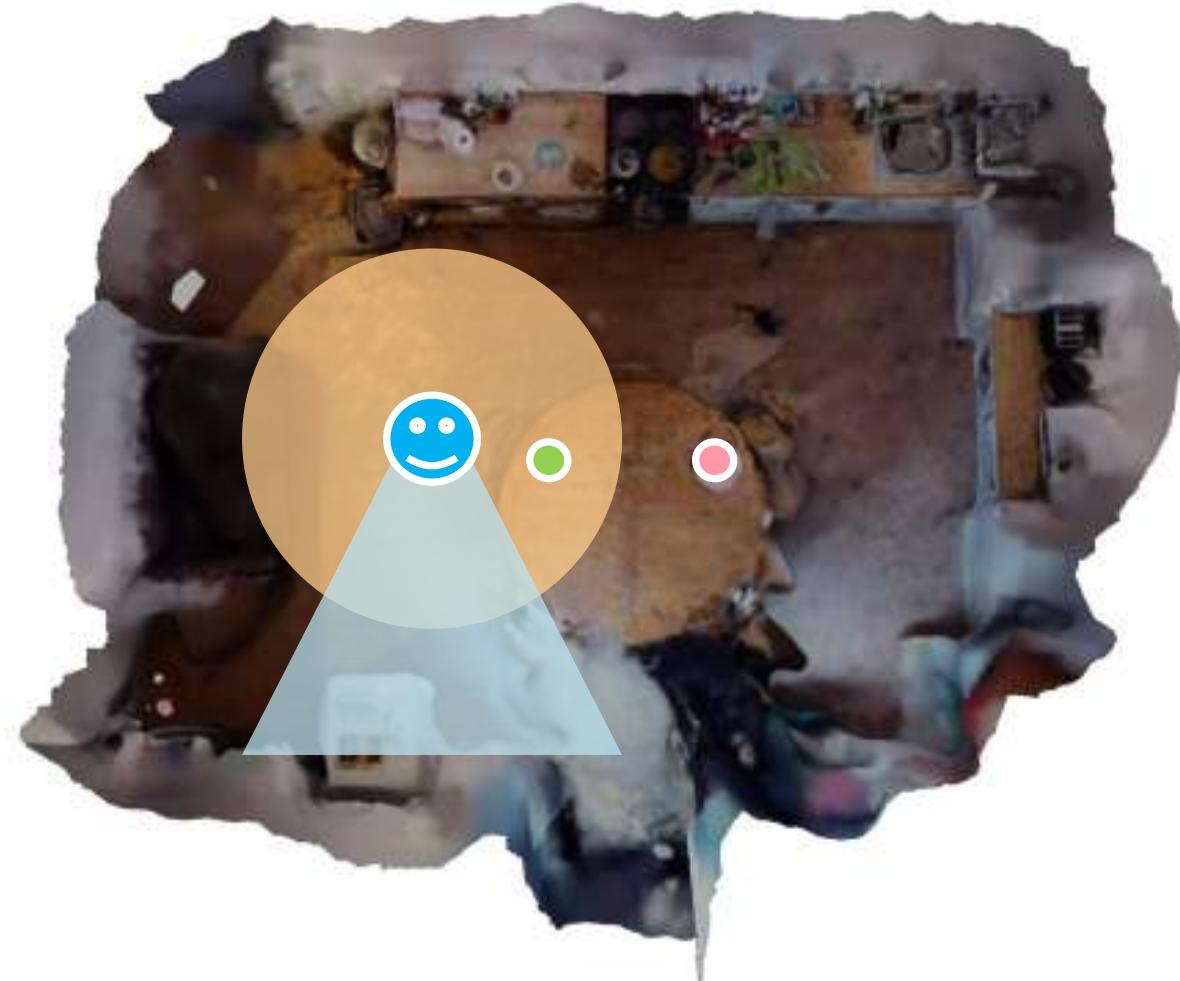
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Spatial Cognition from Egocentric Video: Out of Sight, Not Out of Mind

Chiara Plizzari

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Ground-Truth??

<http://dimadamen.github.io/OSNOM>



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Plizzari et al (2025). Spatial Cognition from Egocentric Video: Out of Sight, Not Out of Mind. 3DV

ma Damen
BinEgo-360 Workshop @ICCV2025



HD-EPIC: A Highly-Detailed Egocentric Video Dataset



Toby Perrett



Ahmad Darkhalil



Saptarshi Sinha



Omar Emara



Sam Pollard



Kranti Parida



Kaiting Liu



Prajwal Gatti



Siddhant Bansal



Kevin Flanagan



Jacob Chalk



Zhifan Zhu



Rhodri Guerrier



Fahd Abdelazim



Bin Zhu



Davide Moltisanti



Michael Wray



Hazel Doughty



Dima Damen

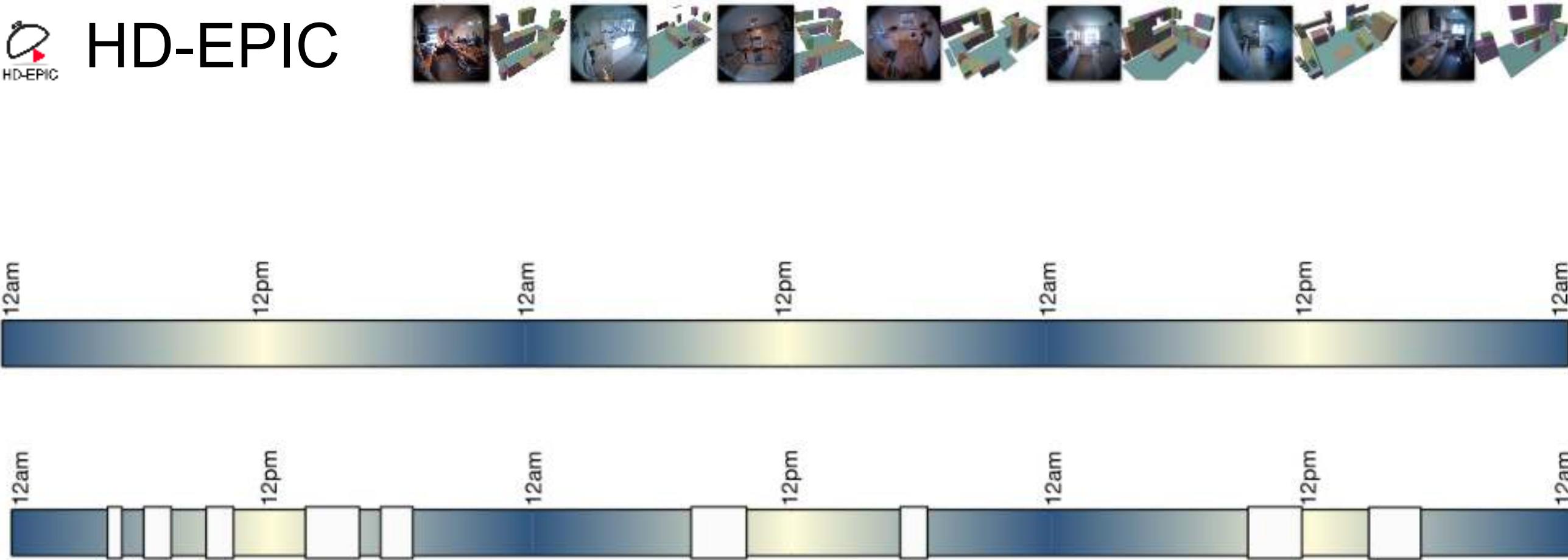


HD-EPIC





HD-EPIC





HD-EPIC



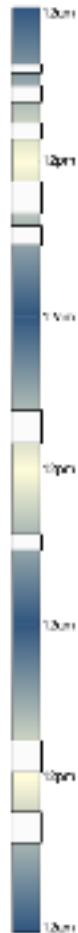
Recorded over 3 days



a Damen
CCV2025

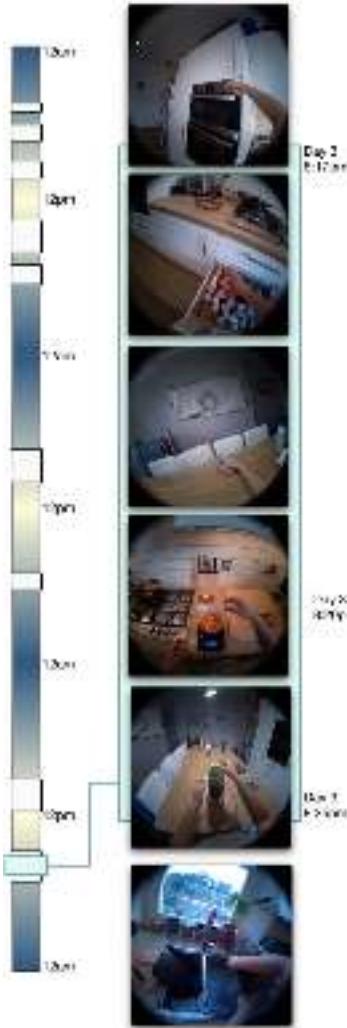


HD-EPIC





HD-EPIC





HD-EPIC



Recipe: Southwestern Salad

1: Preheat the oven to 400F

Day 3
1:17pm

2: Wash and peel the sweet potatoes and chop into bite-sized pieces. Put the sweet potatoes in a bowl and add the olive oil, cumin, and chili powder. Pour onto tray and roast for 10 mins.

3: Pulse all the dressing ingredients in a food processor until mostly smooth.

**Recipe
and nutrition**



Cacio e Pepe (modified)

Ingredients:

200 g penne
 400g of pasta of your choice
 (we recommend bucatini)
 2 tablespoon of black peppercorn
 30 g parmigiano
 200g of freshly grated pecorino cheese
 +25g of slightly salted butter



Steps:



1. Toast the peppercorns until fragrant in a dry frying pan over medium heat, about 2 minutes. Keep them moving to prevent them from burning.

~~Once toasted, roughly crush.~~



step 2



2. Cook your choice of pasta in a large pot of generously salted boiling water ~~for around 1-6 minutes~~, or until al dente.



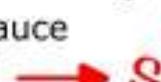
step 1



3. While the pasta cooks, add freshly grated cheese and crushed black

~~on very low heat~~

peppercorns to a large serving bowl. Gradually add a cup of the boiling cooking water constantly mixing to obtain a silky, smooth sauce that's able to completely coat the pasta.



step 3





HD-EPIC



- The **prep** of a corresponding **step** is defined as all essential actions the participant takes to get ready to execute a given step.
- For example, the **step** ‘chop tomato’:
 - **Prep:** retrieve tomato from storage, wash tomato, retrieve a knife and chopping board.
- the **step** ‘add chopped onions and stir’:
 - **Prep:** retrieve onion from storage, retrieve a knife and chopping board, **and chop the onions.**



HD-EPIC



- Prep



- Step



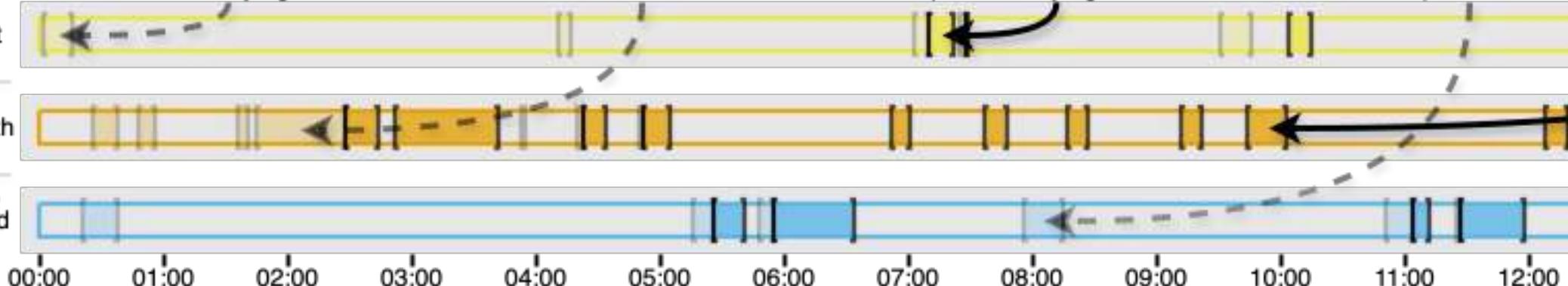
Cook the pasta in a pan of boiling salted water according to the packet instructions.

pick up kettle from its base on the counter with my right hand

pick up packet of bacon

pour water from kettle into the pan with my right hand

pick up block of cheese that from the top shelf of the ...

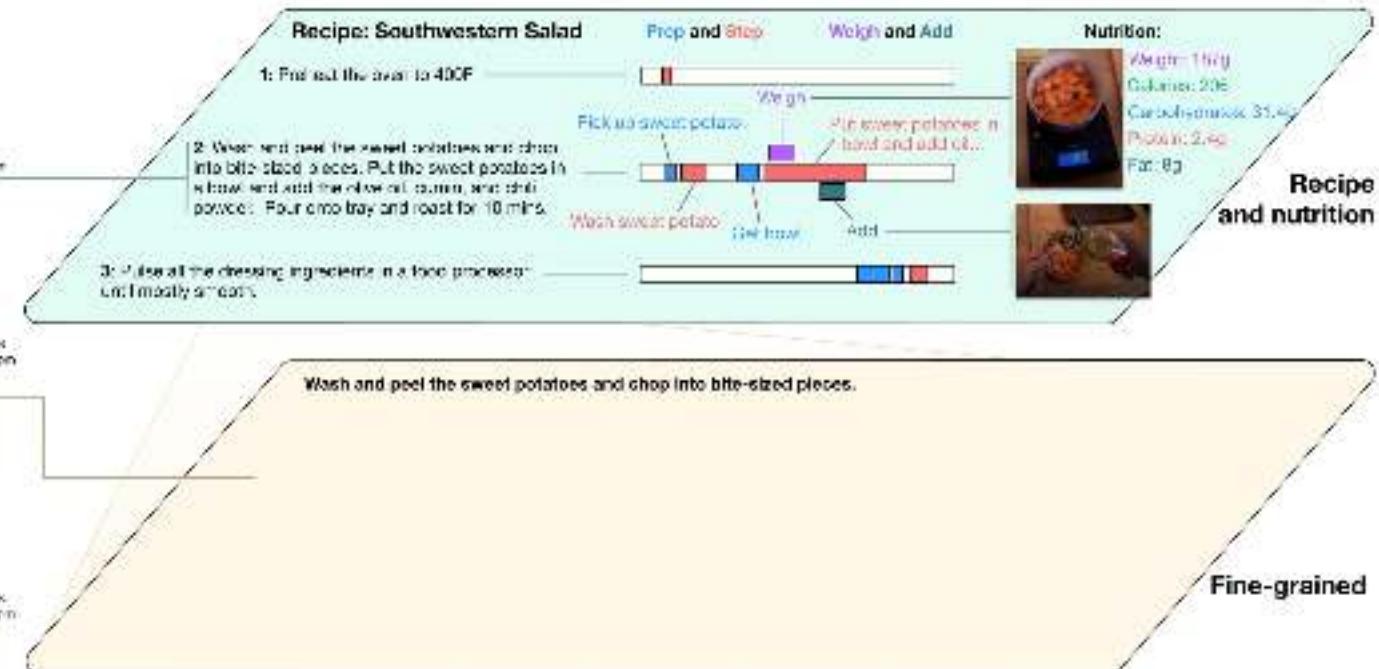


Slice the bacon and place in a non-stick frying pan on a medium heat with half a tablespoon of olive oil and ...

Meanwhile, beat the eggs in a bowl, then finely grate in the Parmesan and mix well.

