

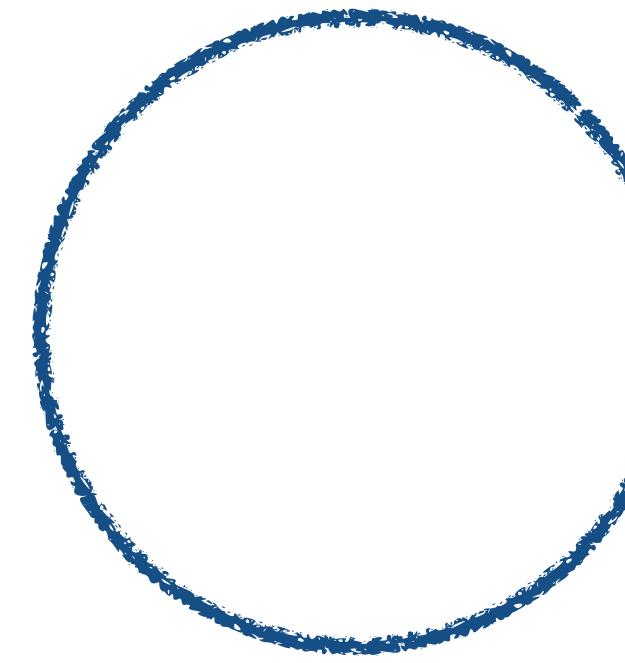
Modern Self-supervised Image Representation Learning from Videos

YUKI ASANO
NEURIPS 2023

Van Gogh self-portraits 1888, 1889

Why do we want Self-supervised Learning in the age of CLIP et al?

Massive scale



sup. << weak sup. << raw

Cost of (re)labelling



Problems of labels



Fundamentals



Especially videos open exiting new directions



Visual development for AI

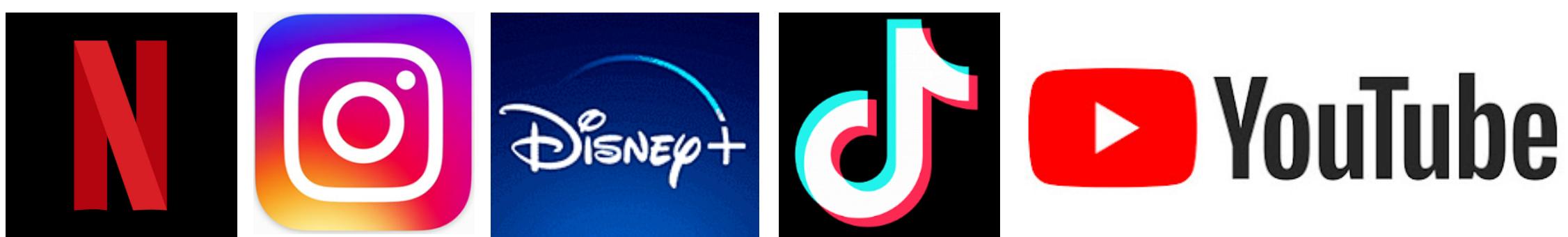


"Get" physics

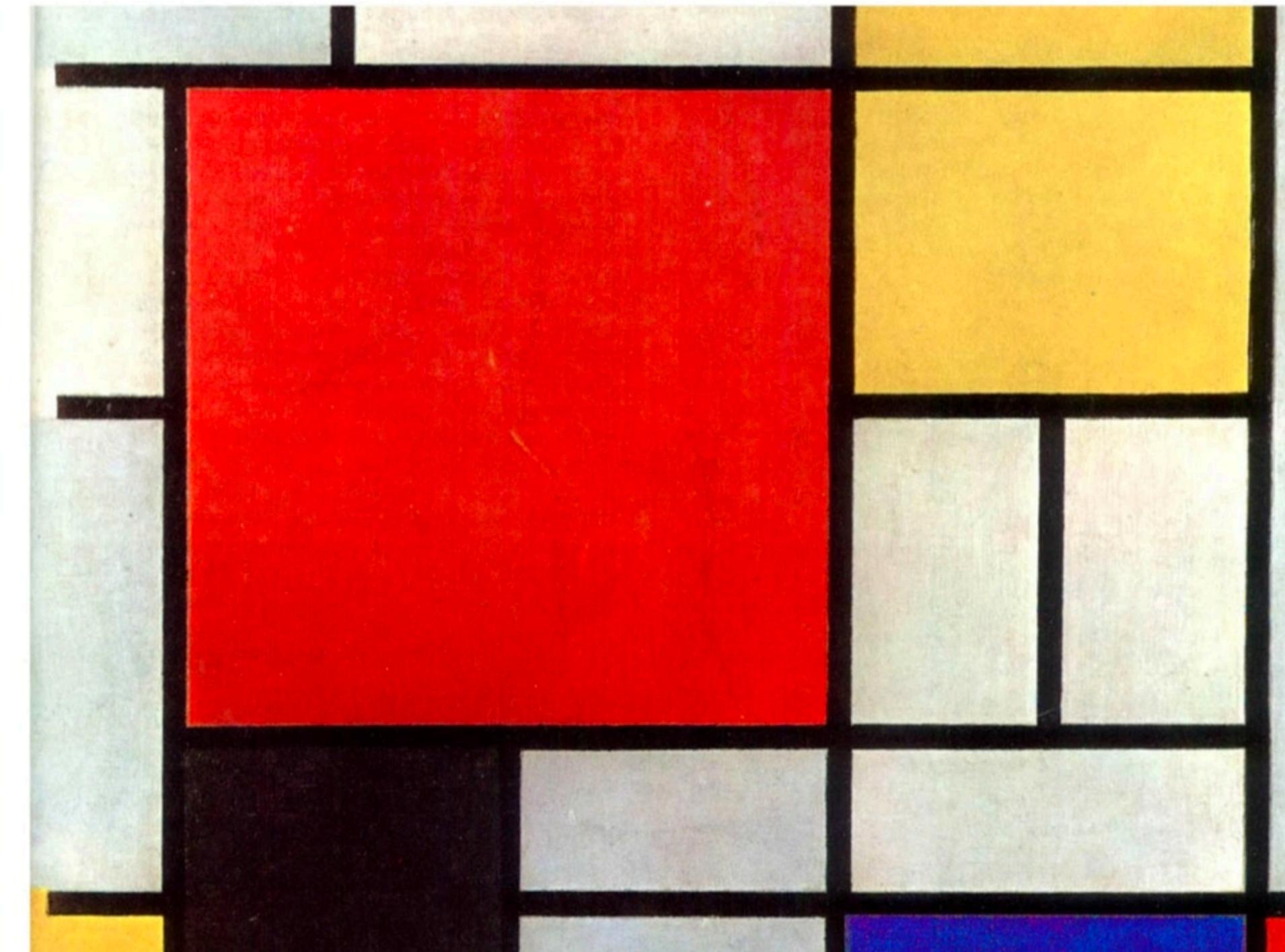
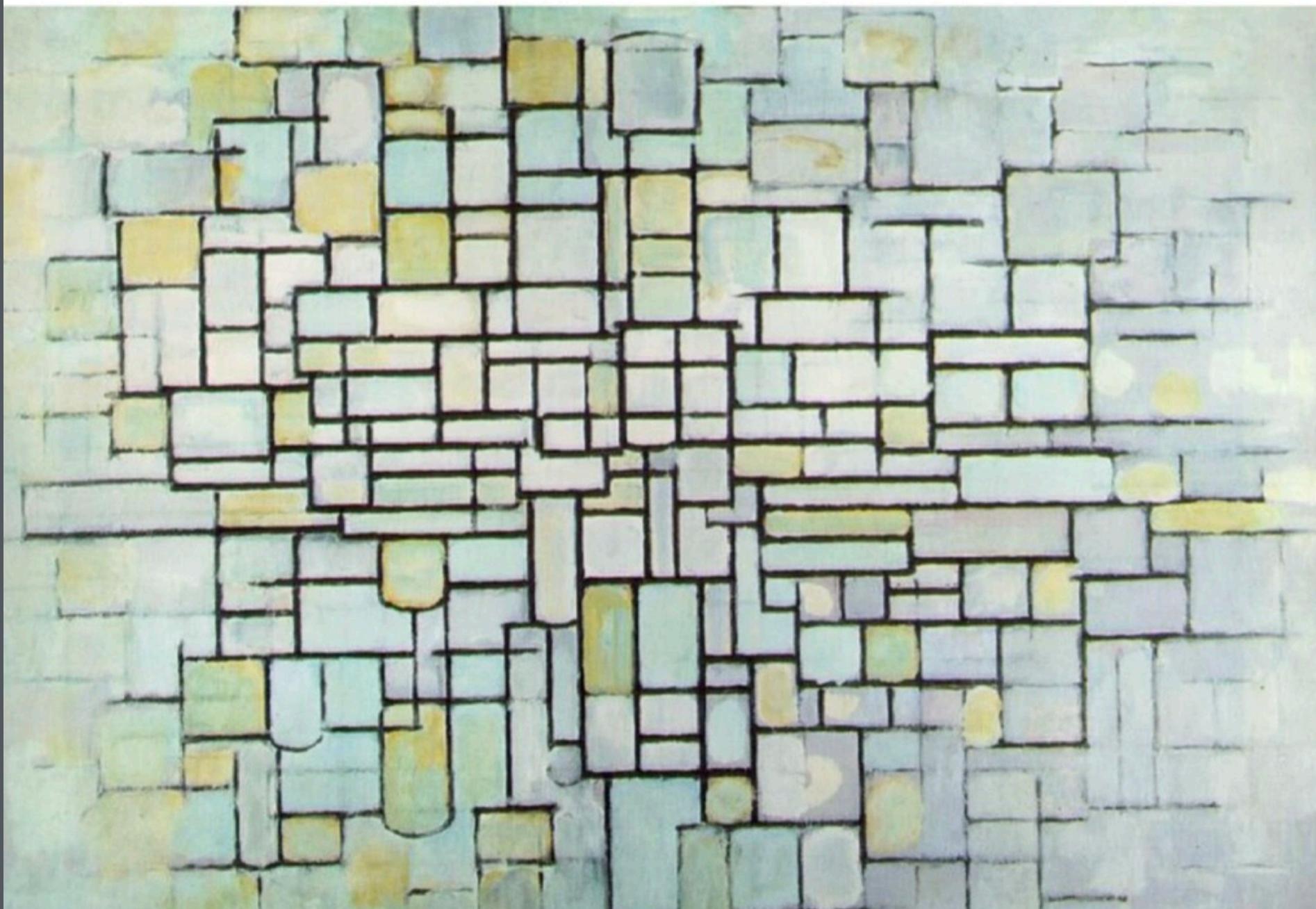


Embodied AI

Bonus: *insane scale:*



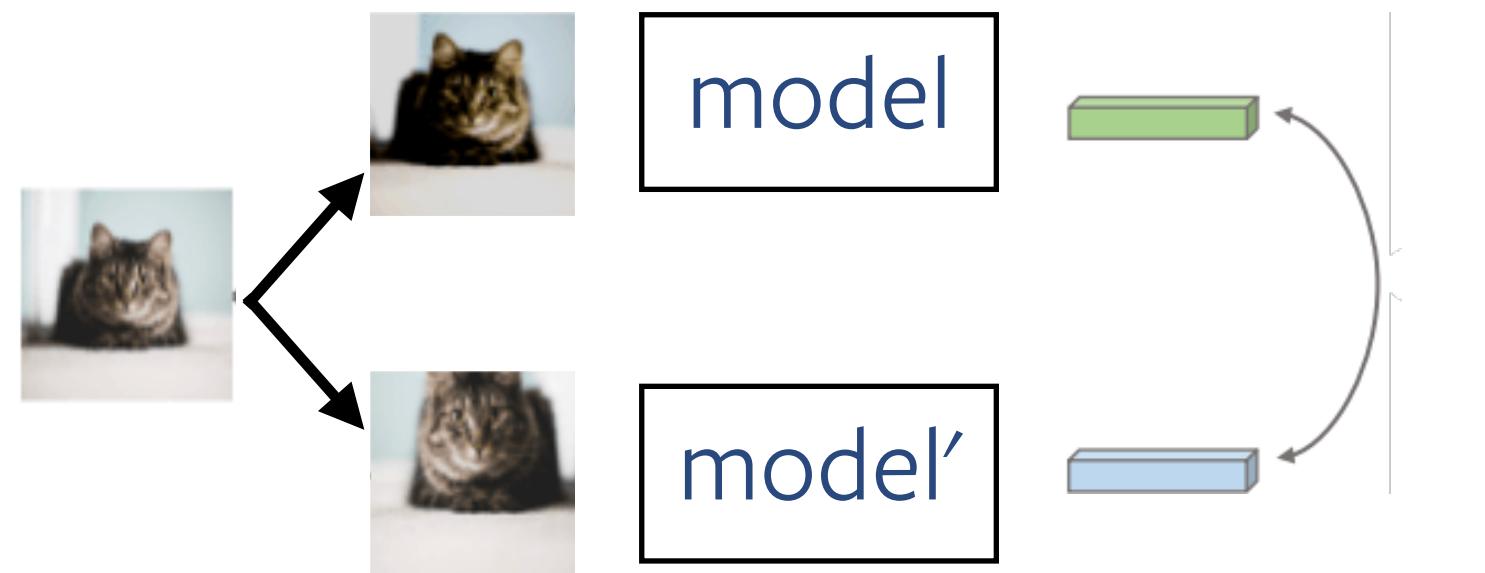
LEARNING IMAGE ENCODERS FROM TIME



Piet Mondrian, paintings 1910, 1911, 1913, 1930

Augmentations are crucial in classic image-SSL, but forcing frames to be invariant is limiting

Images: SimCLR, MoCo, SwaAV et al.