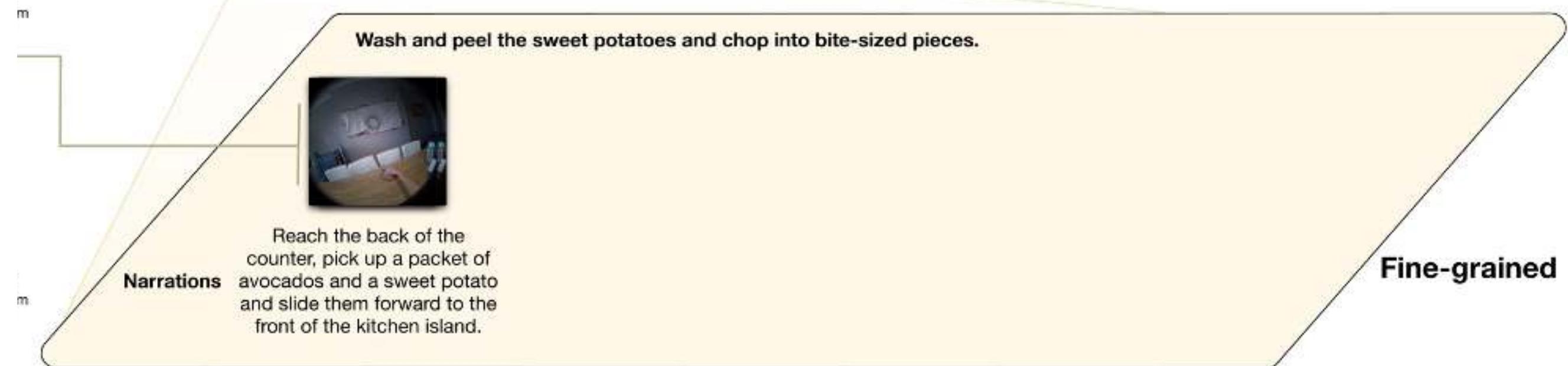


HD-EPIC





HD-EPIC



Highly-Detailed Narrations

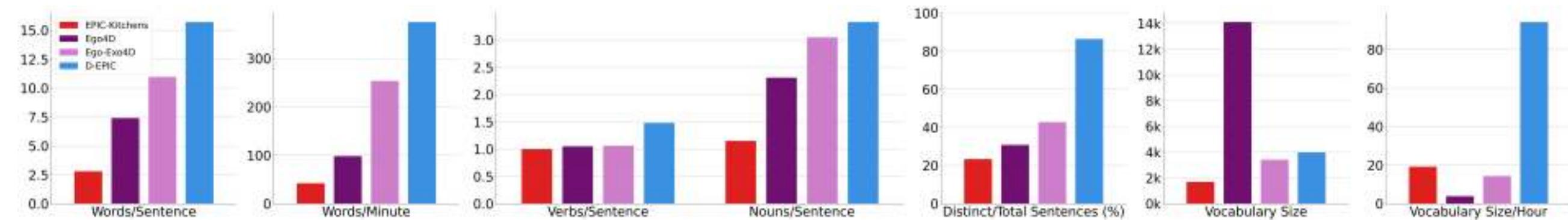




HD-EPIC

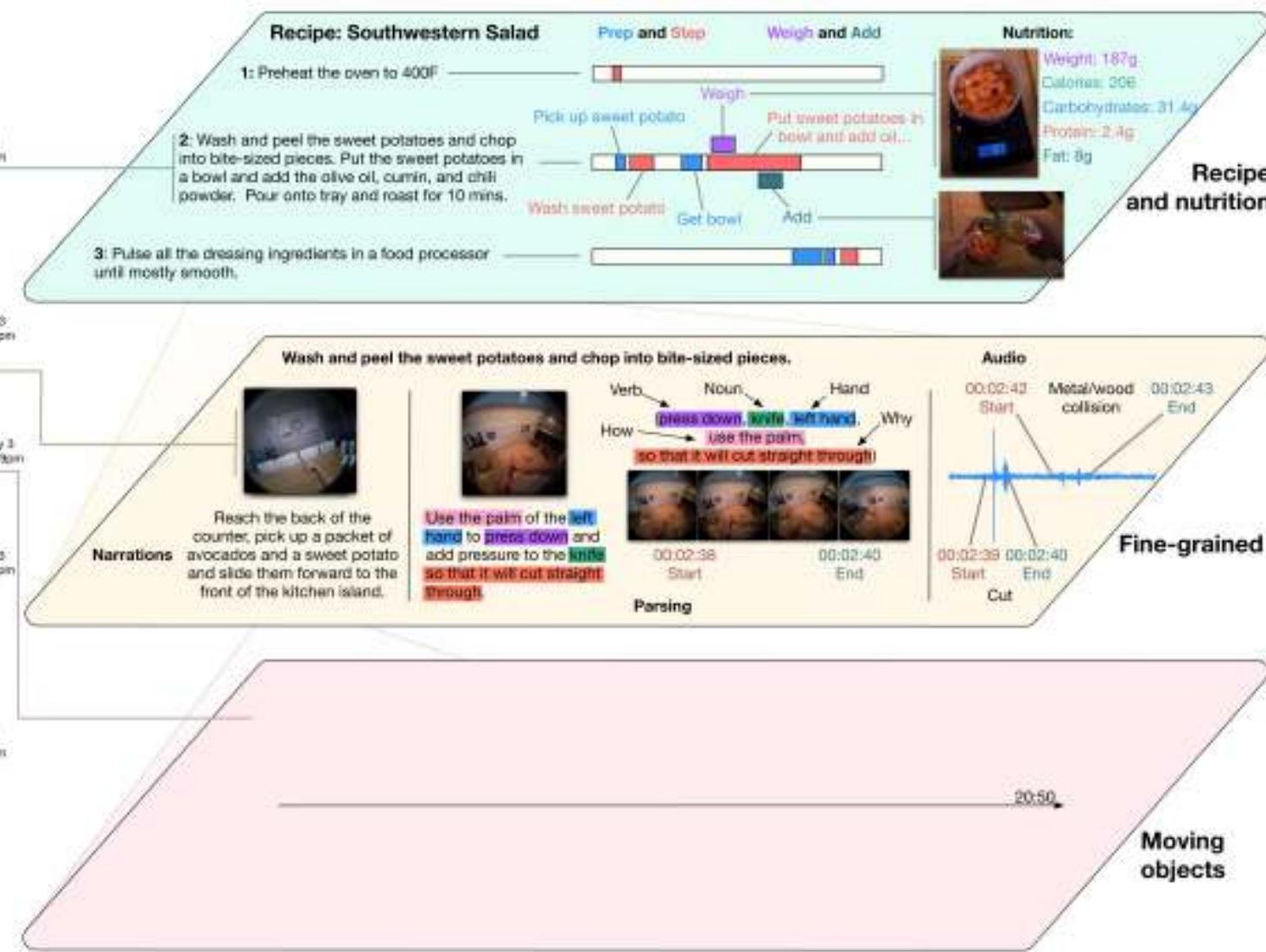
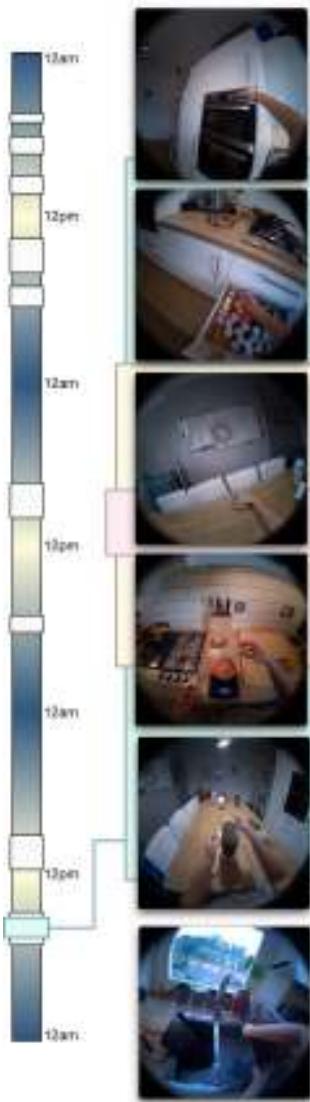


- 59,454 fine-grained actions, with a mean duration of 2.0s (± 3.4 s).



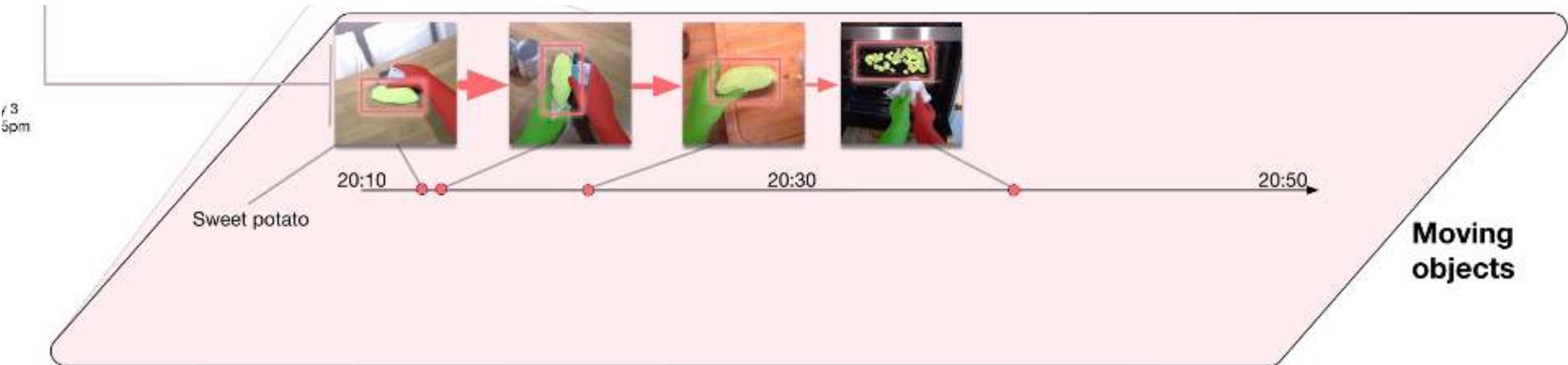


HD-EPIC





HD-EPIC

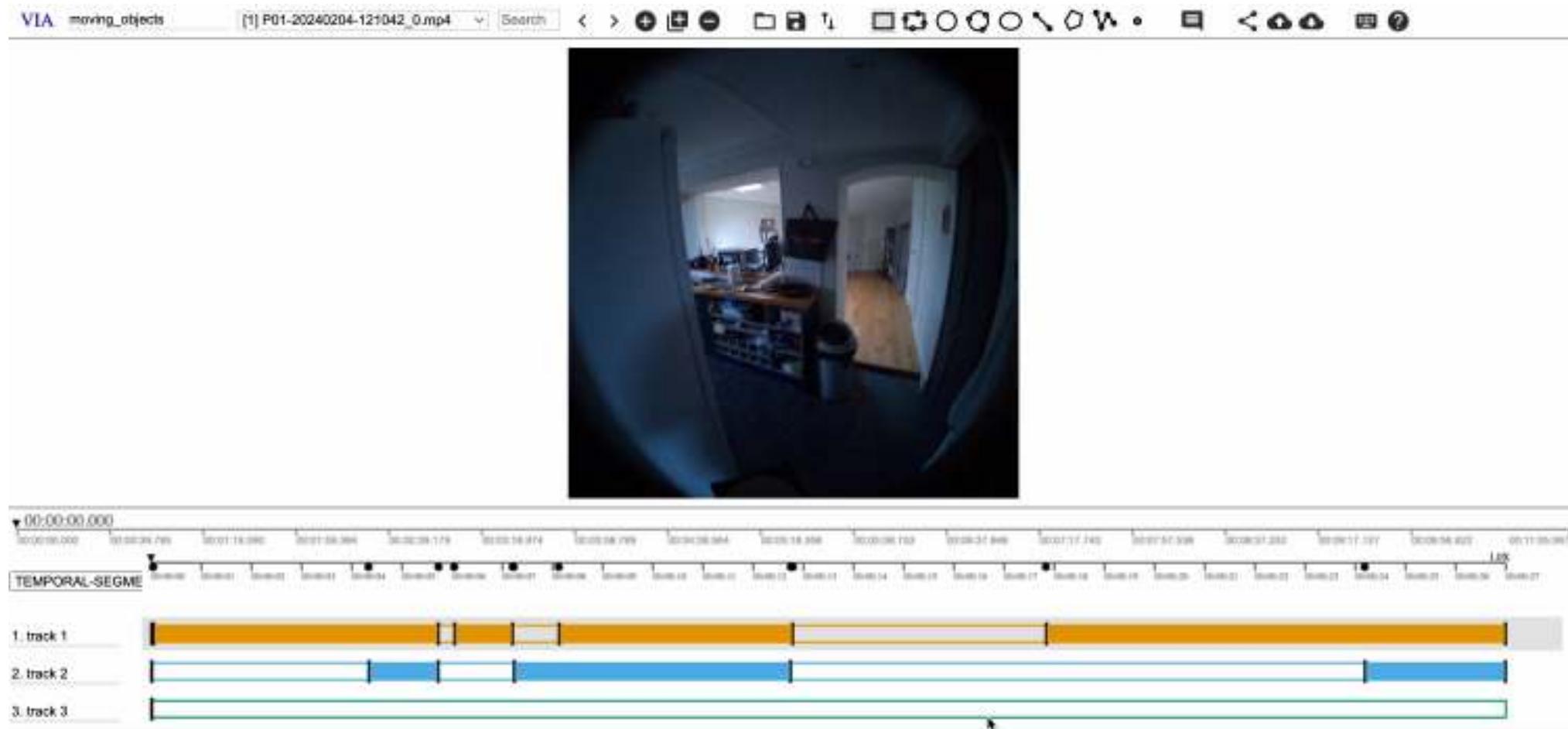




HD-EPIC



- How to minimize the annotations for tracking objects...

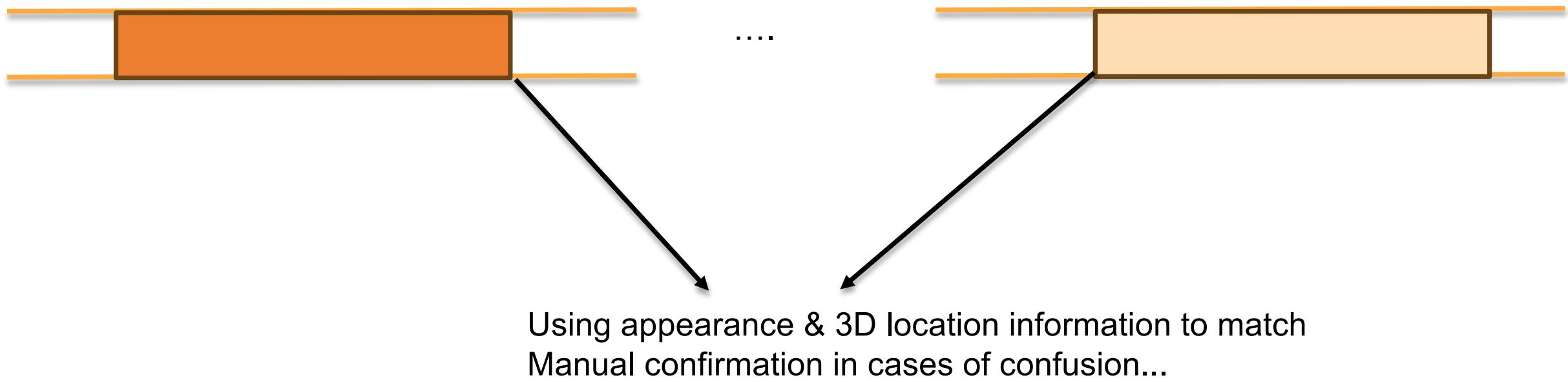




HD-EPIC



- How to minimize the annotations for tracking objects...





HD-EPIC



Current Track



← Previous Next → Undo

▼ rubbish bin box of chicken wooden chopping board

Enter Track Name (optional)

Create New Track

Inconsistent Query

Previous Tracks

Sort by Distance

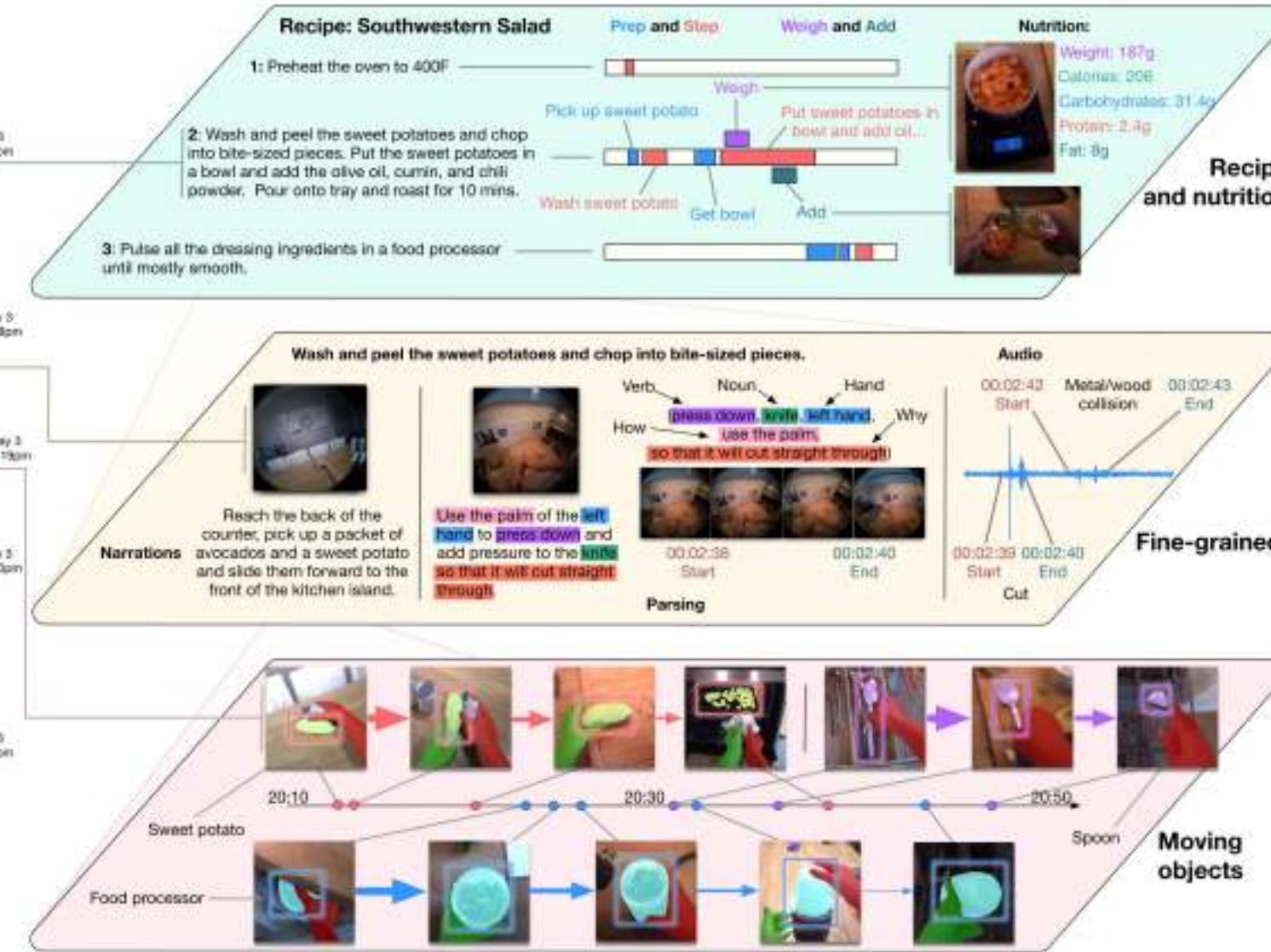
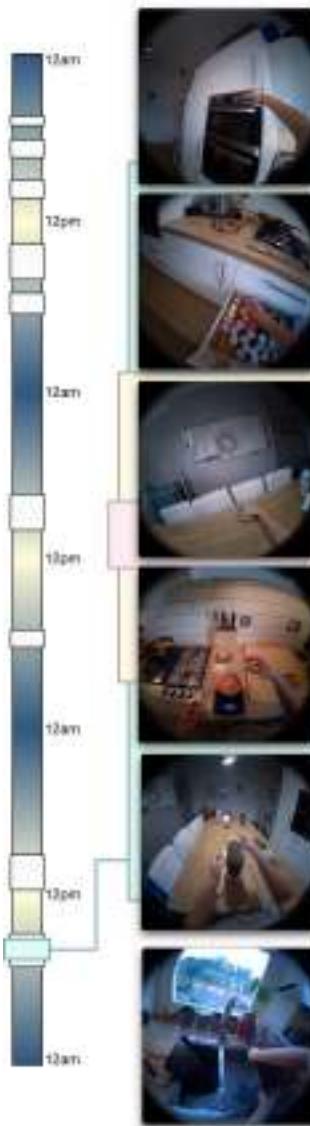
Save Tracks

Object	Distance	Add
box of chicken (0.0m)		
plastic chopping board (0.3m)		
metal cooling rack (0.6m)		
plastic measuring cup (1.0m)		
hand washing liquid (1.3m)		
kitchen towel (1.5m)		

01:00 01:05 01:10 01:15 01:20 01:25 01:30 01:35



HD-EPIC

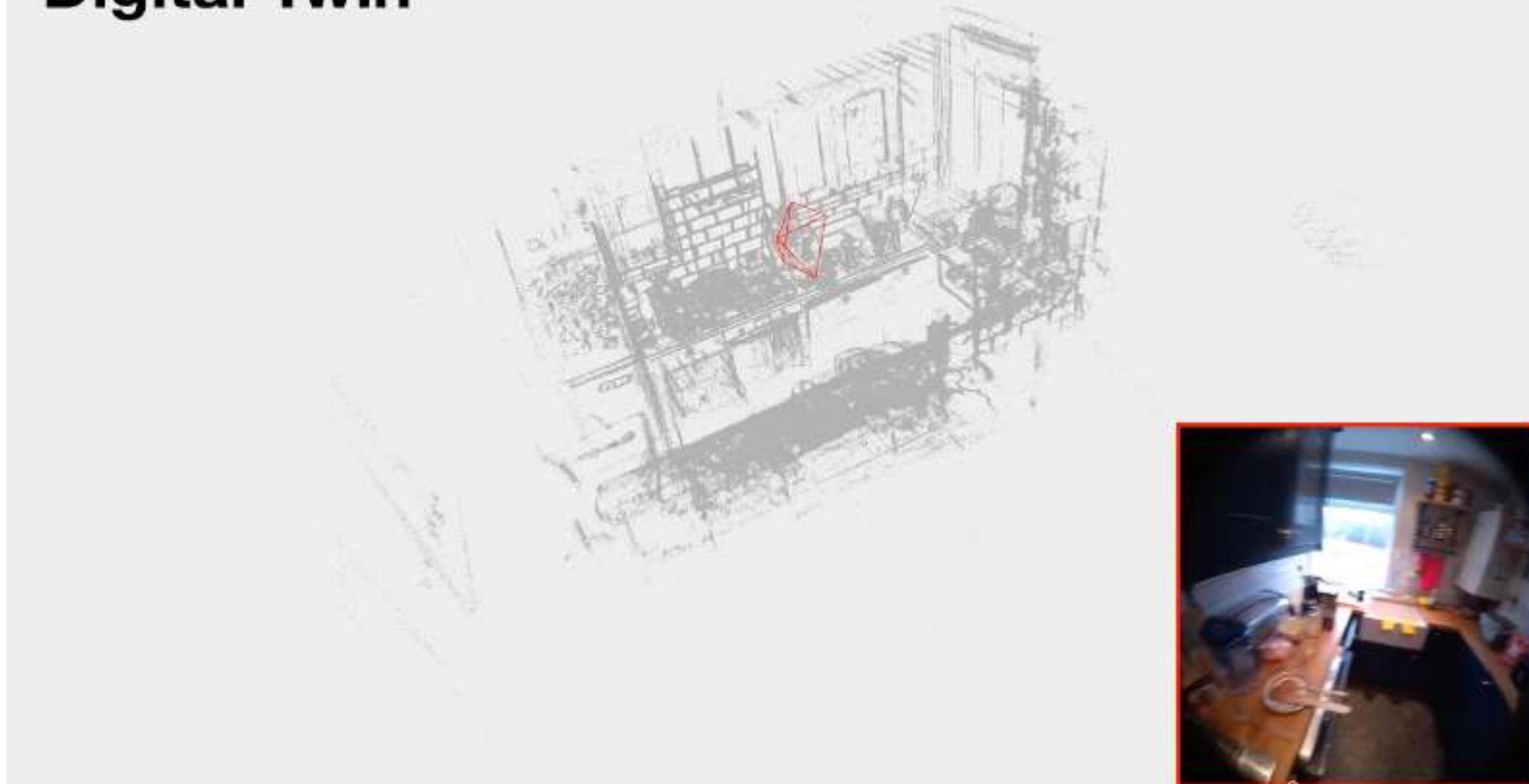




HD-EPIC

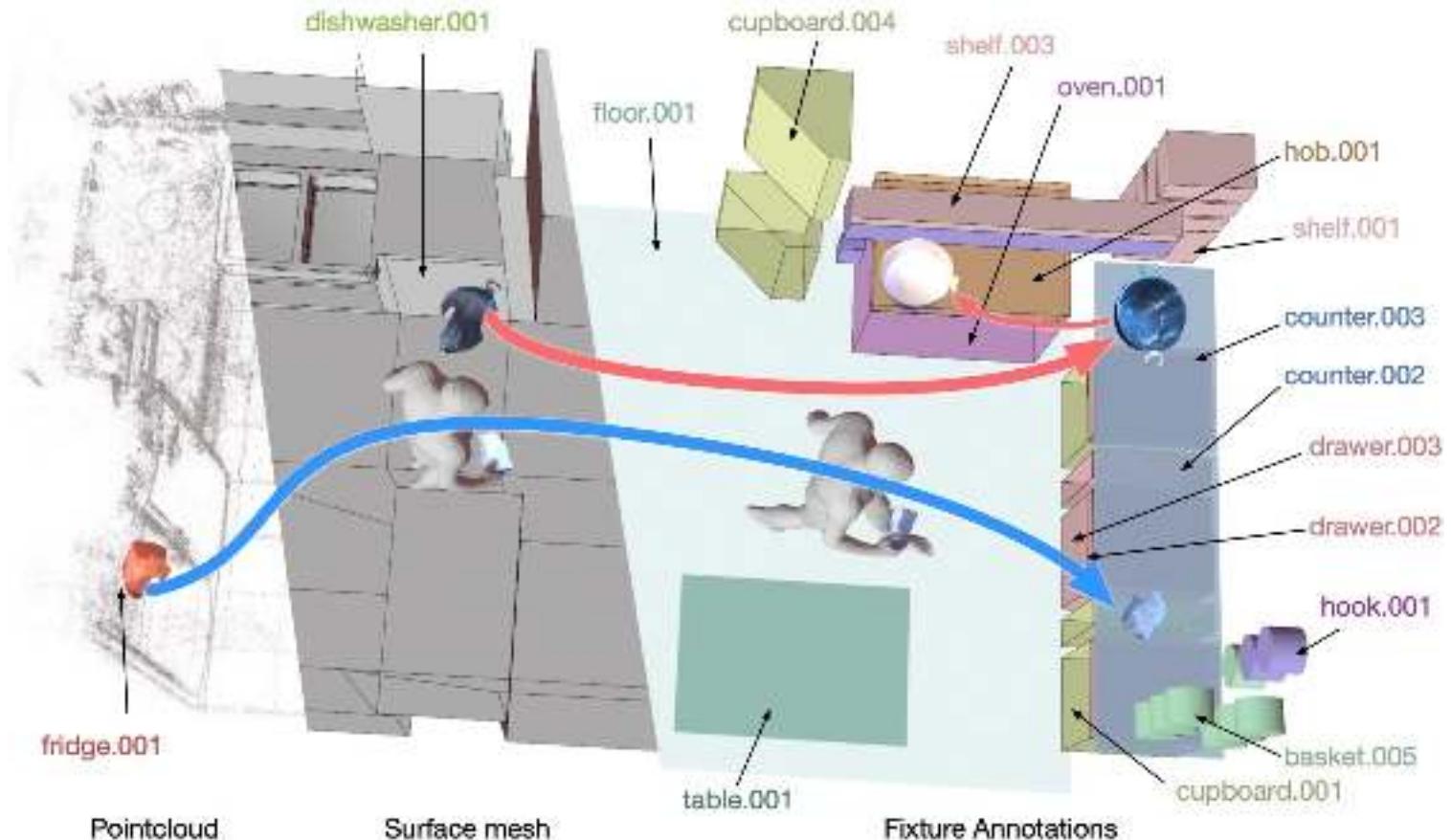


Digital Twin



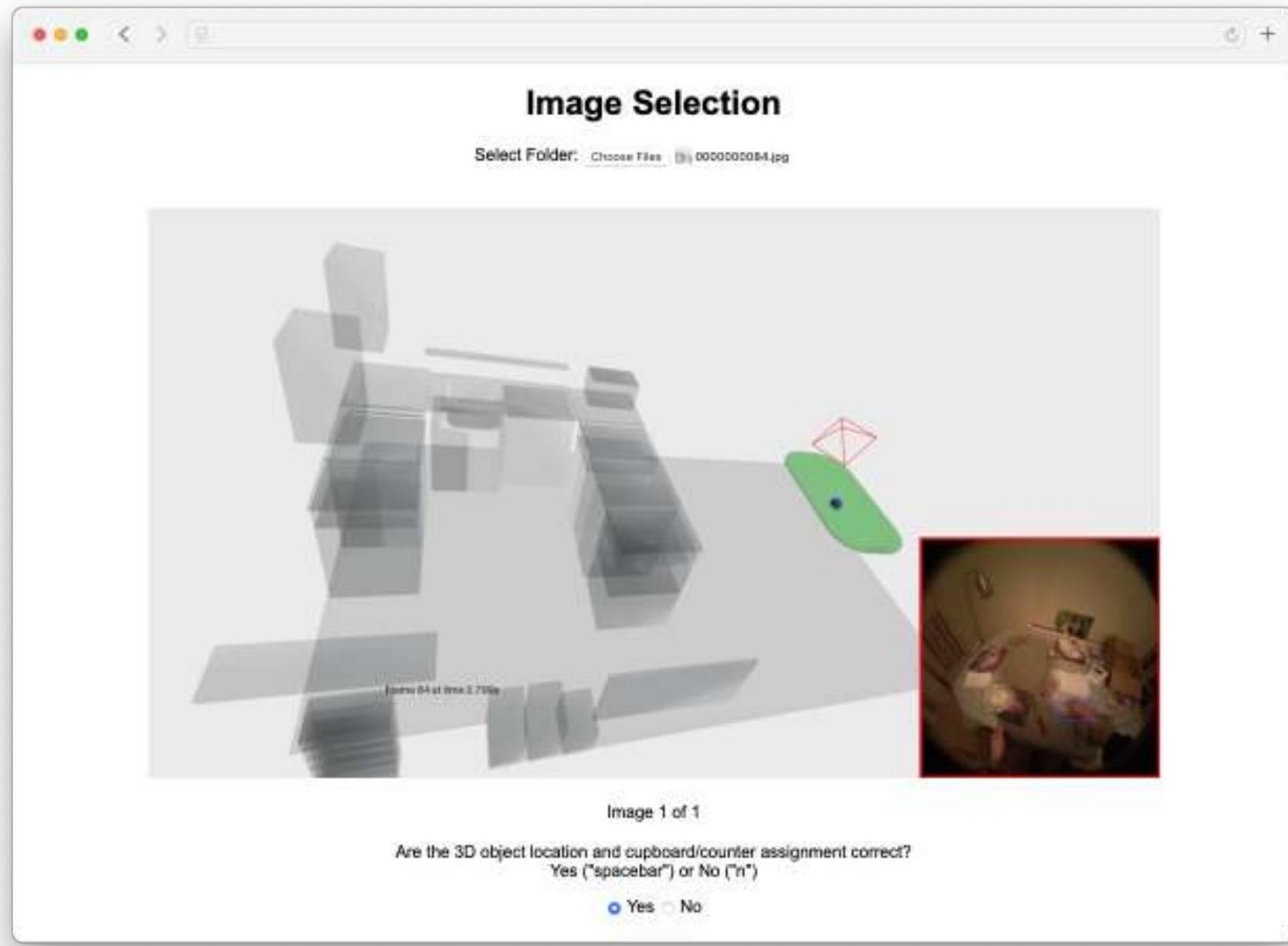


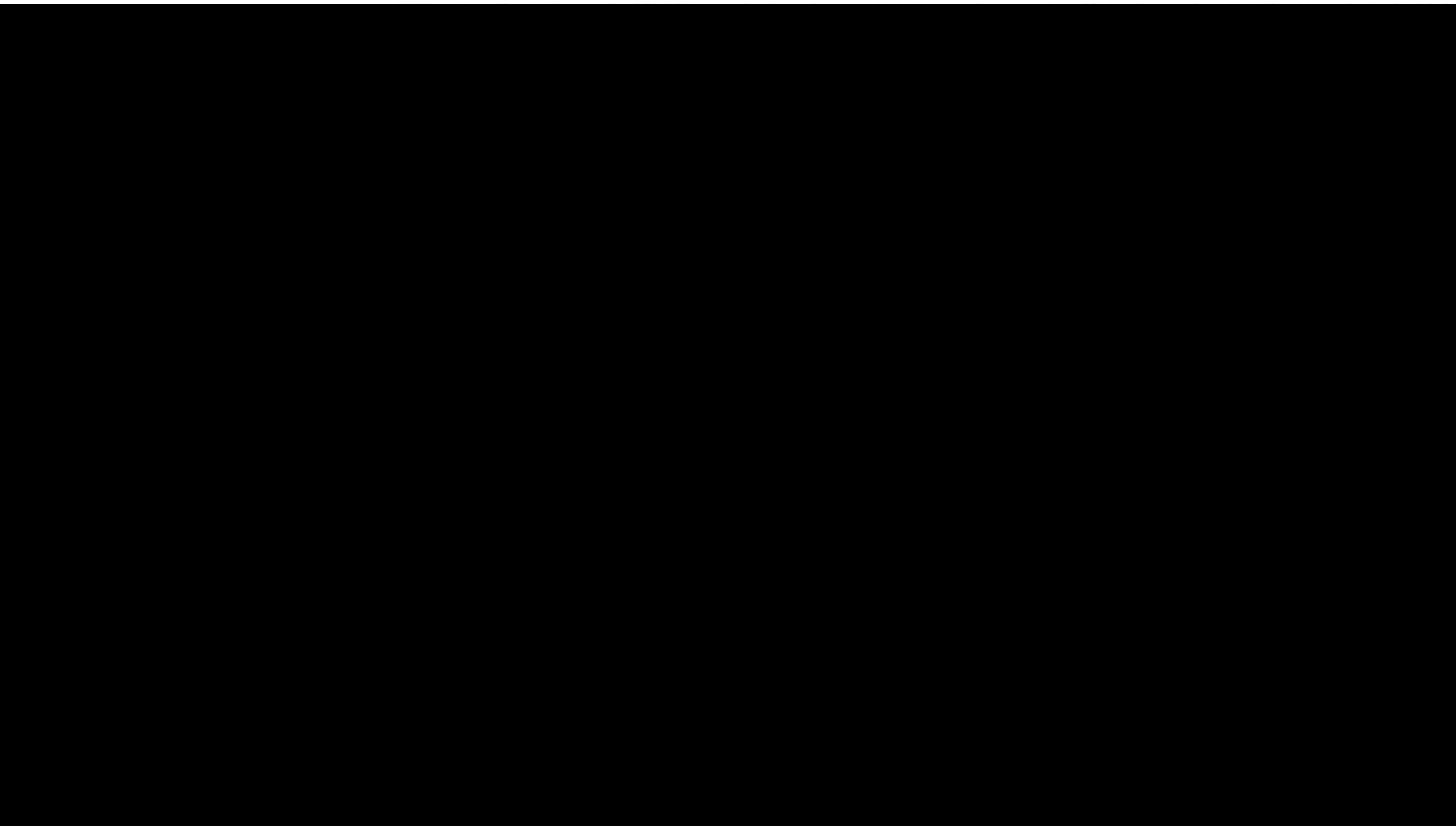
HD-EPIC





HD-EPIC





In today's talk...