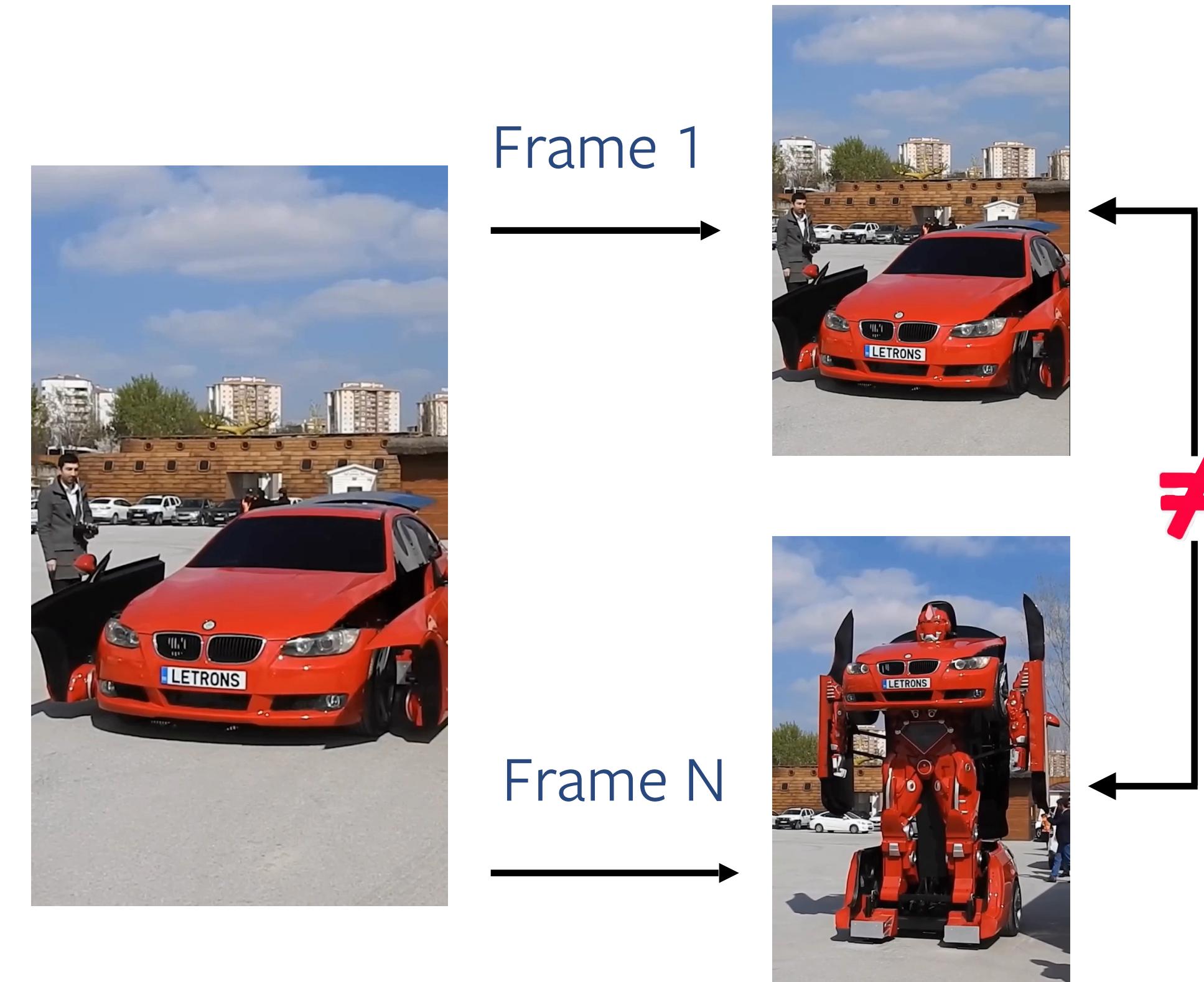


key principle: view-invariance

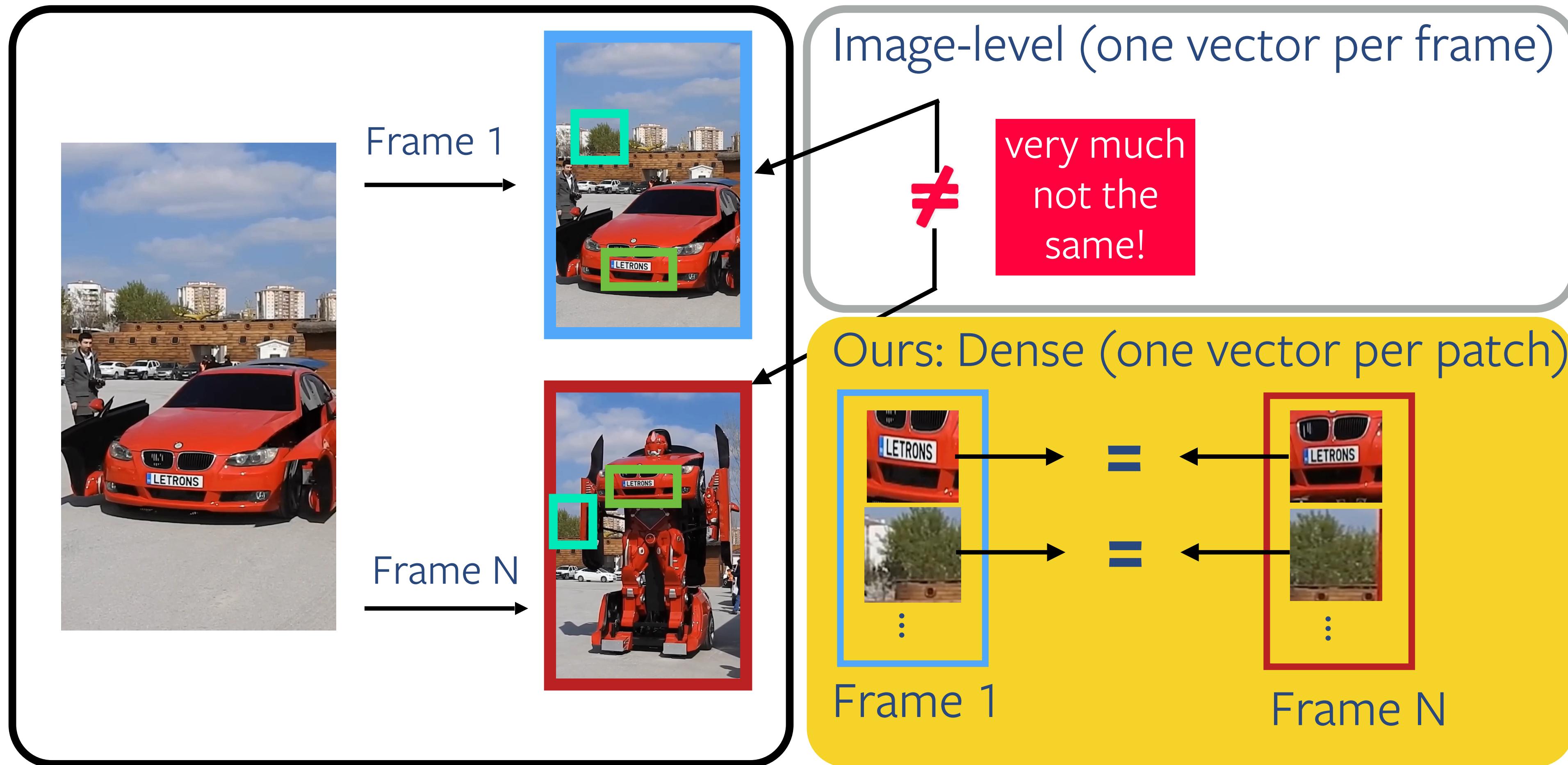
Might be ok for videos like this:



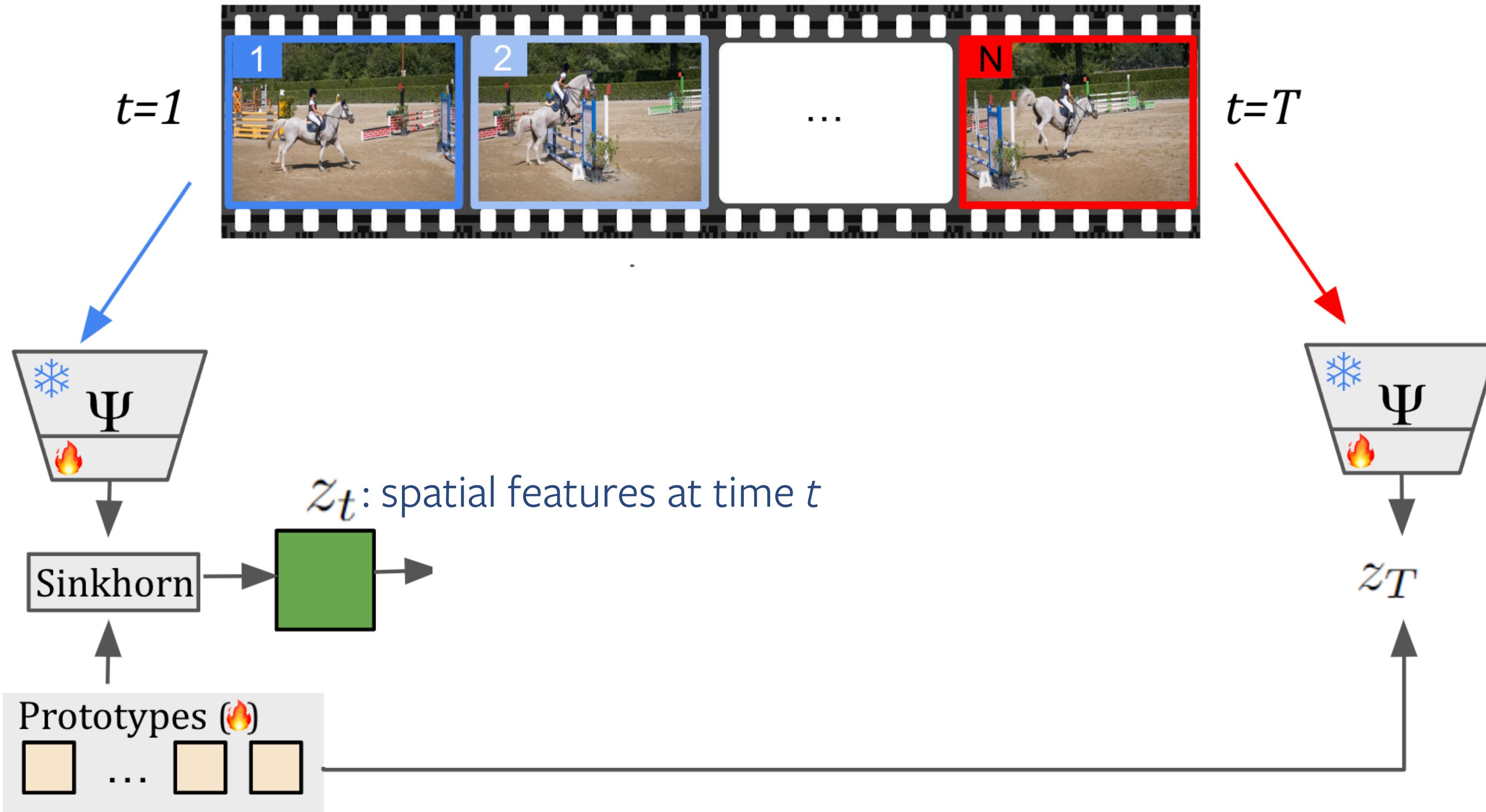
But does this generally make sense?