Motivation and Datasets in
Egocentric Video Understanding



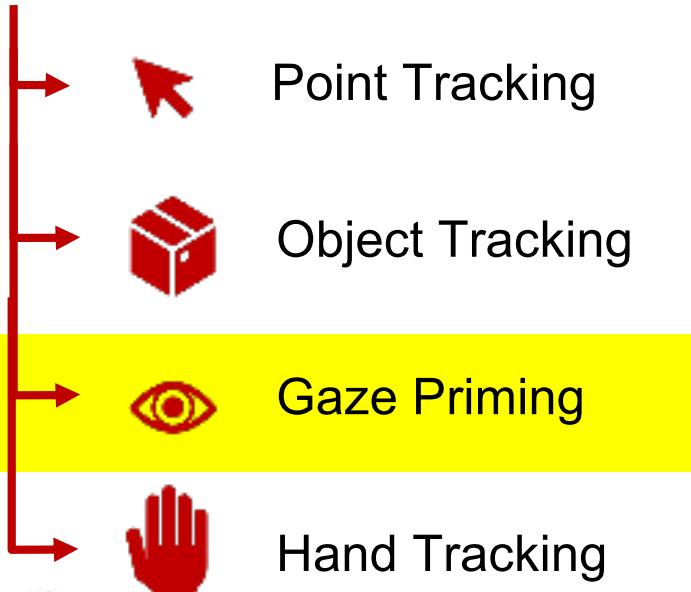
Teaser: The Wizard of Oz
& Genie 3



Video Understanding
Out of the Frame



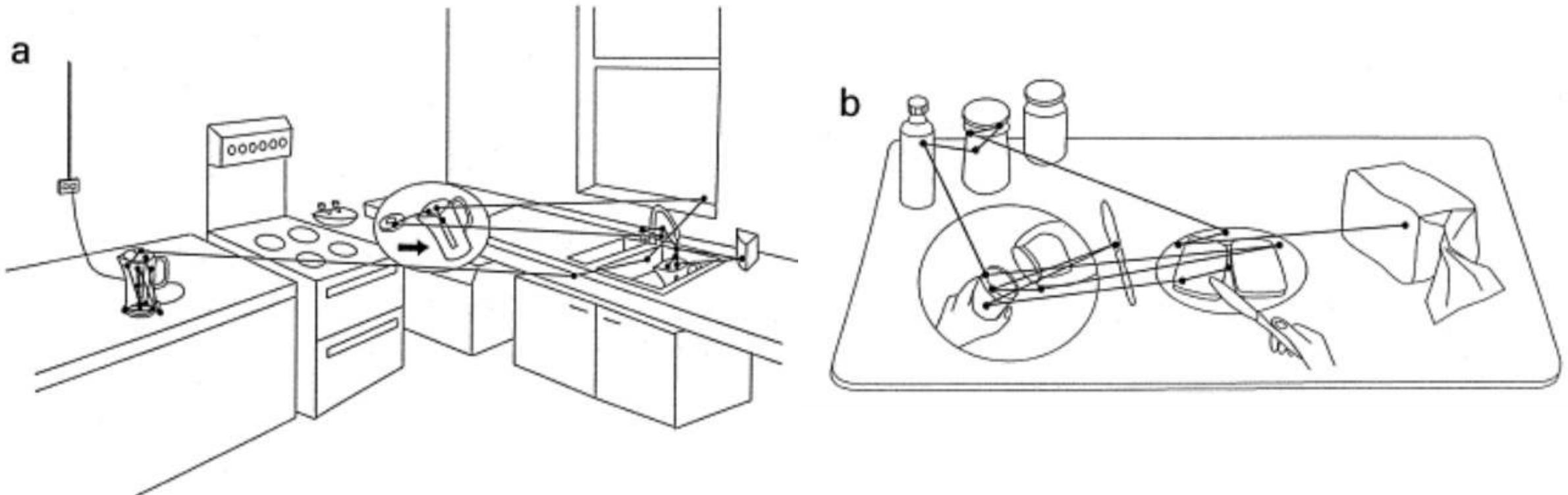
Outlook into the Future of
Egocentric Vision



Conclusion



Gaze and Fixations

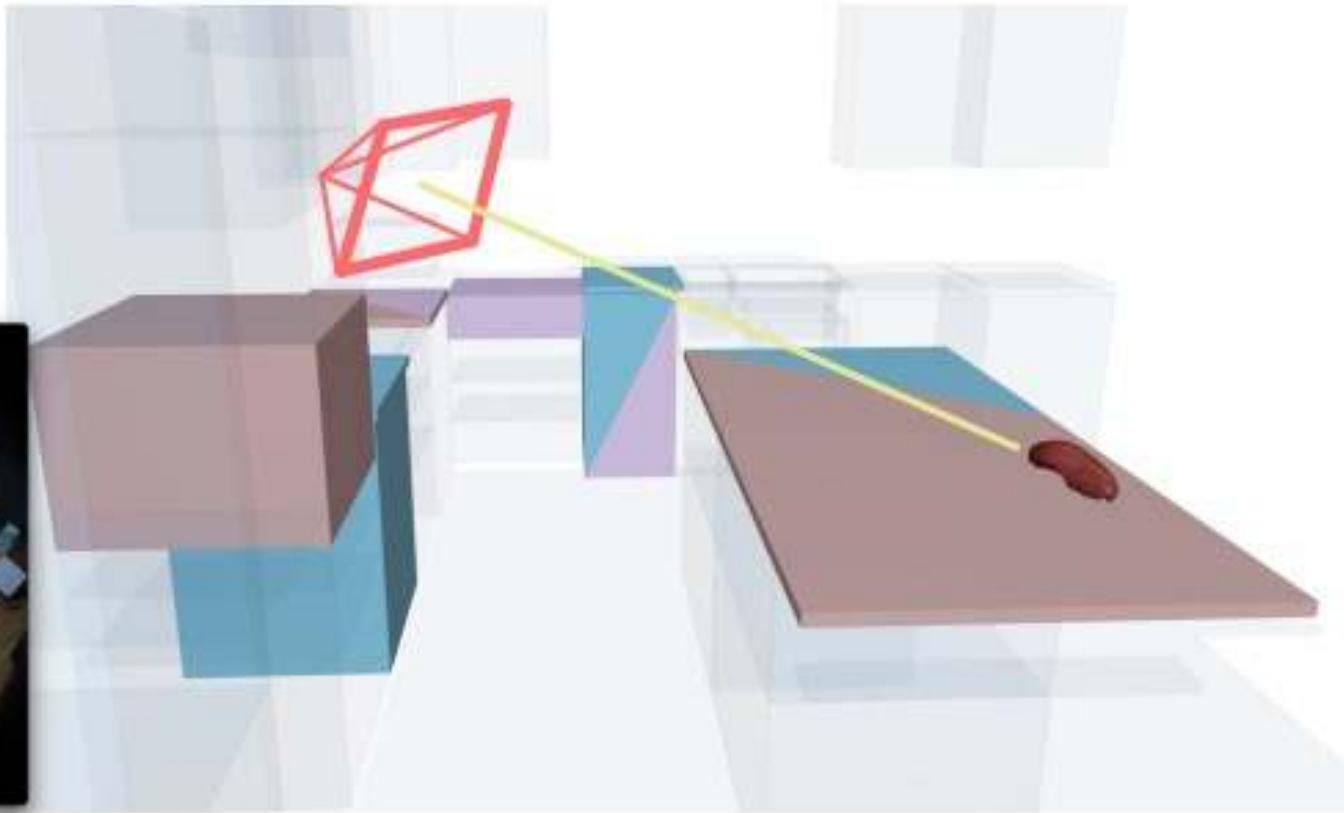




HD-EPIC



Gaze priming





HD-EPIC



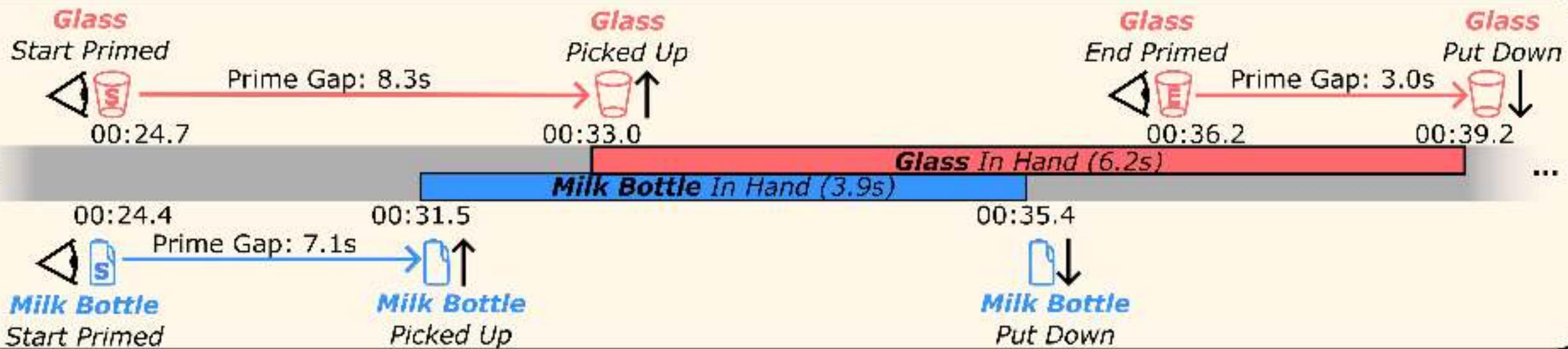
3D Scene



Frames w/ 2D Gaze



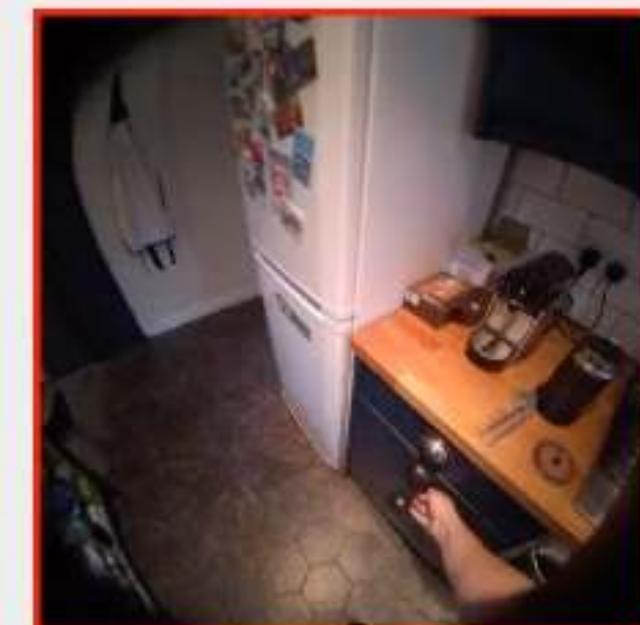
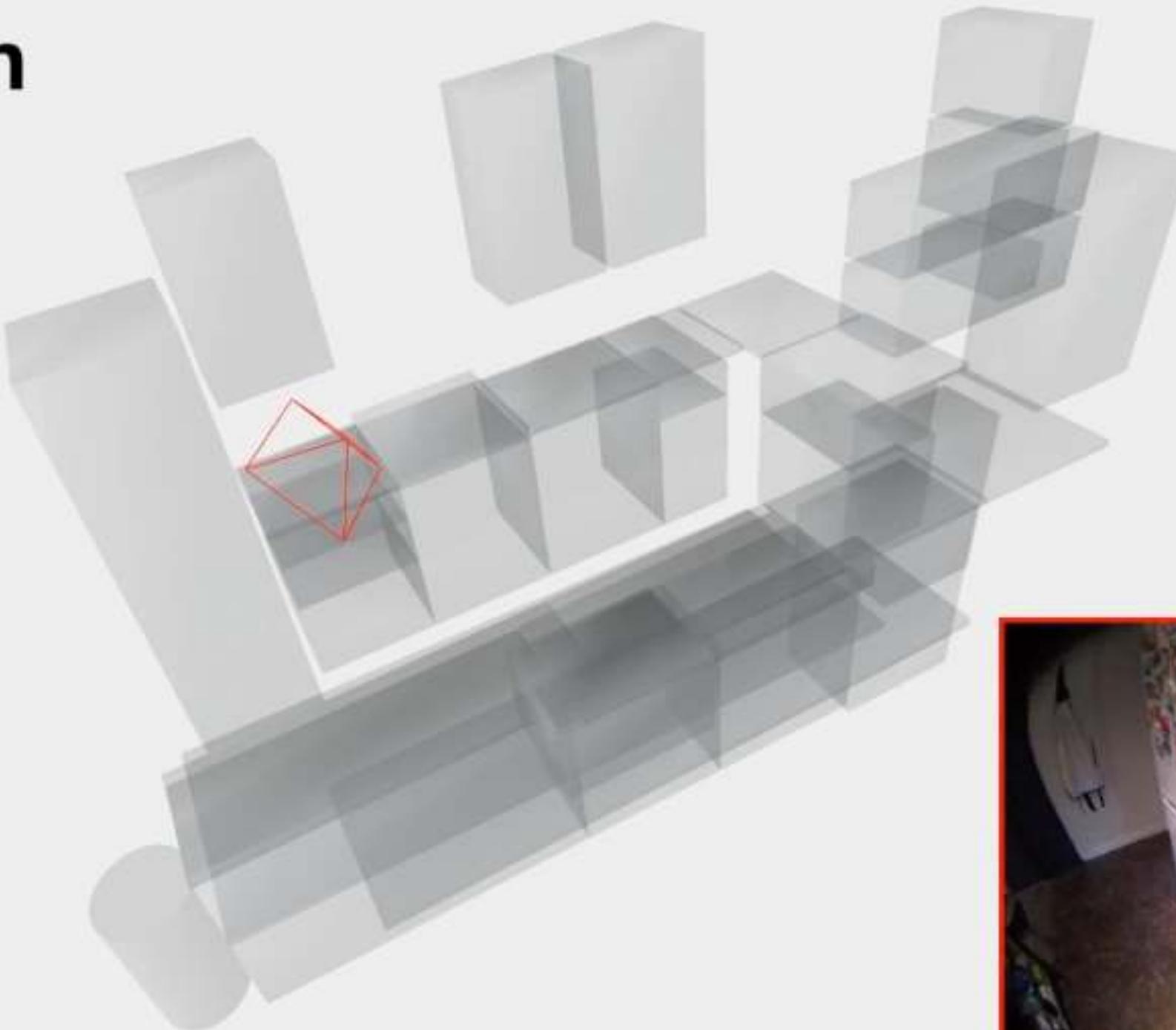
Object Movement



Digital Twin

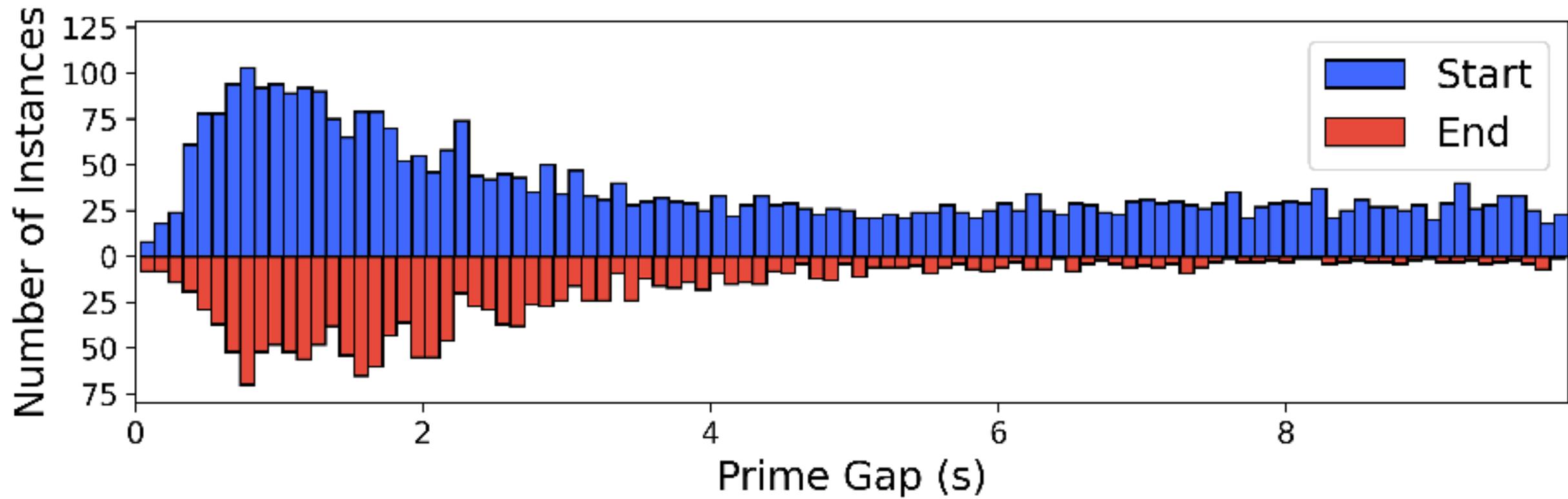
Fixtures

Open drawer



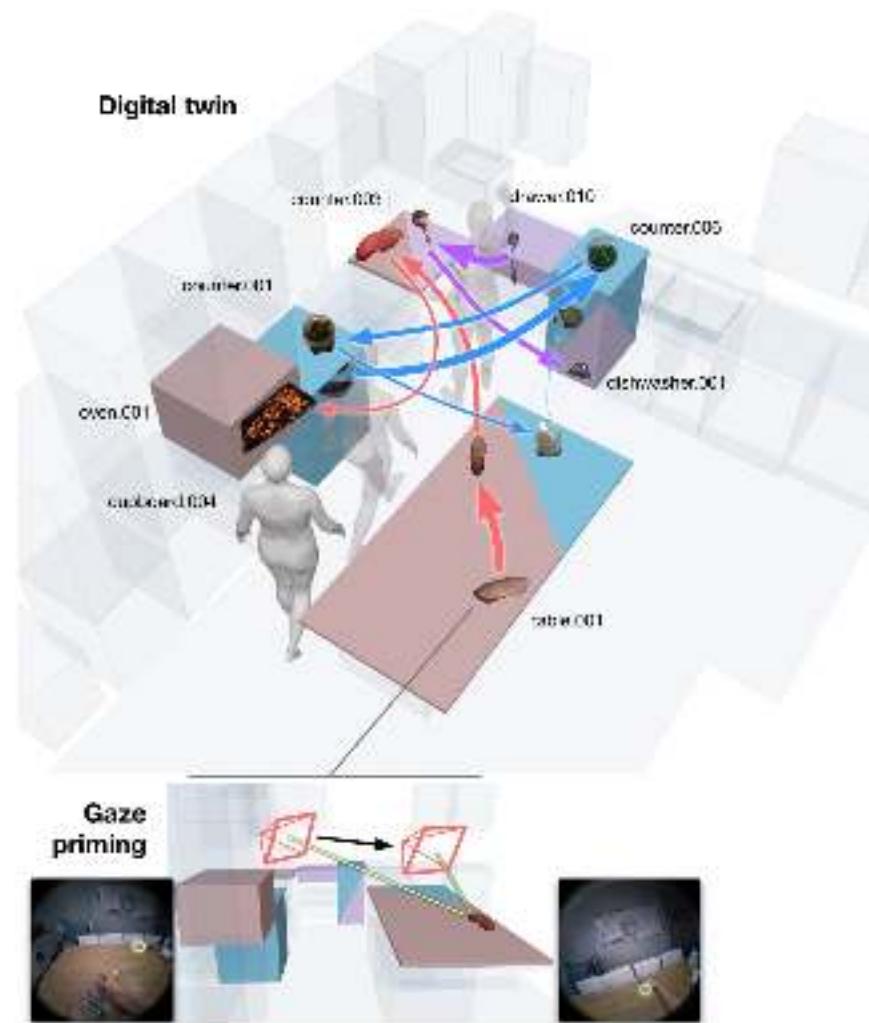
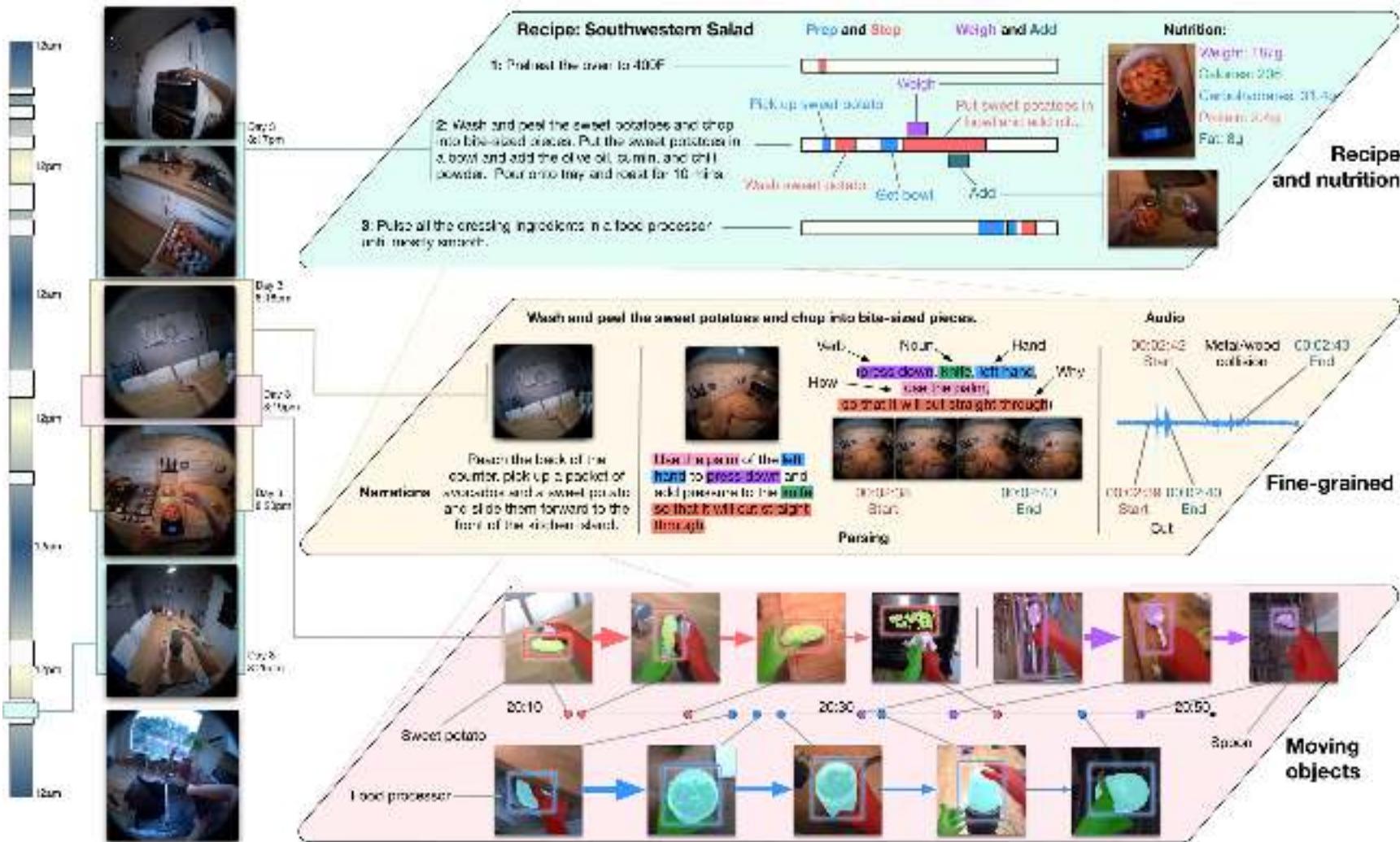


HD-EPIC





HD-EPIC



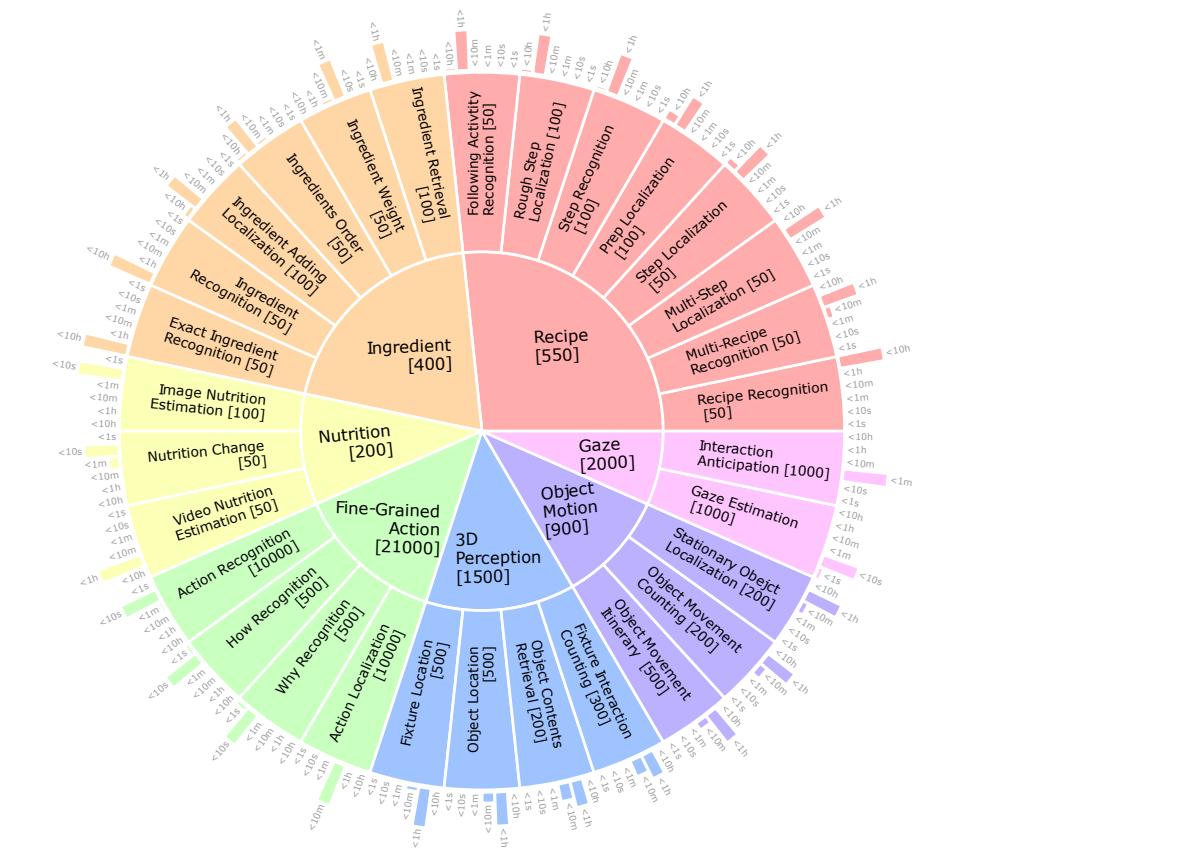
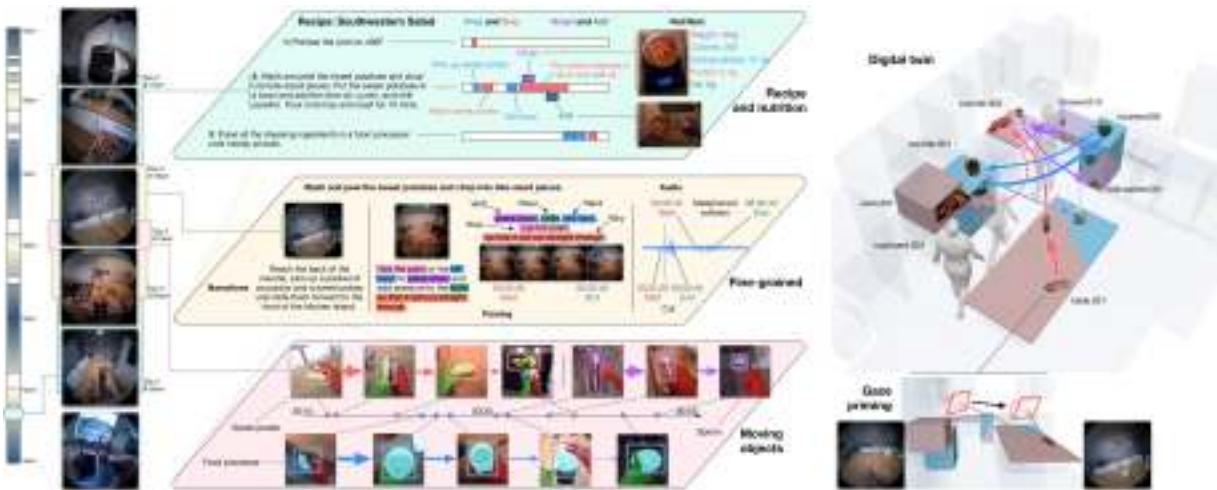


Annotation Type	Total annotations	Annotations/min
Narrations	59,454	24.0
Parsing (Verbs + Nouns + Hands + How + Why)	303,968	122.7
Recipes (Preps + Steps)	4,052	1.6
Sound	50,968	20.6
Action boundaries	59,454	24.0
Object Motion (Pick up + Put down + Fixtures + Bboxes + Masks)	153,480	62.0
Object Itinerary	4,881	2.0
Object Priming (Starts + Ends)	18,264	7.4
Total	263.2	

Table A3. HD-EPIC annotations per minute



HD-EPIC



Sec 1: Highly-Detailed Dataset

Sec 2: HD-EPIC VQA Benchmark



HD-EPIC



Try it Yourself

Use Wise to Search
through HD-EPIC



<https://meru.robots.ox.ac.uk/HD-EPIC/>

In today's talk...



Motivation and Datasets in
Egocentric Video Understanding



Teaser: The Wizard of Oz
& Genie 3



Video Understanding
Out of the Frame



Outlook into the Future of
Egocentric Vision



Point Tracking



Object Tracking



Gaze Priming



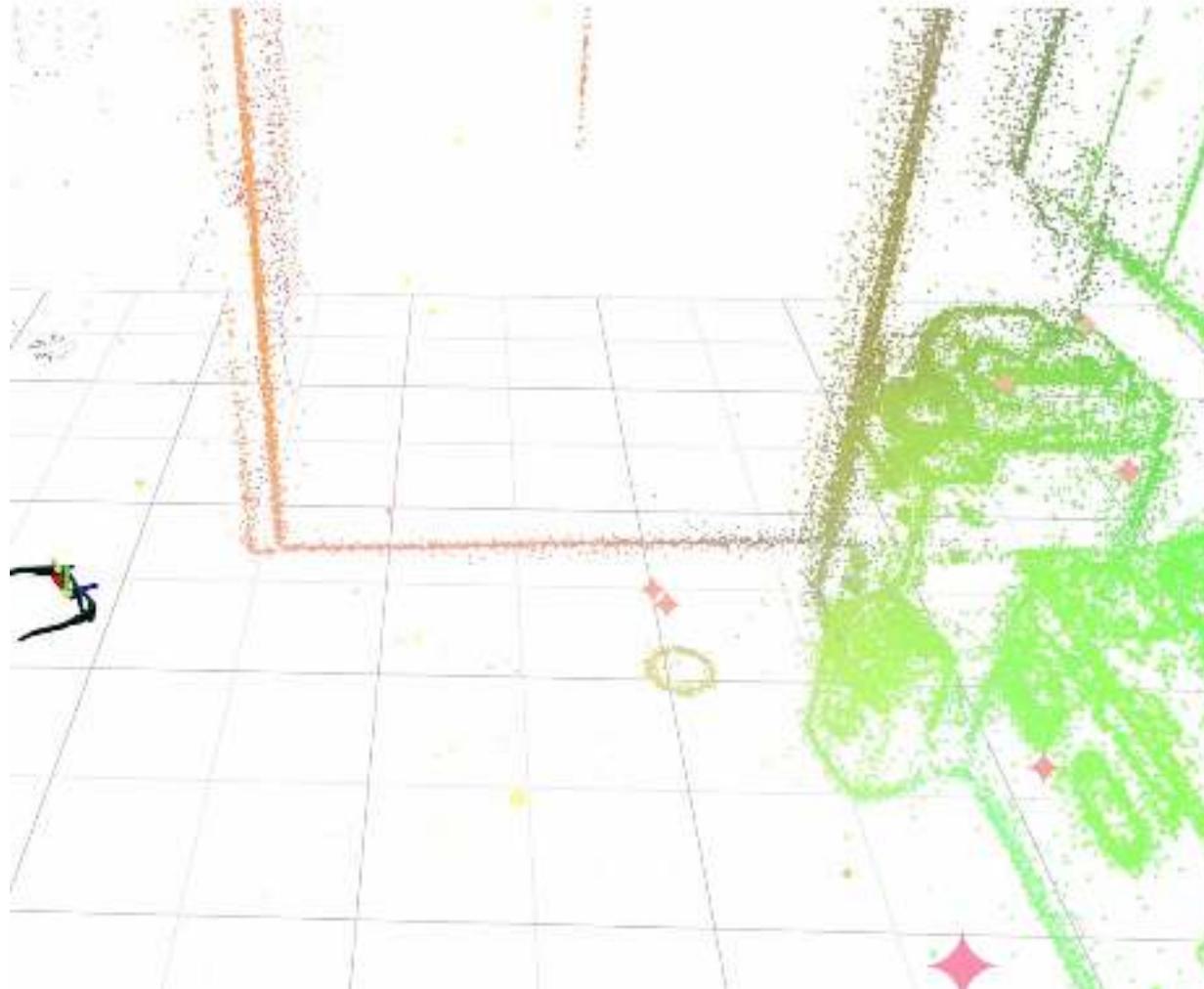
Hand Tracking



Conclusion

EgoBody

EgoAllo uses egocentric (↳) SLAM poses and images



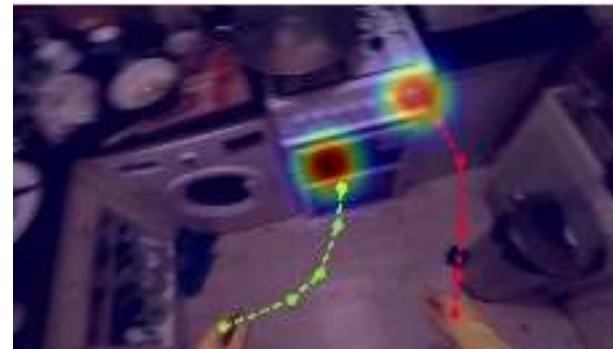
EgoHand Forecasting – Previous Works

with: Masashi Hatano
Zhifan Zhu
Hideo Saito

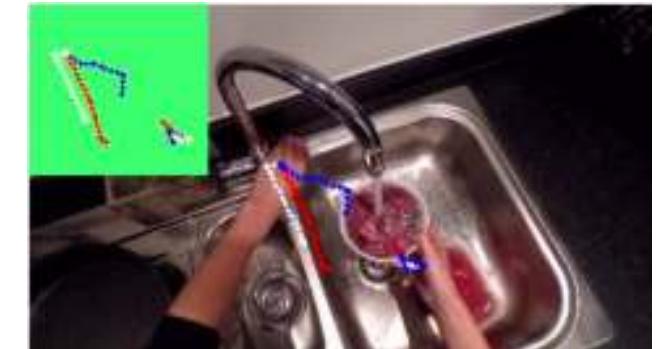
2D Hand Forecasting

Given an egocentric video,
forecast 2D hand positions of both hands

→ Limited in 2D image plane



OCT [CVPR'22]



Diff-IP2D [IROS'25]