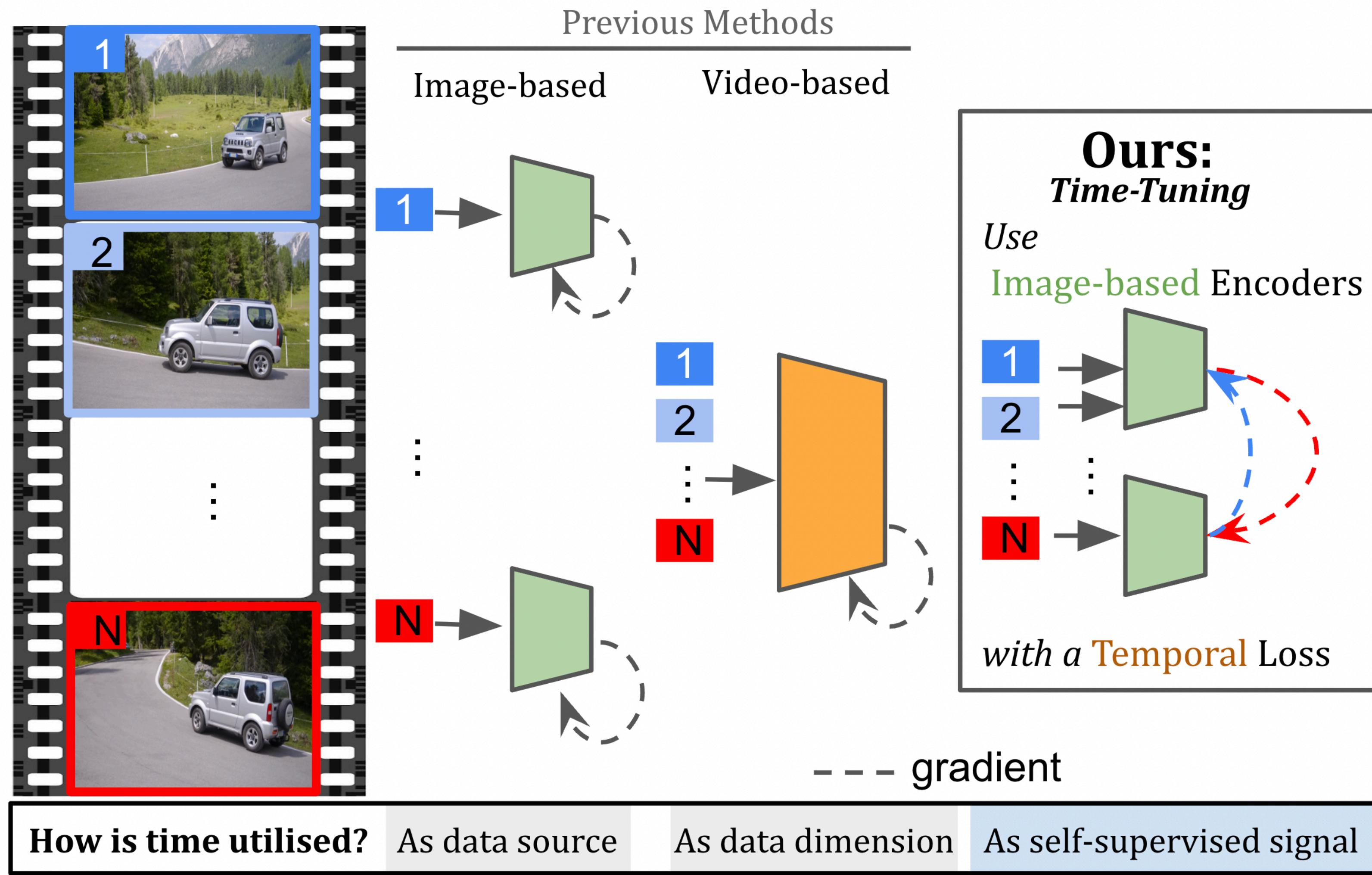
Solution is obvious



We model a video by tracking image patches,
and aligning their clustered features

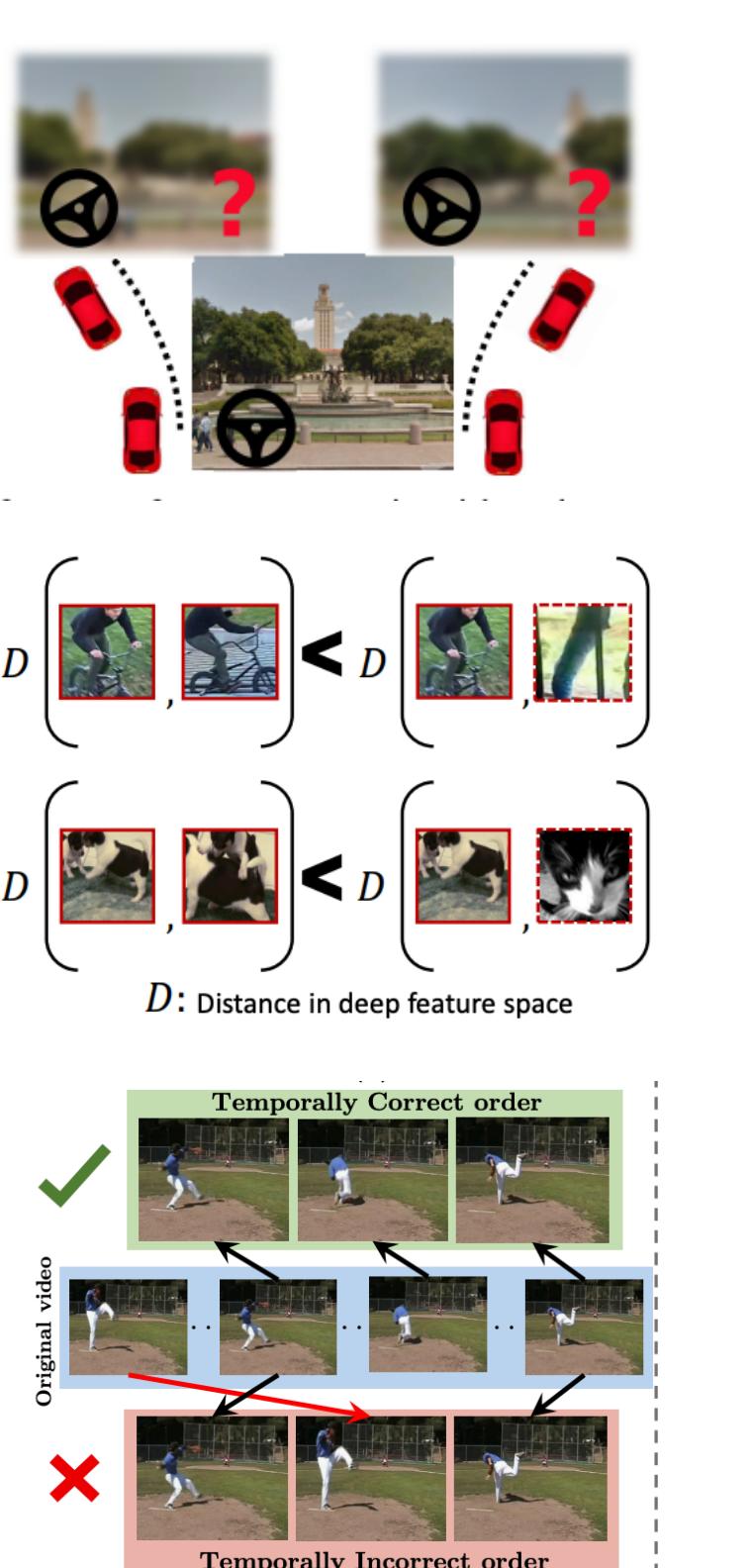


Using videos to learn self-supervised image encoders



This field has a rich history. And now it's time to get back to it

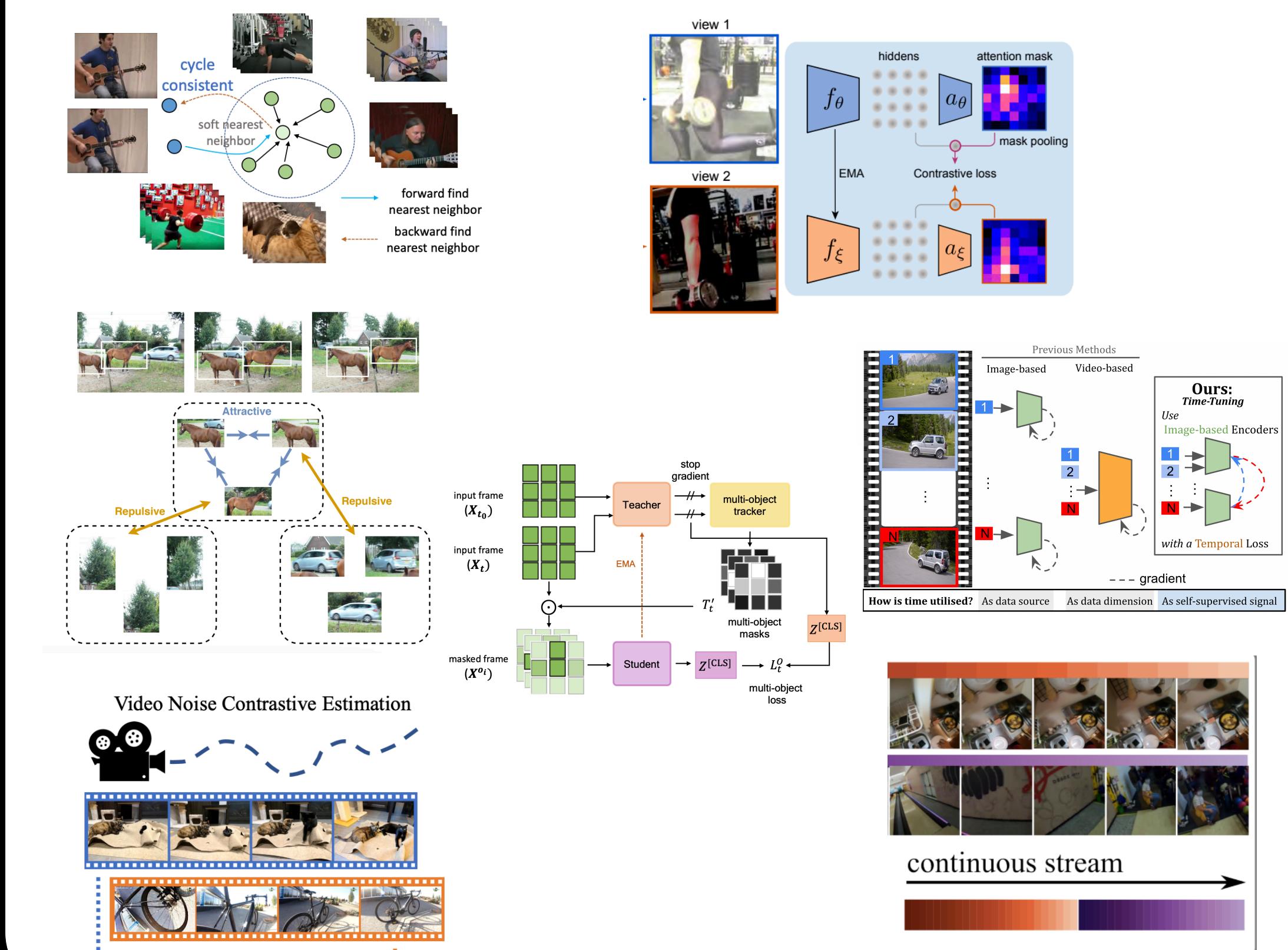
2015-2019



Some references:

- 2002 Wiskott, Sejnowski. Slow Feature Analysis: Unsupervised Learning of Invariances
- 2015 Agrawal, Carreira, Malik. Learning to See by Moving: predict egomotion from frames
- 2015 Wang, Gupta. Unsupervised Learning of Visual Representations using Videos
- 2015 Goroshin, Bruna, Eigen, LeCun. Unsupervised feature learning from temporal data
- 2015 Ramanathan, Tang, Mori, Fei-Fei. Learning Temporal Embeddings for Complex Video Analysis
- 2016 Gao, Jayaraman, Graumann. Object-Centric Representation Learning from Unlabeled Videos
- 2017 Wang, Kaiming, Gupta. Transitive Invariance for Self-supervised Visual Representation Learning
- 2018 Wei, Lim, Zisserman, Freeman. Learning and Using the Arrow of Time
- 2019 Jayaraman, Ebert, Efros, Levine: Time-Agnostic Prediction: Predicting Predictable Video Frames
- 2019 Mahendran, Thewlis, Vedaldi. focus on motion: cross-pixel flow

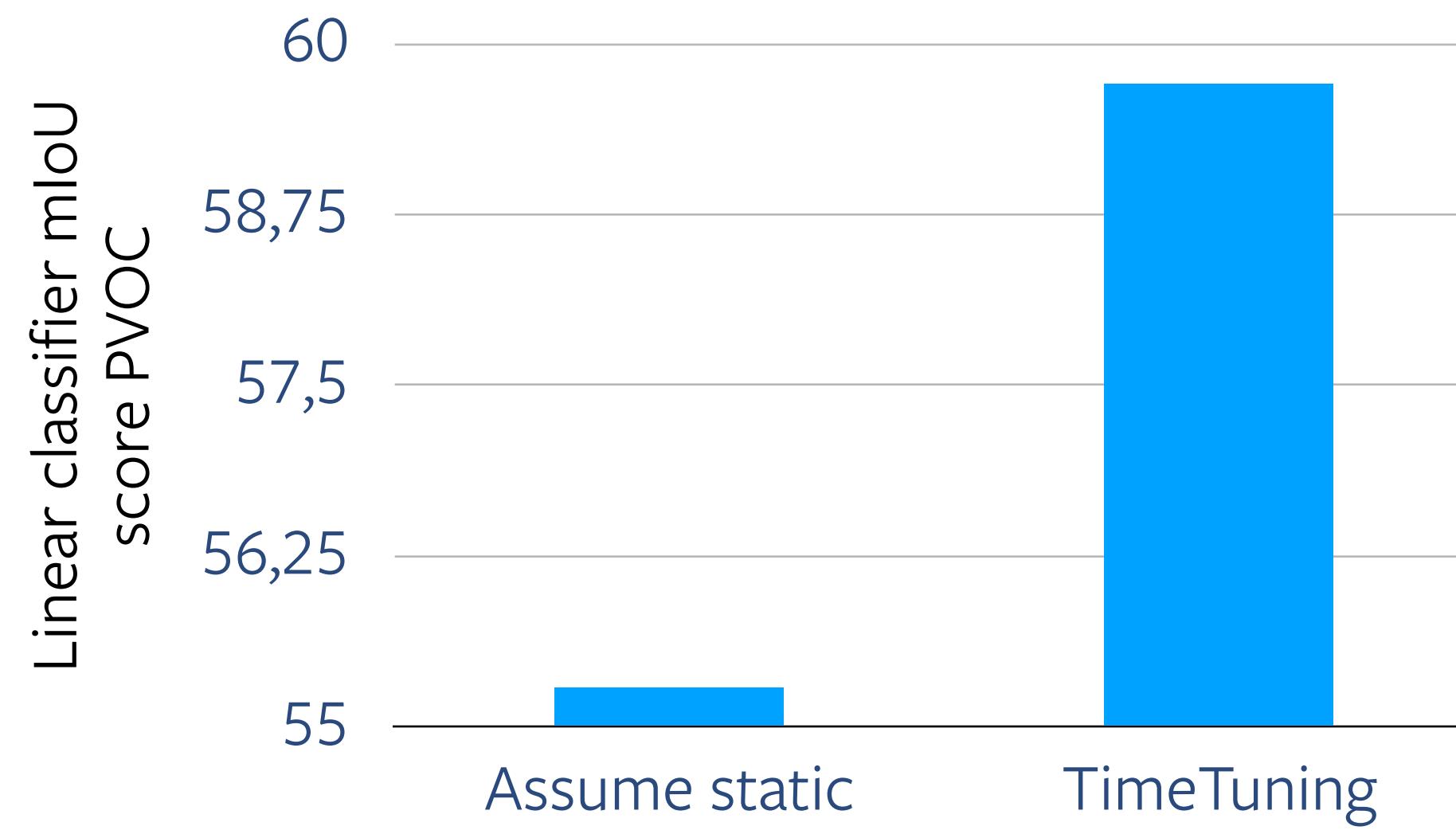
2020 onwards getting competitive to ImageNet