3D Hand Forecasting

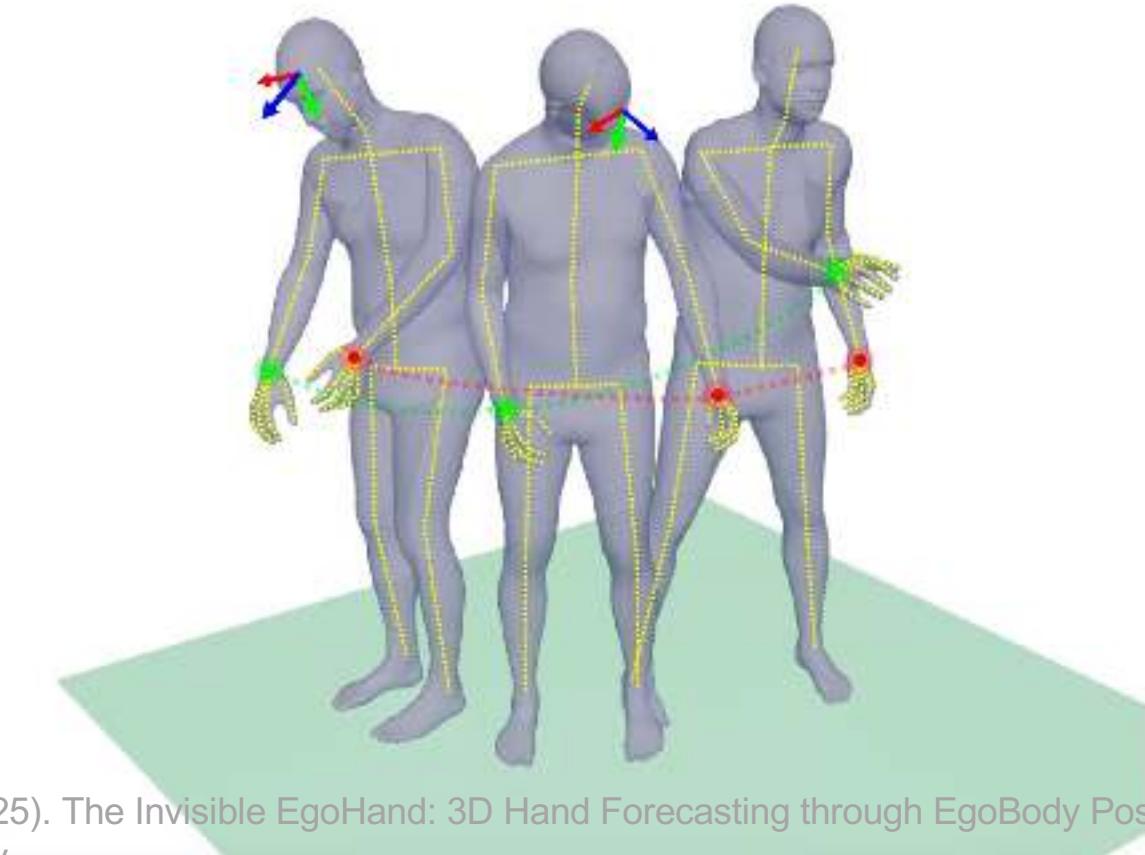
Given an egocentric video & 3D hand trajectory,
forecast 3D hand positions of one hand



USST [ICCV'23]

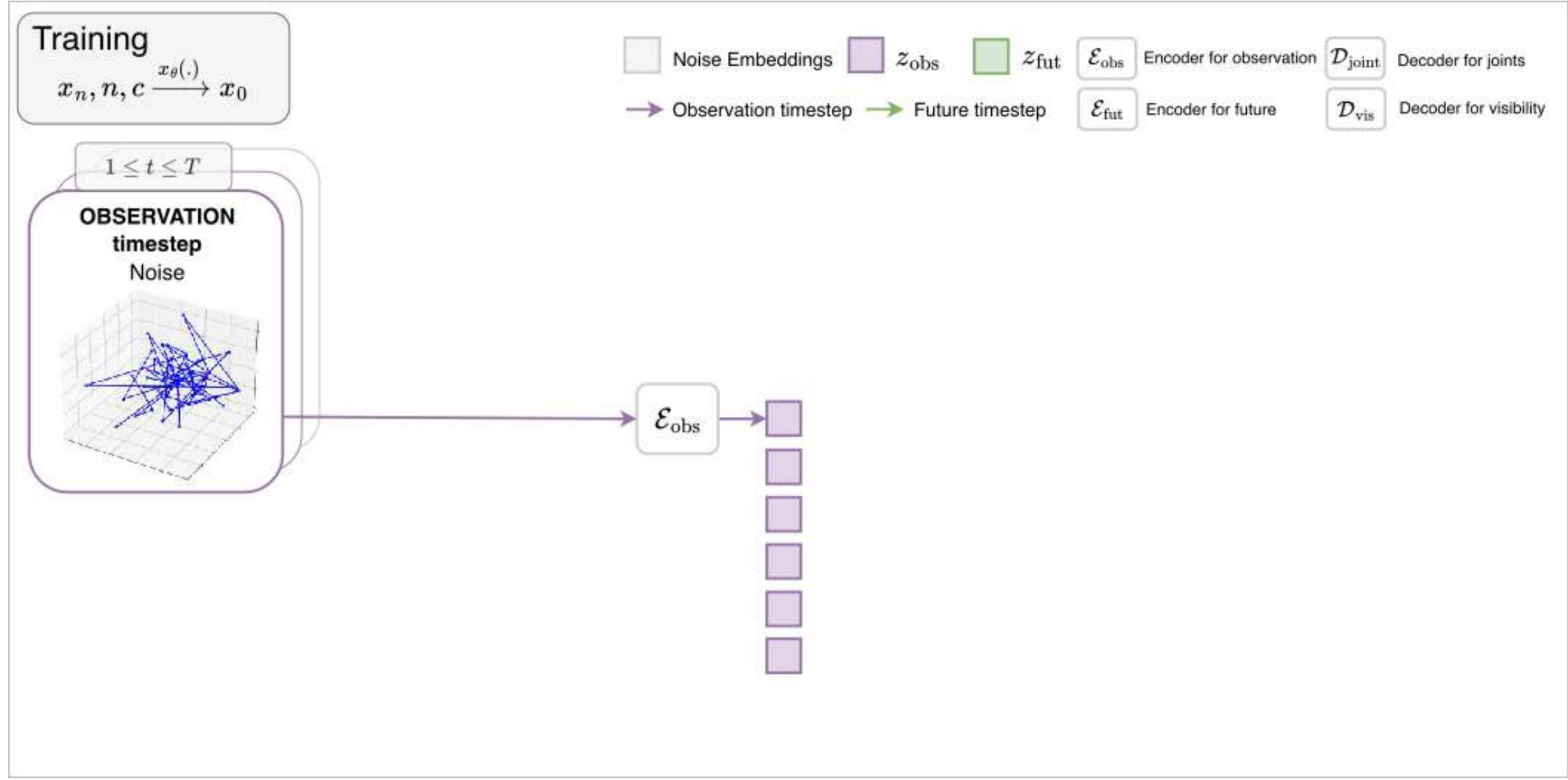
The Invisible EgoHand

with: Masashi Hatano
Zhifan Zhu
Hideo Saito



The Invisible EgoHand

with: Masashi Hatano
Zhifan Zhu
Hideo Saito



The Invisible EgoHand

with: Masashi Hatano
Zhifan Zhu
Hideo Saito

Method	Hand Trajectory Forecasting				Hand Pose Forecasting			
			All				All	
	ADE	FDE	MPJPE	MPJPE-F				
Static	0.335	0.405	0.166	0.179				
CVM [61]	0.346	0.467	0.166	0.183				
EgoEgoForecast	0.295	0.352	0.166	0.177				
USST [3]	0.562	0.581	-	-				
Ours	0.261	0.324	0.115	0.143				

The Invisible EgoHand

with: Masashi Hatano
Zhifan Zhu
Hideo Saito

Method	Hand Trajectory Forecasting			Hand Pose Forecasting		
	In-view	Out-of-view	All	In-view	Out-of-view	All
EgoEgoForecast	0.171	0.385	0.295	0.162	0.299	0.166
Ours w/o. 2D joint	0.151	0.377	0.282	0.139	0.269	0.142
Ours w/o. image	0.116	0.367	0.261	0.117	0.234	0.120
Ours w/o. $\mathcal{L}_{\text{reproj}}$	0.132	0.368	0.269	0.125	0.250	0.128
Ours w/o. \mathcal{L}_{vis}	0.127	0.377	0.272	0.121	0.240	0.124
Ours w/o. $\mathcal{L}_{\text{body}}$	0.129	0.385	0.277	0.120	0.258	0.123
Ours w/o. \mathcal{L}_{obs}	0.149	0.390	0.289	0.139	0.250	0.142
Ours	0.116	0.366	0.261	0.112	0.240	0.115

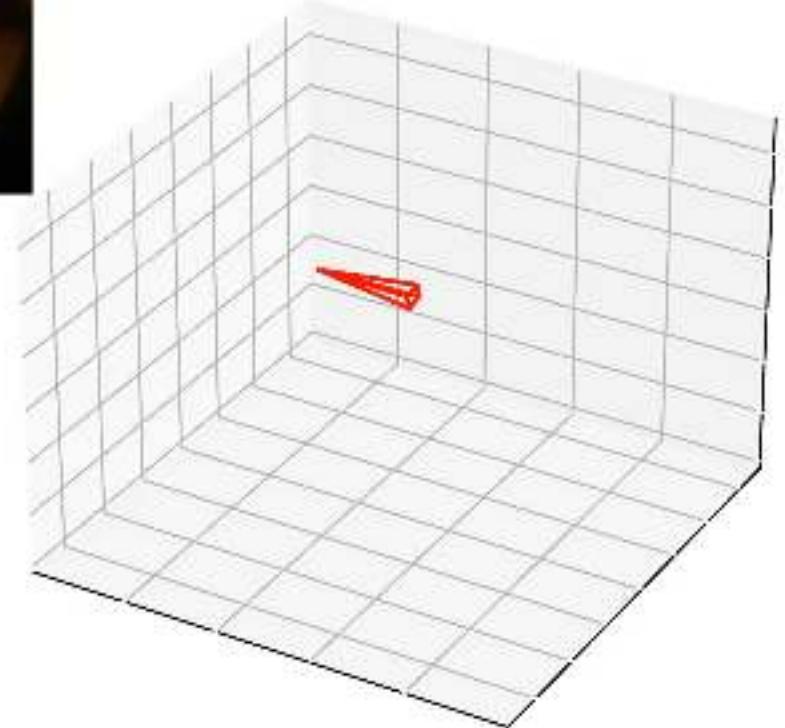
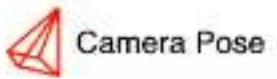
- Without visible 2D joints, significant performance drops can be seen
- 2D reprojection loss serves as effective regularization
- Visibility loss & Body joints loss contribute for out-of-view scenario

The Invisible EgoHand

with: Masashi Hatano
Zhifan Zhu
Hideo Saito



Observation



Observation



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Teaser: The Wizard of Oz
& Genie 3



Video Understanding
Out of the Frame



Outlook into the Future of
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Point Tracking

Object Tracking

Gaze Priming

Hand Tracking



Conclusion

The Wizard of Oz at the Sphere

Sold out tickets – August 2025

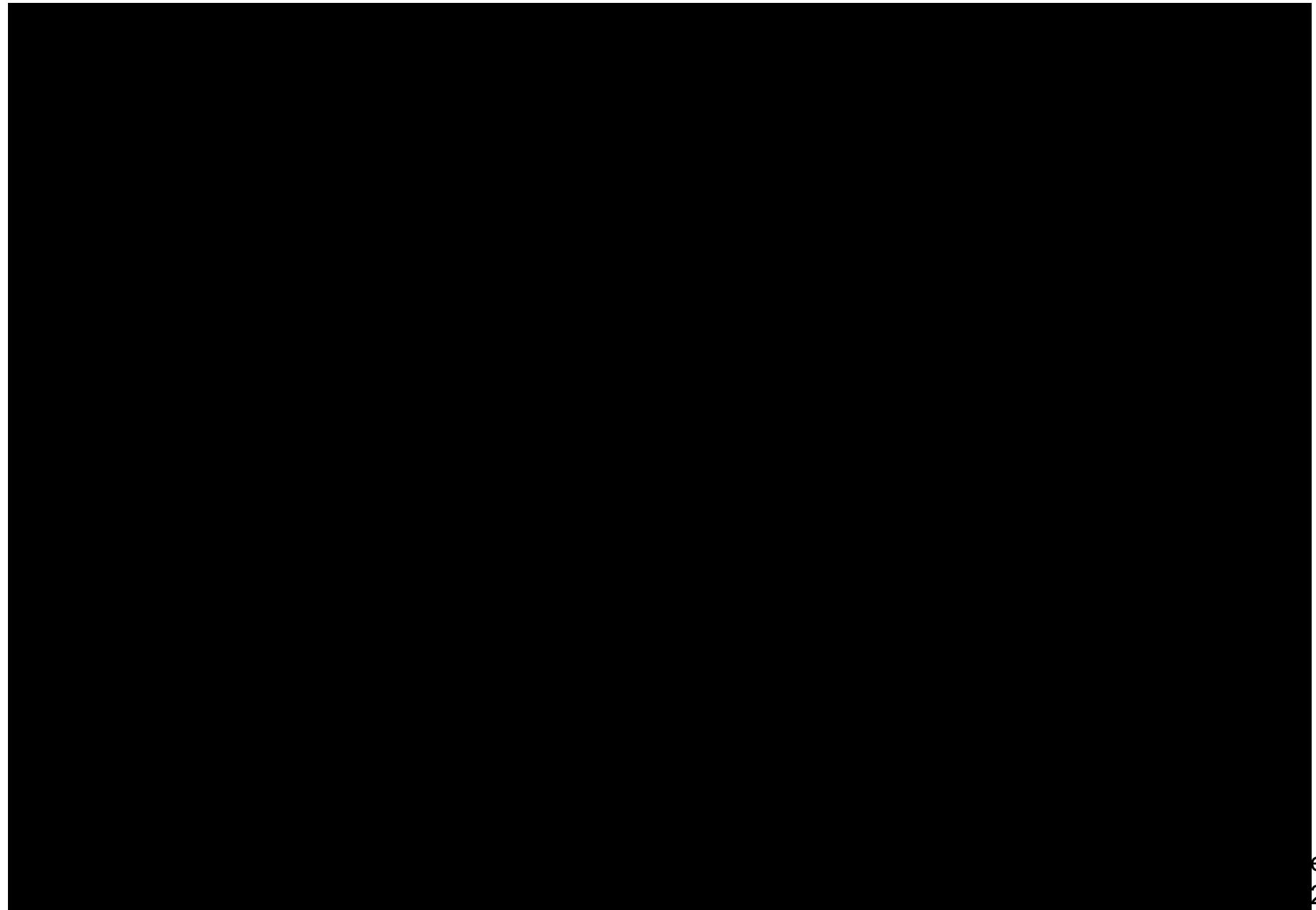


<https://behindthecurtain.withgoogle.com>

Dima Damen
BinEgo-360 Workshop @ICCV2025

The Wizard of Oz @ The Sphere

- The Movie (1939)
- Technicolour pioneer
- Iconic characters



The Wizard of Oz @ The Sphere



Ralph Winte

Head of Physical Production -  sphere

Dima Damen
Workshop @ICCV2025

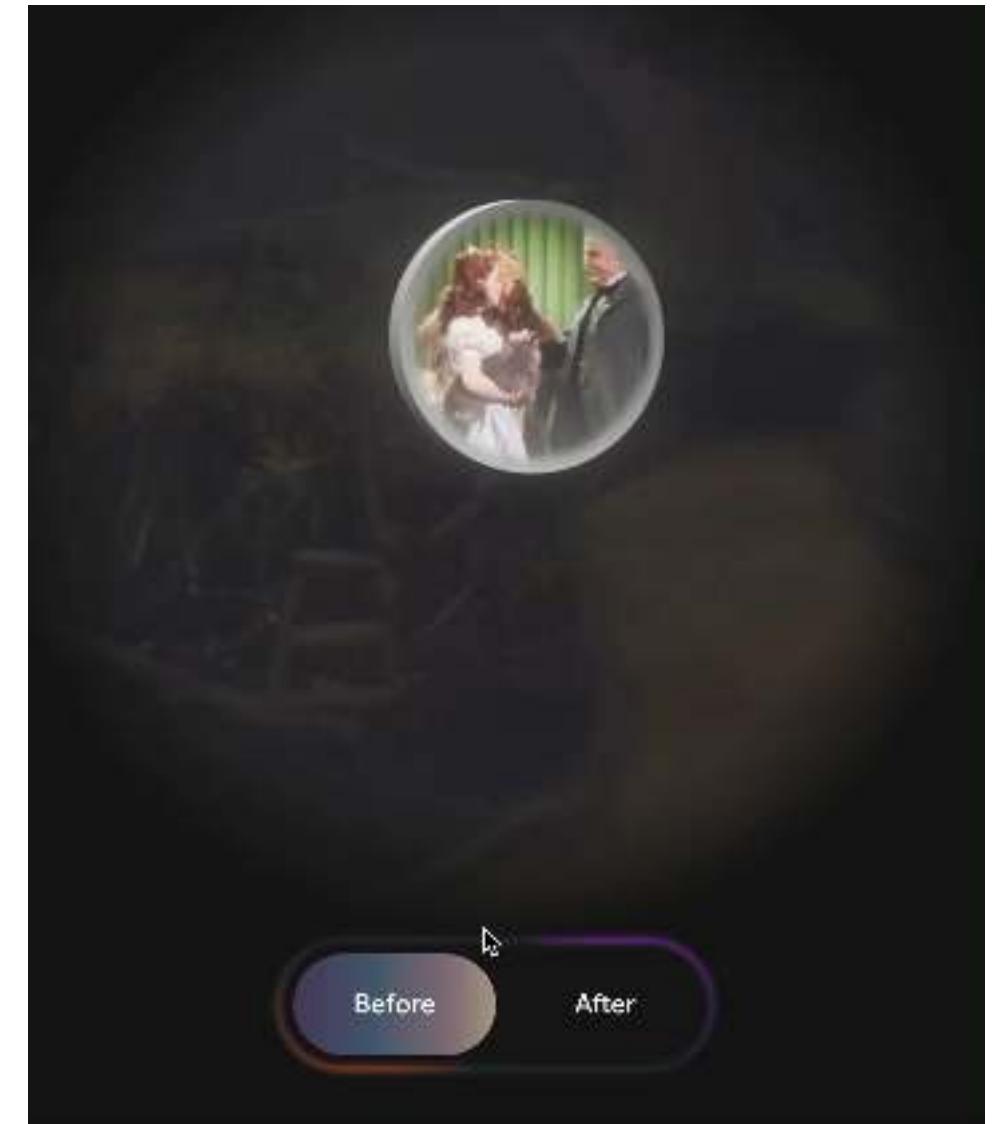
The Wizard of Oz @ The Sphere



Dima Damen
orkshop @ICCV2025

The Wizard of Oz @ The Sphere

- Super-resolution,
- Outpainting...