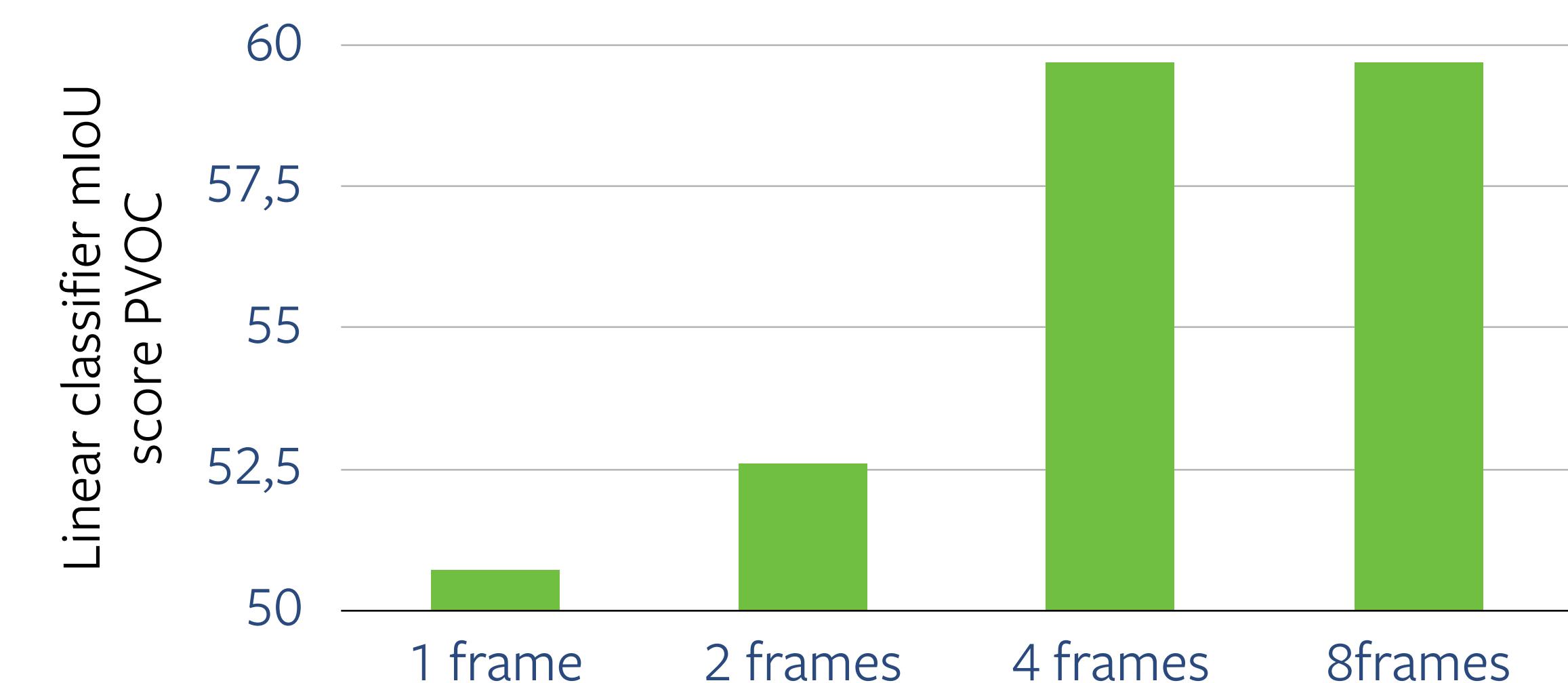
- 2020 Tschannen, Djolonga, Ritter, Mahendran, Zhai, Houlsby, Gelly, Lucic. Self-Supervised Learning of Video-Induced Visual Invariances.
- 2021 Wu, Wang. Contrastive Learning of Image Representations with Cross-Video Cycle-Consistency
- 2020 Gordon, Ehsani, Fox, Farhadi. Watching the World Go By: Representation Learning from Unlabeled Videos
- 2023 Parthasarathy, Eslami, Carreira, Henaff. Self-supervised video pretraining yieldshuman-aligned visual representations
- 2023 Salehi, Gavves, Snoek, Asano. Time does tell: self-supervised time-tuning of dense image representations
- 2023 Venkataramanan, Rizve, Carreira, Avrithis*, Asano*. Is ImageNet worth 1 video? Learning strong image encoders from 1 long unlabelled video;
- 2023 Carreira et al. Learning from One Continuous Video Stream

Ablations demonstrate using time helps learn better features

Modelling time is esential



Model learns from temporal info



Unsupervised Semantic Segmentation on videos

[simply running k-means on a couple of videos' spatial features, k=10]

DINO



✗ part-centric maps

STEGO



✗ noisy maps

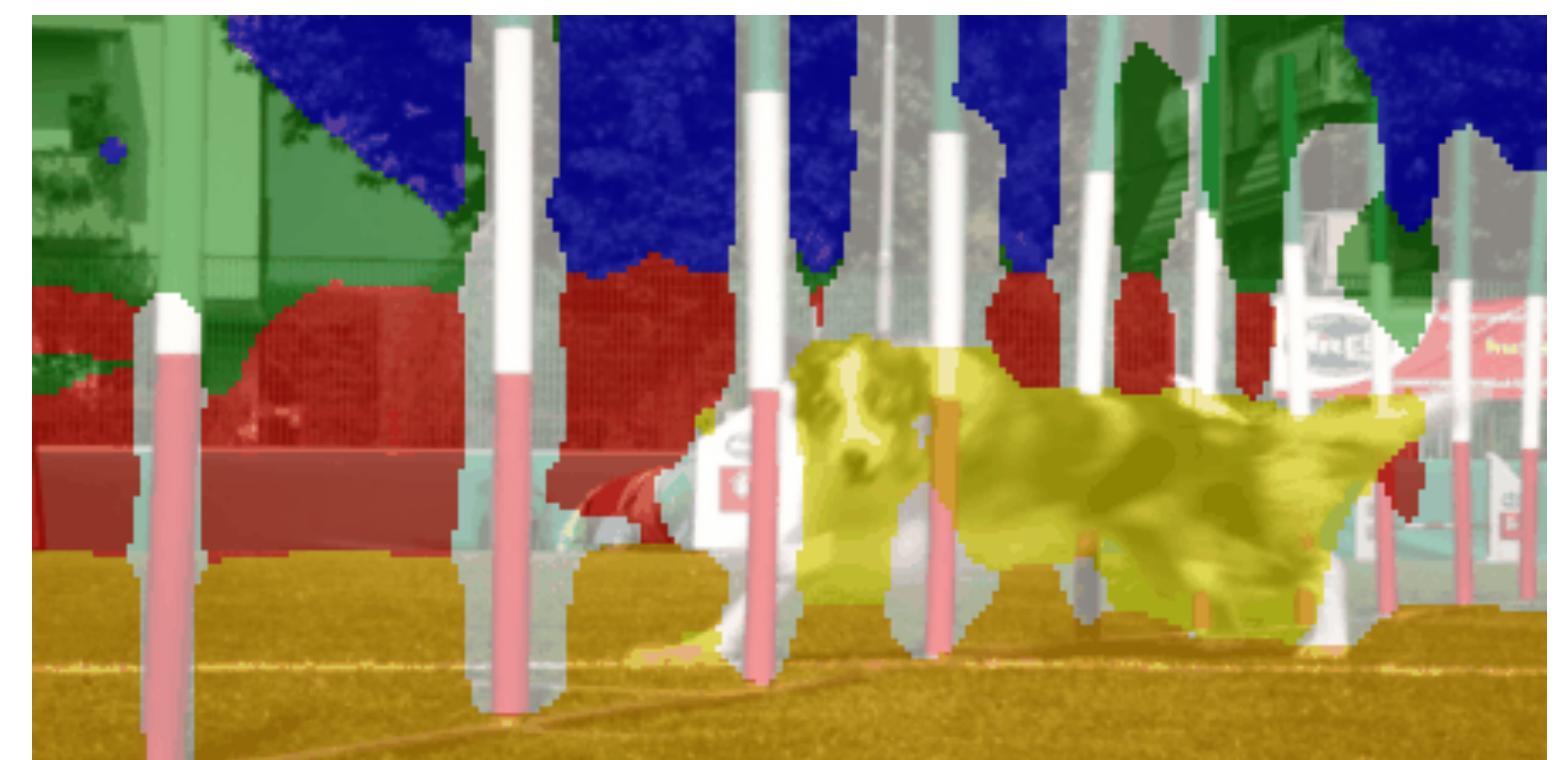
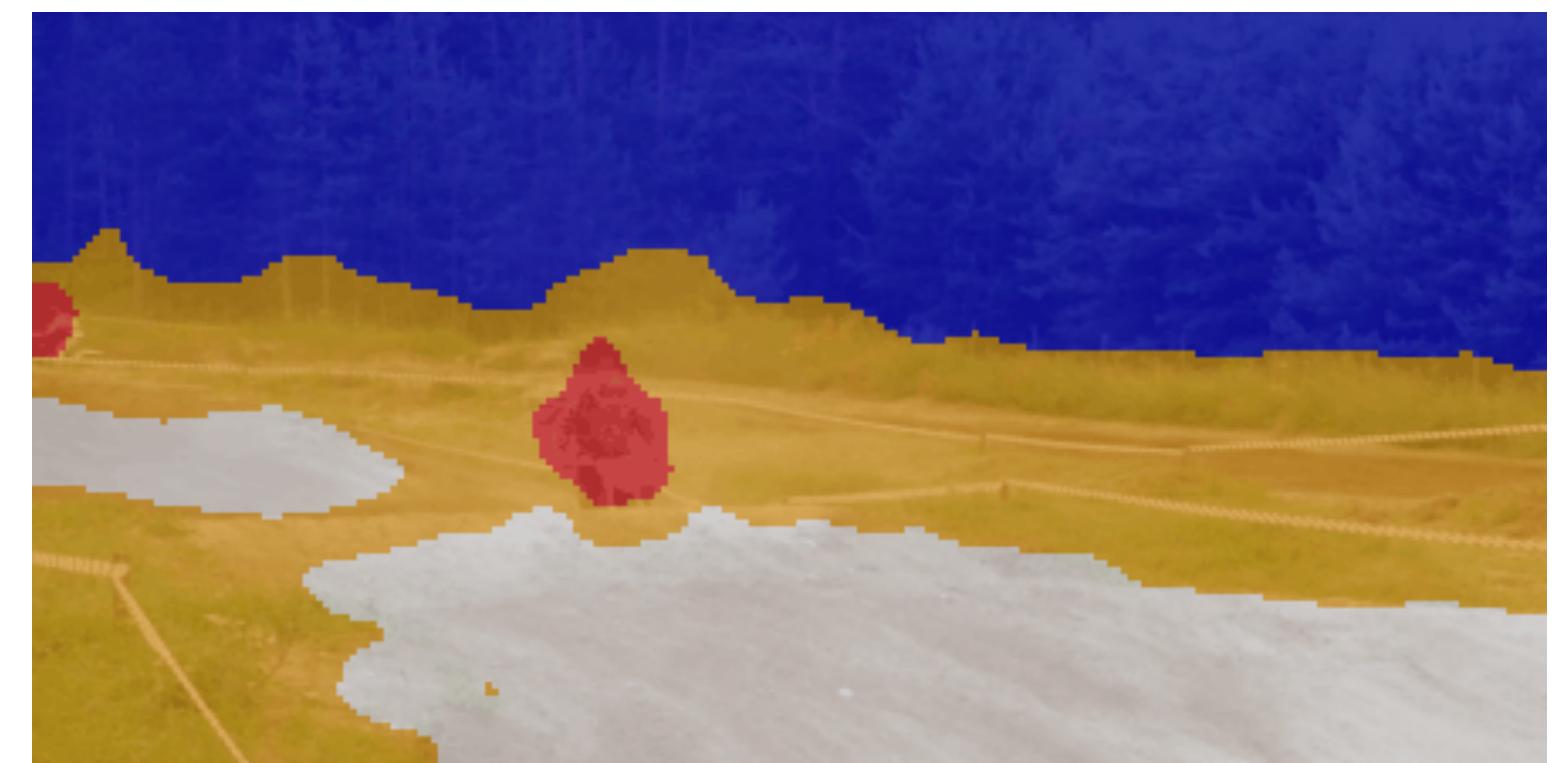
Ours



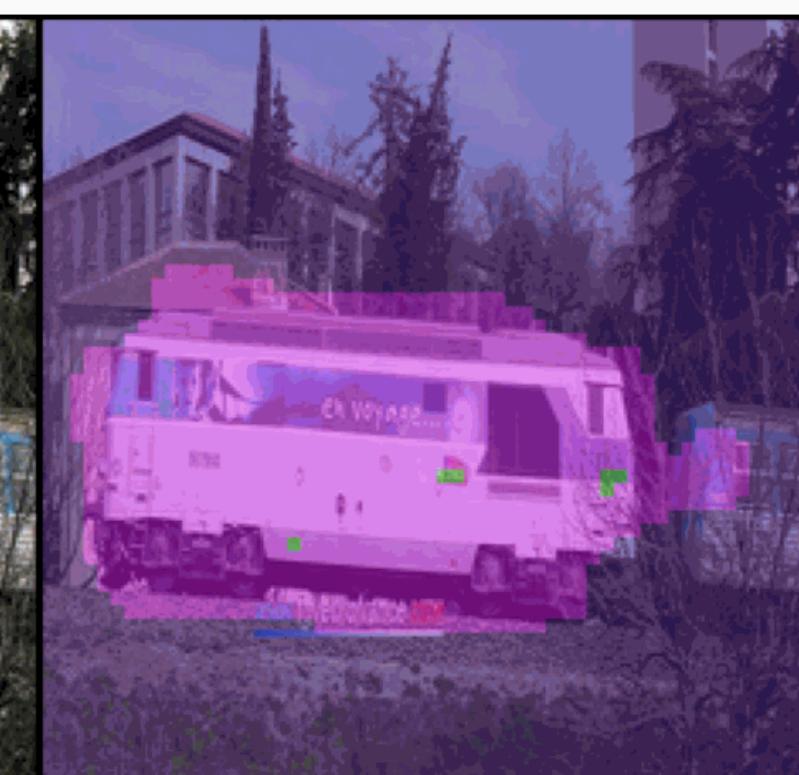
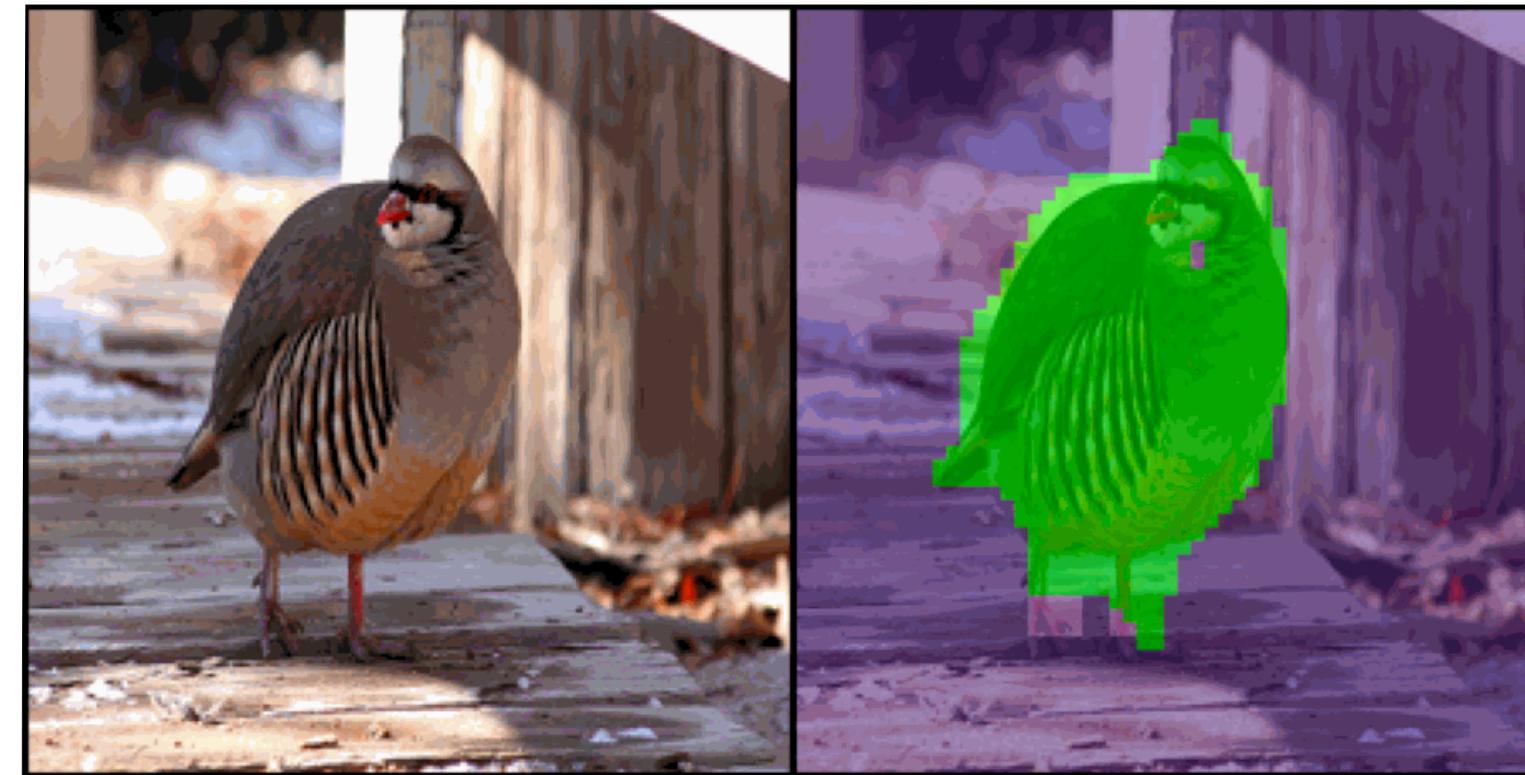
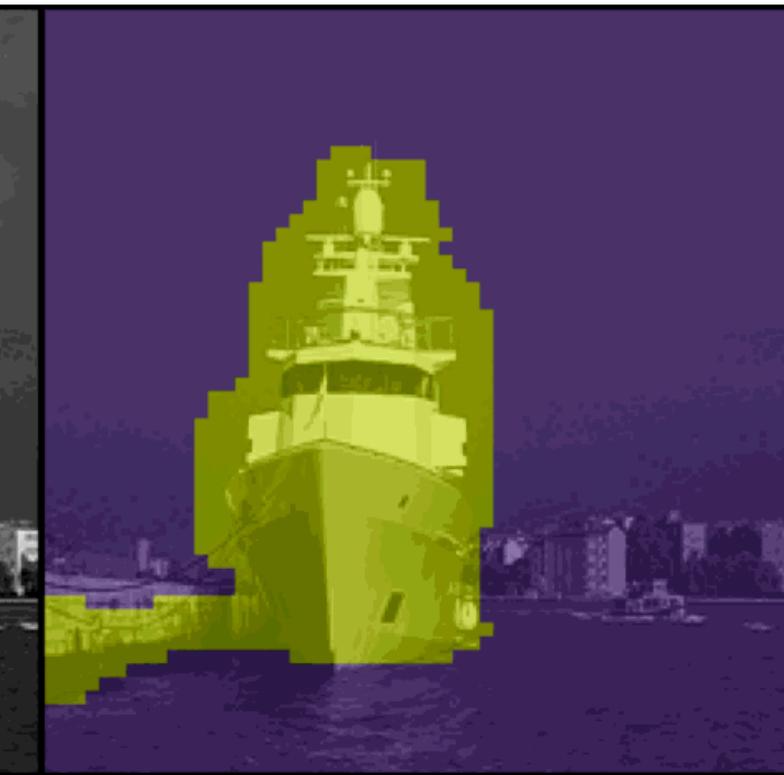
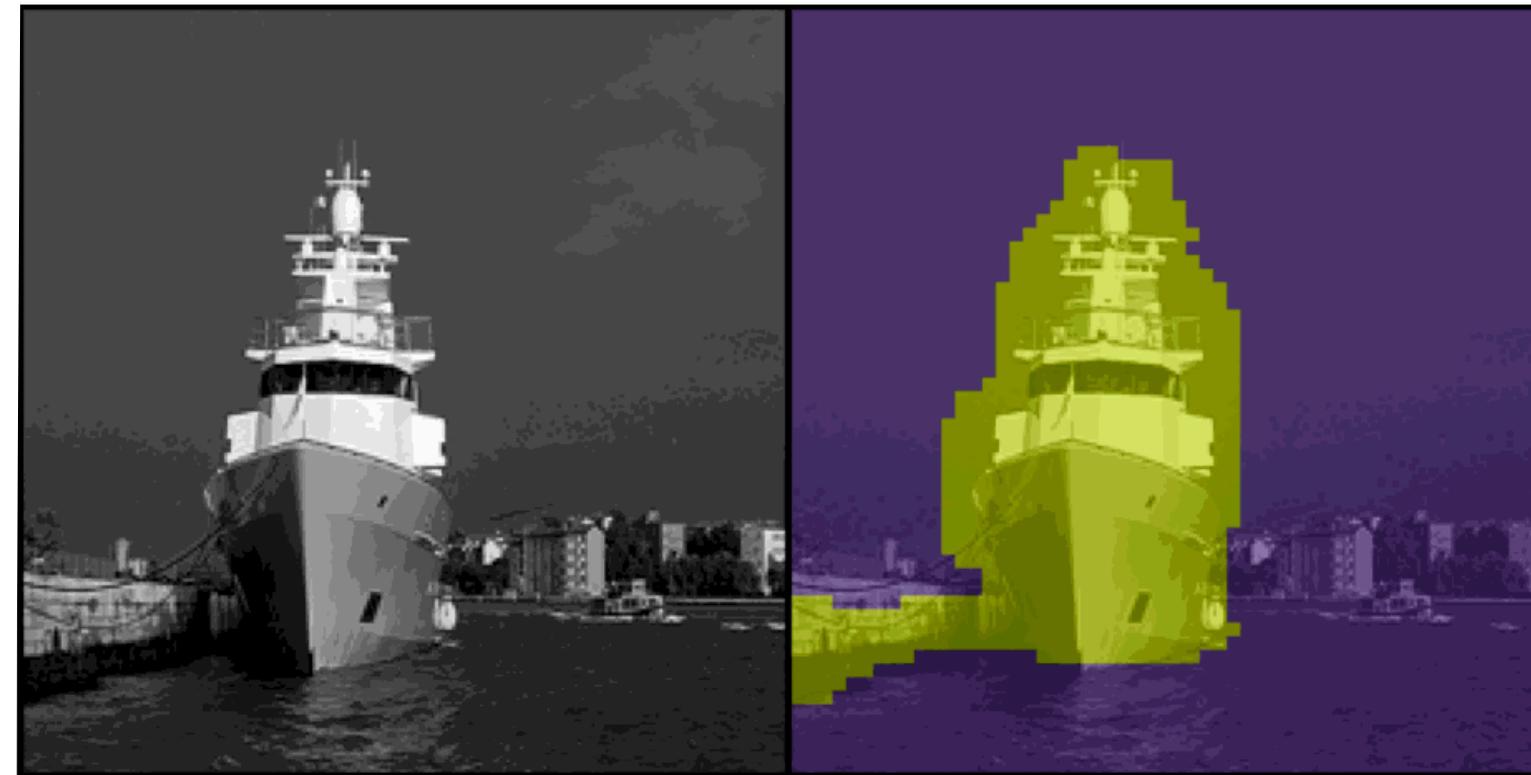
✓ crisp semantic maps