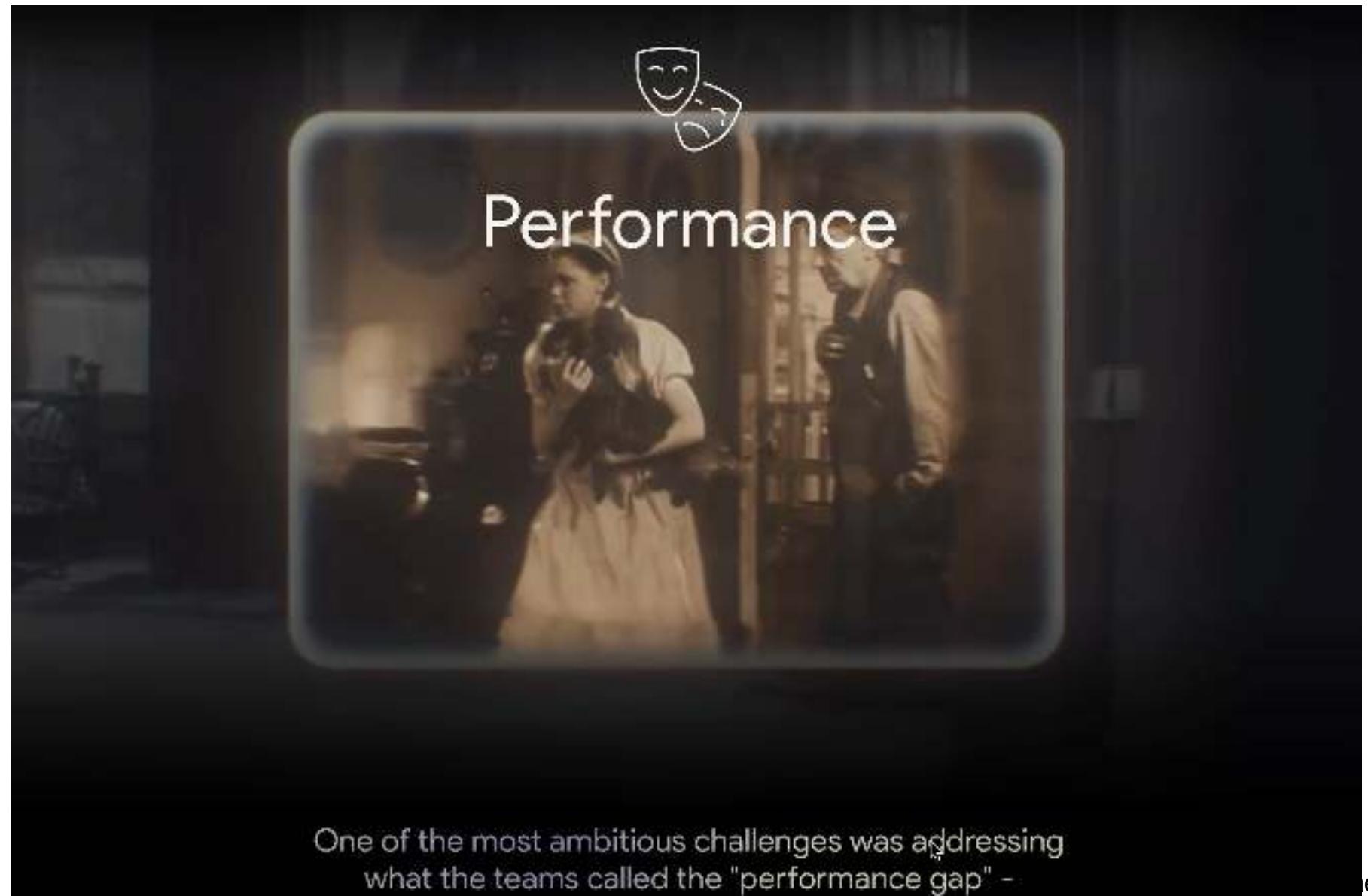


<https://behindthecurtain.withgoogle.com>

Dima Damen
BinEgo-360 Workshop @ICCV2025

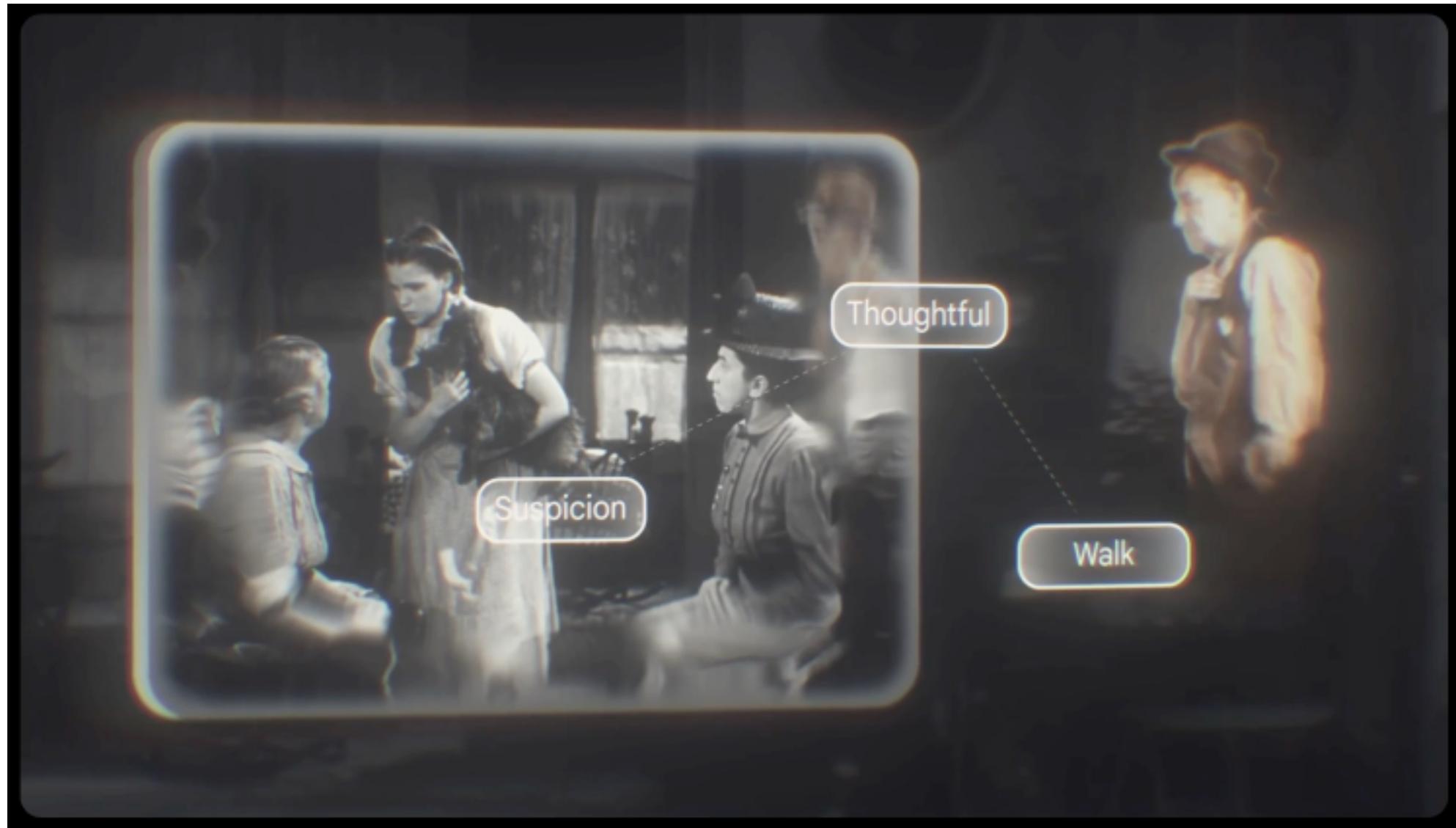
The Wizard of Oz @ The Sphere

- Performance Interpolation,



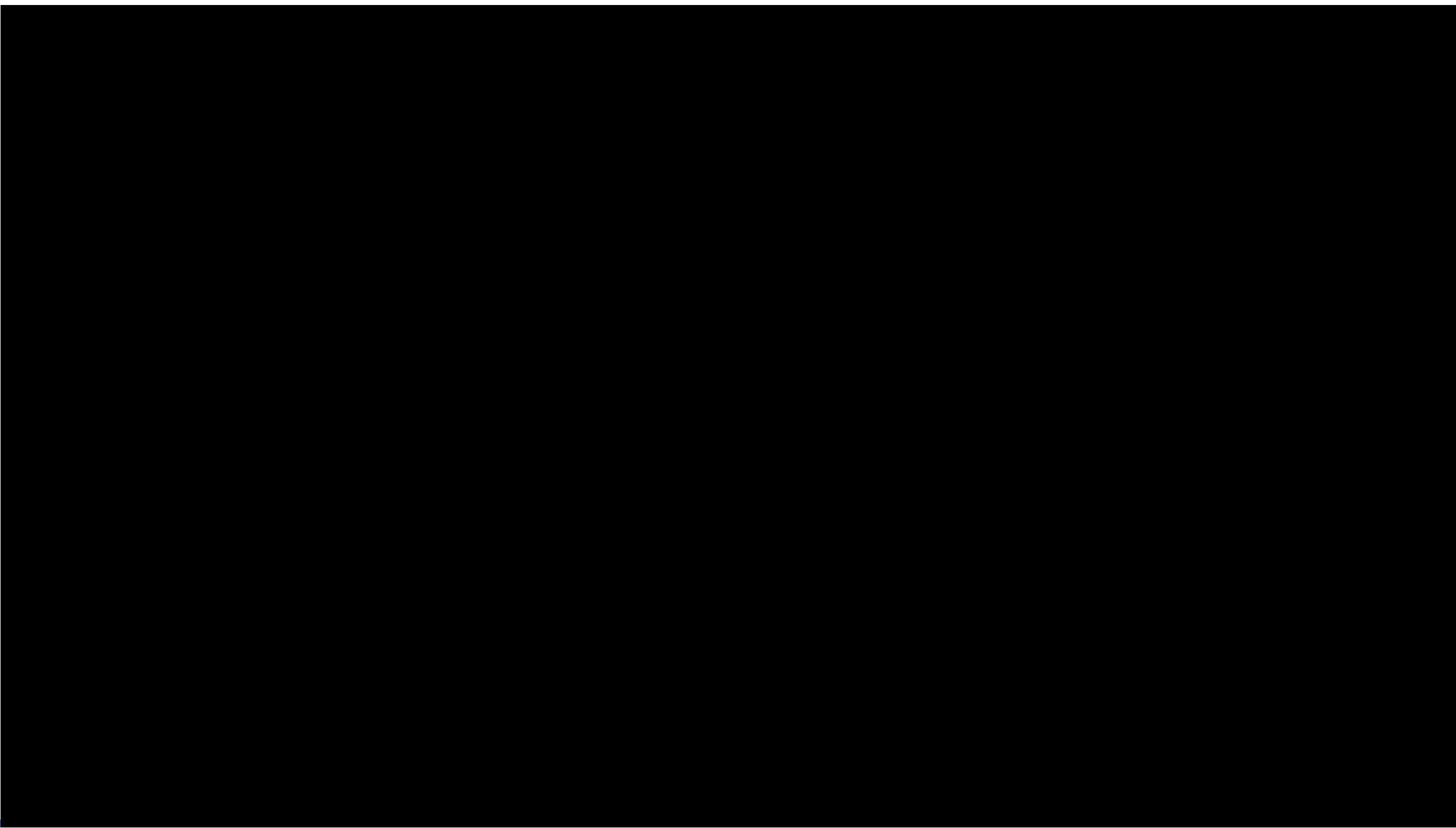
The Wizard of Oz @ The Sphere

- Auto-Director



<https://behindthecurtain.withgoogle.com>

Dima Damen
BinEgo-360 Workshop @ICCV2025



Fine-tuning

At the heart of the enhancement process lay the fine-tuning methodology—a crucial step that transformed standard AI capabilities into specialized tools uniquely attuned to the visual language of The Wizard of Oz.

Learn more



<https://behindthecurtain.withgoogle.com>

Dima Damen
BinEgo-360 Workshop @ICCV2025

Genie 3

Released Aug 2025



<https://deepmind.google/discover/blog/genie-3-a-new-frontier-for-world-models/>

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Genie 3

- A new frontier of world models
- From a text prompt or a starting image/video
- Generate interactive worlds at 24fps and 720px
- Remains consistent for several minutes
- Genie 3's consistency is an emergent capability



In today's talk...



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Video Understanding
Out of the Frame



Outlook into the Future of
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Point Tracking

Object Tracking

Gaze Priming

Hand Tracking



Conclusion



An Outlook into the Future of Egocentric Vision

Chiara Plizzari*, Gabriele Goletto*, Antonino Furnari*, Siddhant Bansal*, Francesco Ragusa*, Giovanni Maria Farinella[†], Dima Damen[†], Tatiana Tommasi[†]



Politecnico
di Torino



University of
BRISTOL



UNIVERSITÀ
degli STUDI
di CATANIA



with: Chiara Plizzari, Gabriele Goletto, Antonio Furnari, Siddhant Bansal,
Francesco Ragusa, Giovanni Maria Farinella, Tatiana Tommasi

Envisioning an Ambitious Future and Analysing the Current Status of Egocentric Vision

How did we do this?

We imagined a device – *EgoAI* and envisioned its utility in multiple scenarios



EGO-Designer



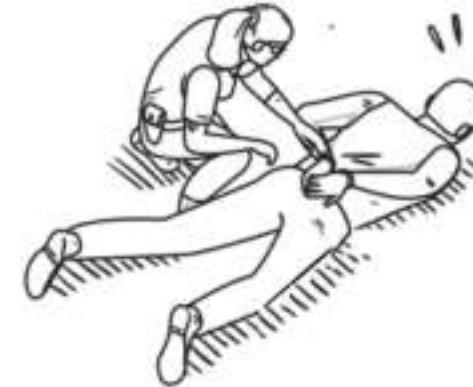
EGO-Worker



EGO-Tourist



EGO-Home

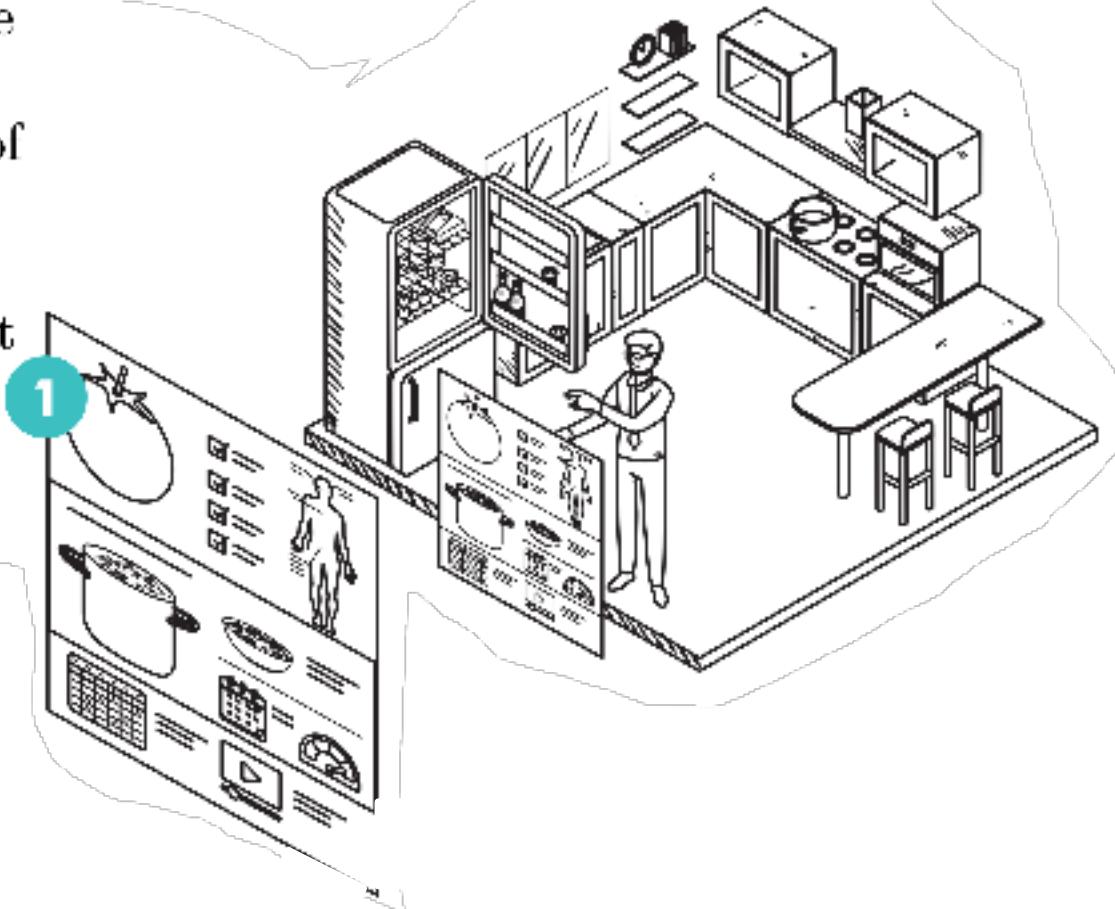


Ego-Police

EGO-Home

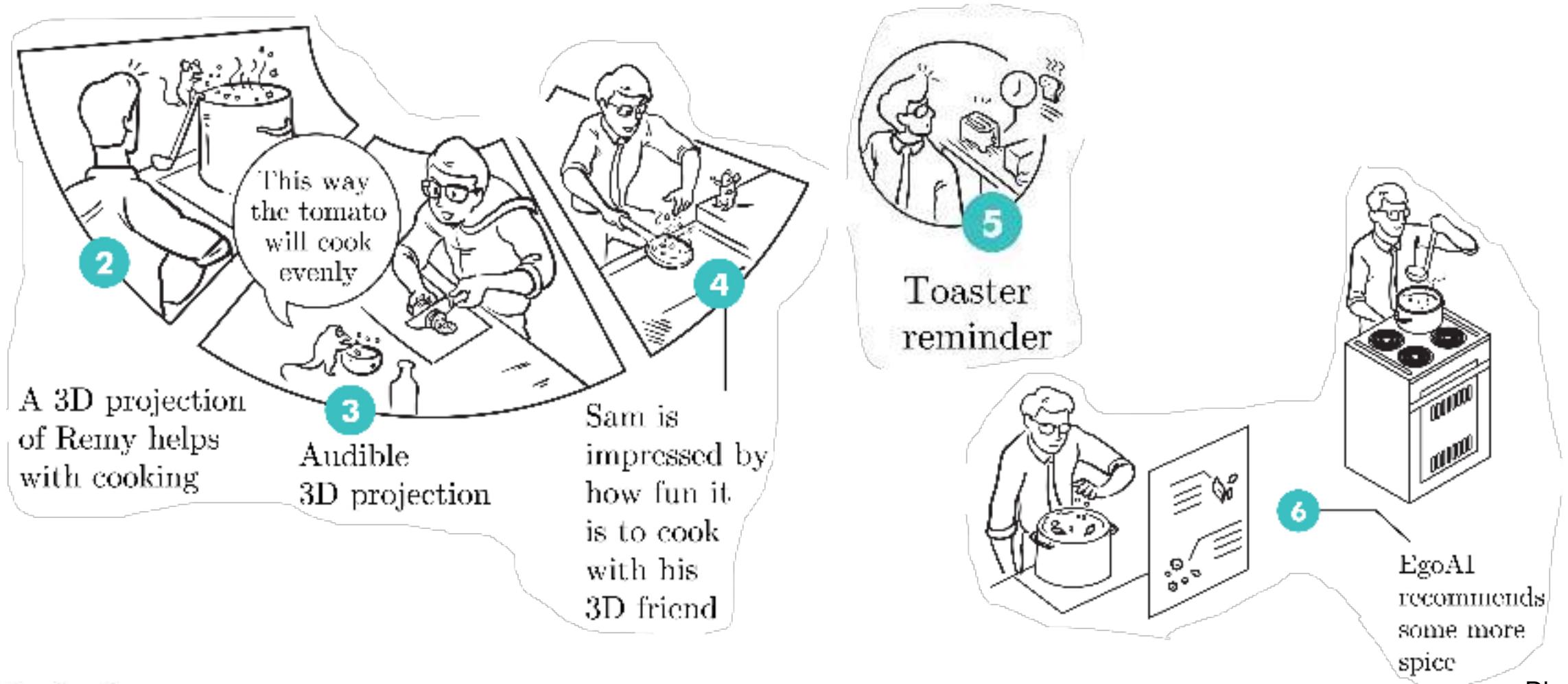
with: Chiara Plizzari, Gabriele Goletto, Antonio Furnari, Siddhant Bansal, Francesco Ragusa, Giovanni Maria Farinella, Tatiana Tommasi

Sam is finally home after a long day.
EgoAI kept track of Sam's food intake and a tomato soup sounds like the best complementary nutrition



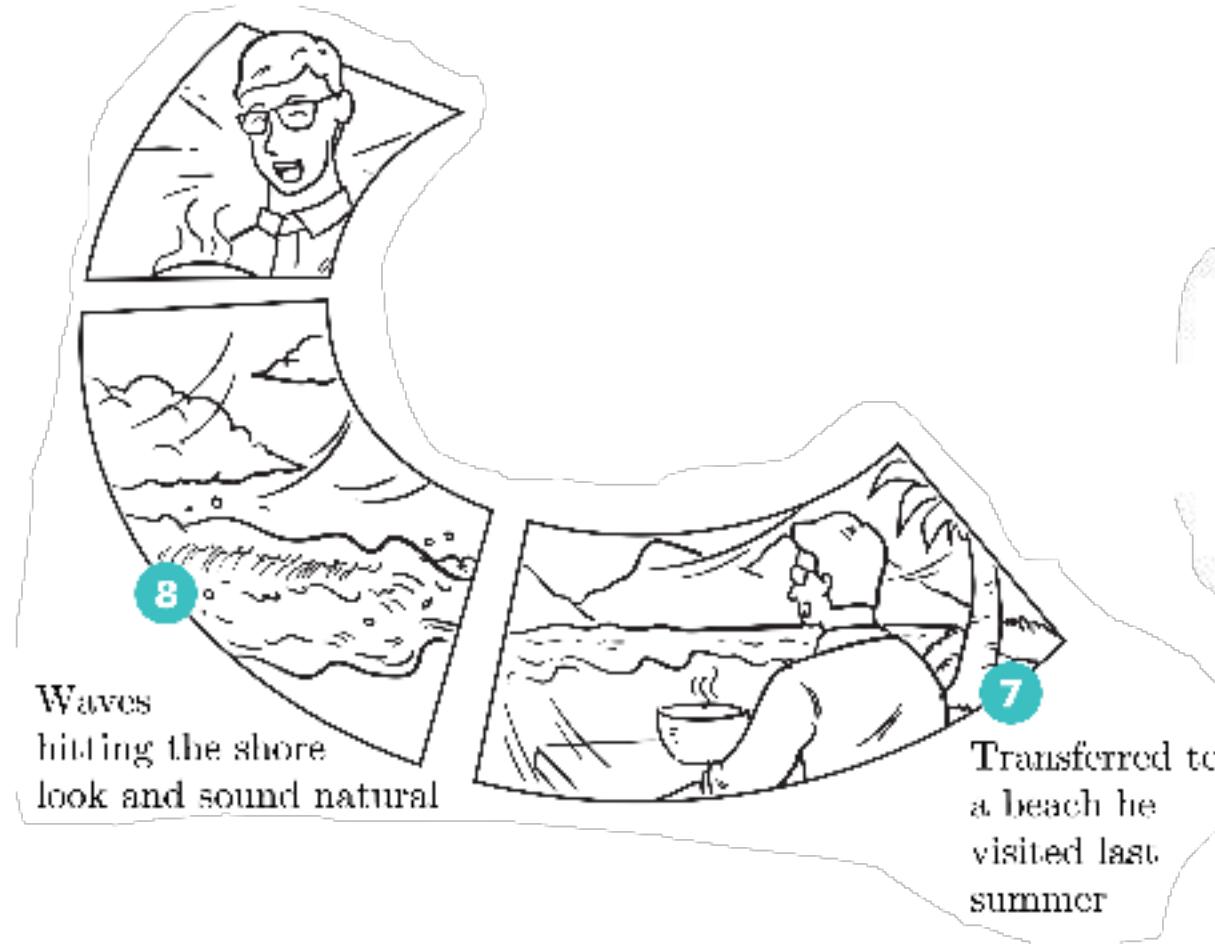
EGO-Home

with: Chiara Plizzari, Gabriele Goletto, Antonio Furnari, Siddhant Bansal, Francesco Ragusa, Giovanni Maria Farinella, Tatiana Tommasi



EGO-Home

with: Chiara Plizzari, Gabriele Goletto, Antonio Furnari, Siddhant Bansal, Francesco Ragusa, Giovanni Maria Farinella, Tatiana Tommasi

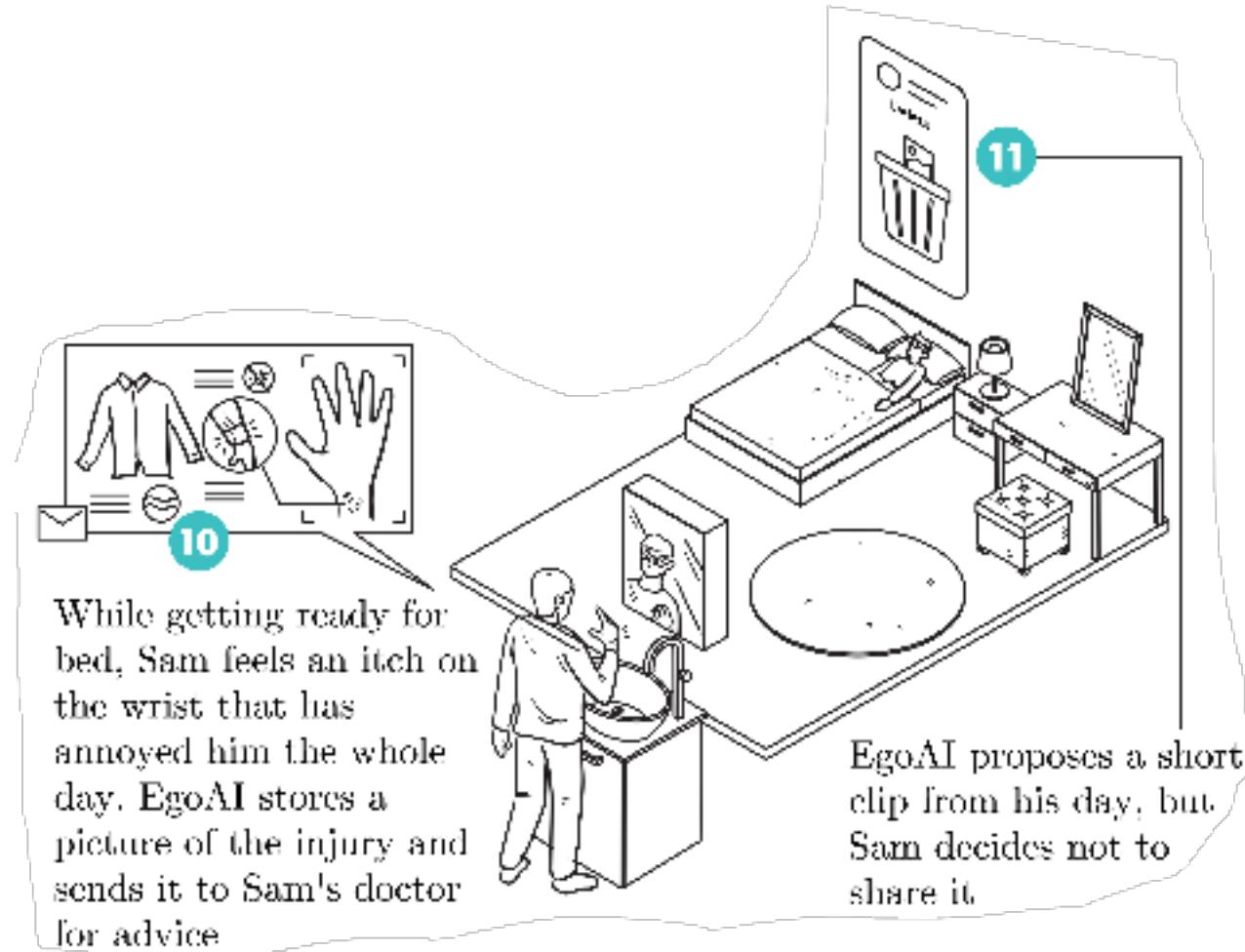


After dinner, Sam enjoys a group card game with his friends, who are connected through their own EgoAI



EGO-Home

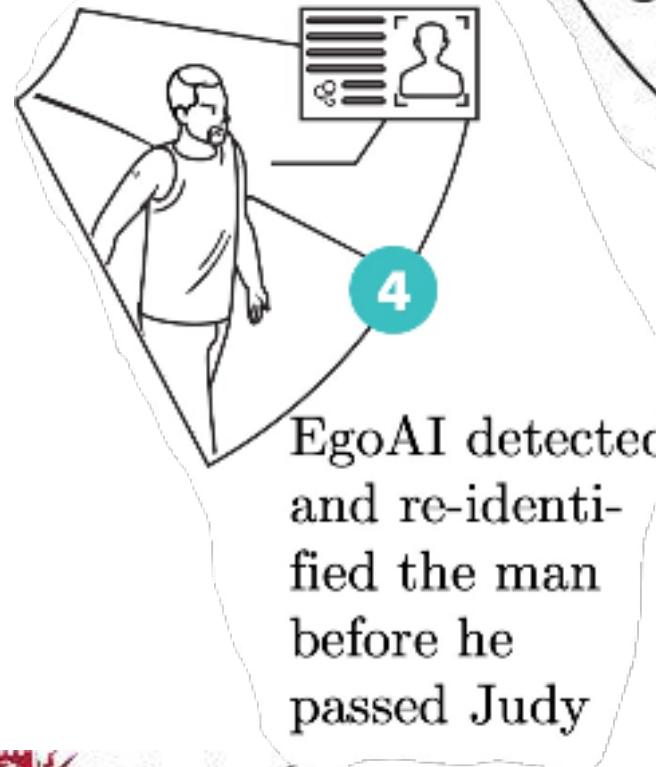
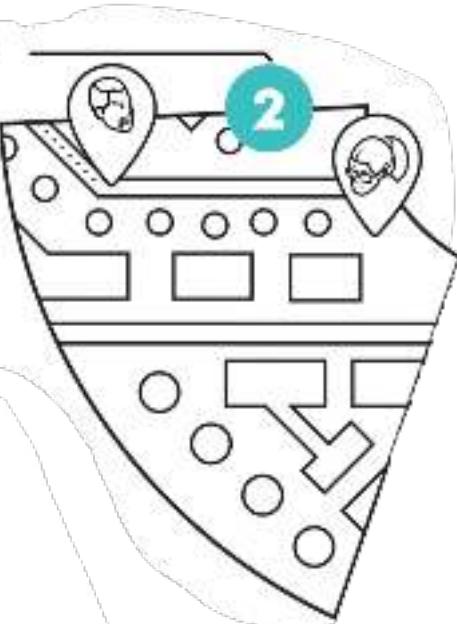
with: Chiara Plizzari, Gabriele Goletto, Antonio Furnari, Siddhant Bansal, Francesco Ragusa, Giovanni Maria Farinella, Tatiana Tommasi



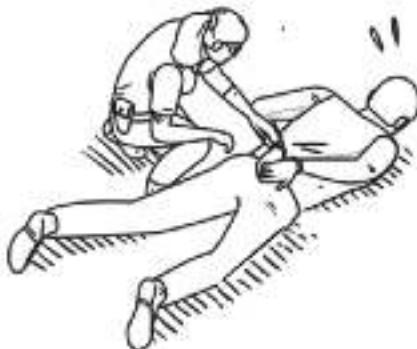
From Stories to Tasks

with: Chiara Plizzari, Gabriele Goletto, Antonio Furnari, Siddhant Bansal, Francesco Ragusa, Giovanni Maria Farinella, Tatiana Tommasi

EgoAI helps Judy navigate through the shortest safe path to target places



EgoAI detected and re-identified the man before he passed Judy



EGO-Police

Localisation and Navigation

1 2

Messaging

1 3 11

Action Recognition

2 13

Person Re-ID

2 4

Object Detection and Retrieval

7

Measuring System

8 9

Decision Making

9

3D Scene Understanding

10

Hand-Object Interaction

12

Summarisation

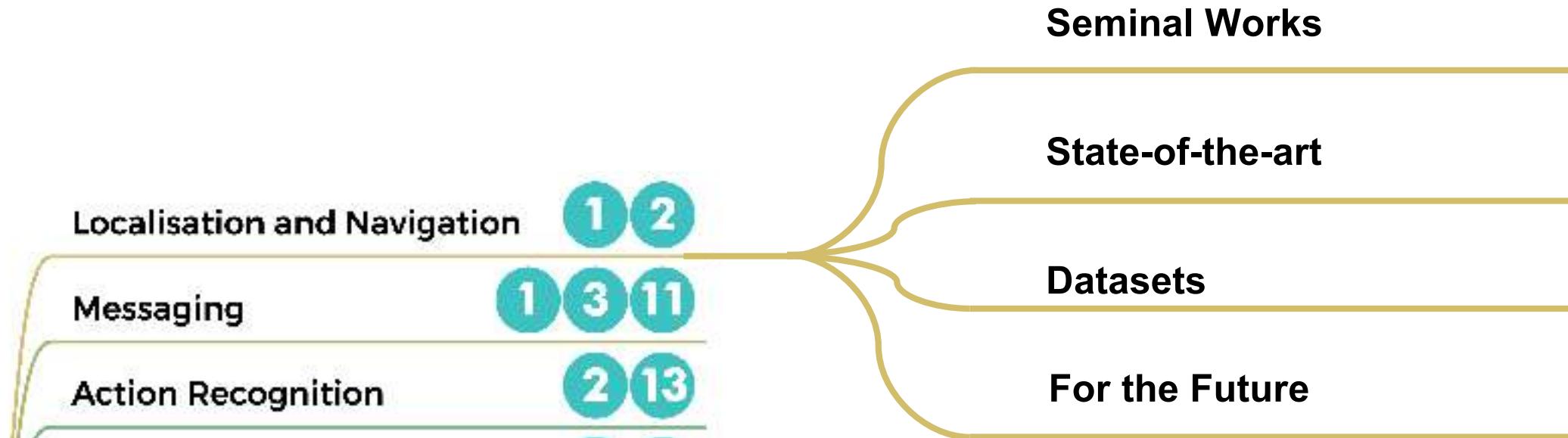
13

Privacy

14

The Survey Part

with: Chiara Plizzari, Gabriele Goletto, Antonio Furnari, Siddhant Bansal,
Francesco Ragusa, Giovanni Maria Farinella, Tatiana Tommasi



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Video Understanding
Out of the Frame



Outlook into the Future of
Egocentric Vision



→ Point Tracking

→ Object Tracking

→ Gaze Priming

→ Hand Tracking



Conclusion

My research team...

grateful



Thank you

For further info, datasets, code, publications...

<http://dimadamen.github.io>



@dimadamen



@dimadamen.bsky.social



<http://www.linkedin.com/in/dimadamen>

Q&A