Unsupervised Semantic Segmentation on videos

[here: running k-means on the whole video's spatial features, k=5]



Also good performance on images, despite having been tuned on videos.



TimeTuning:

DINO as init & use temporal info of videos.

How powerful is time
without image-pretraining?

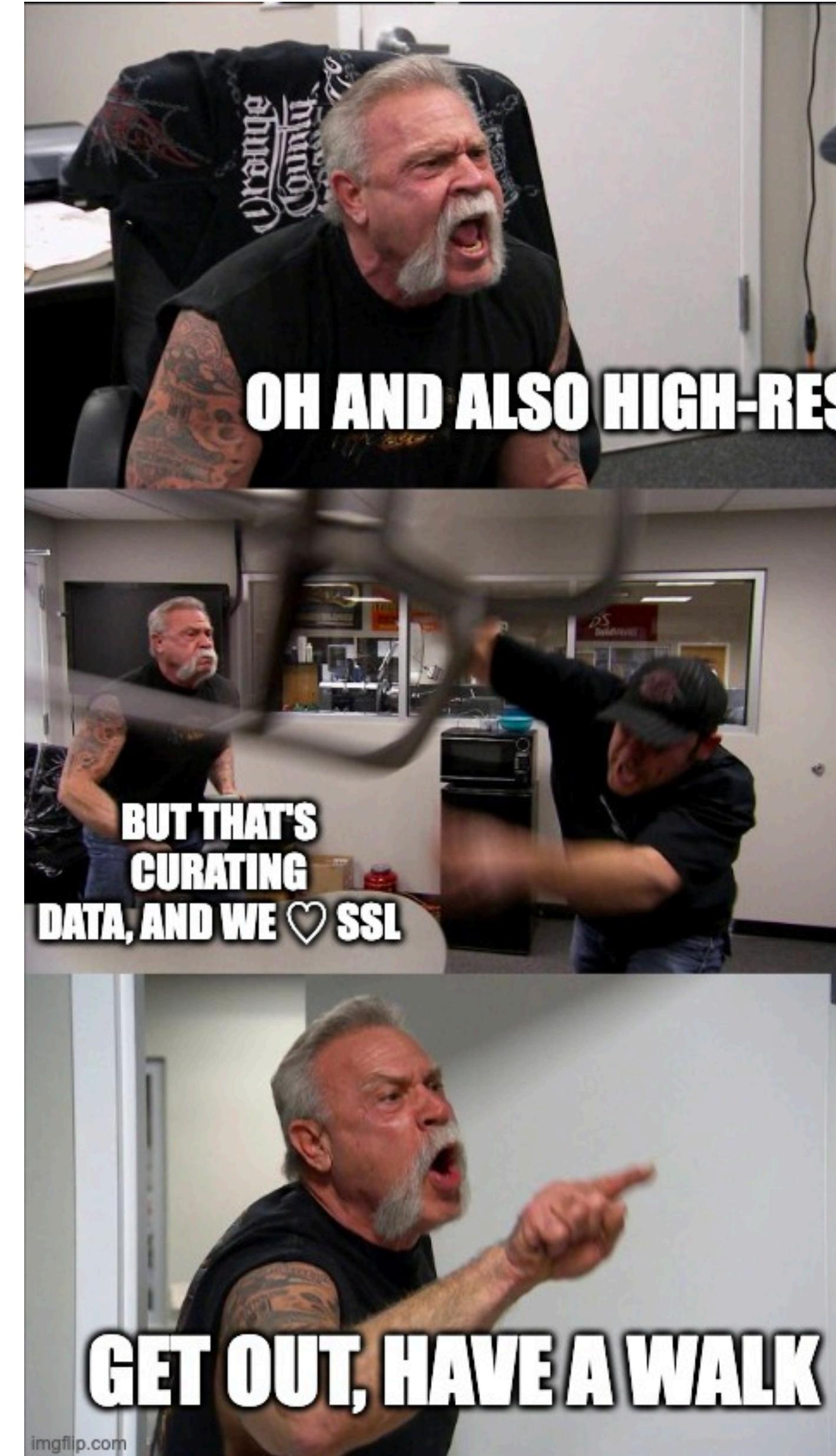
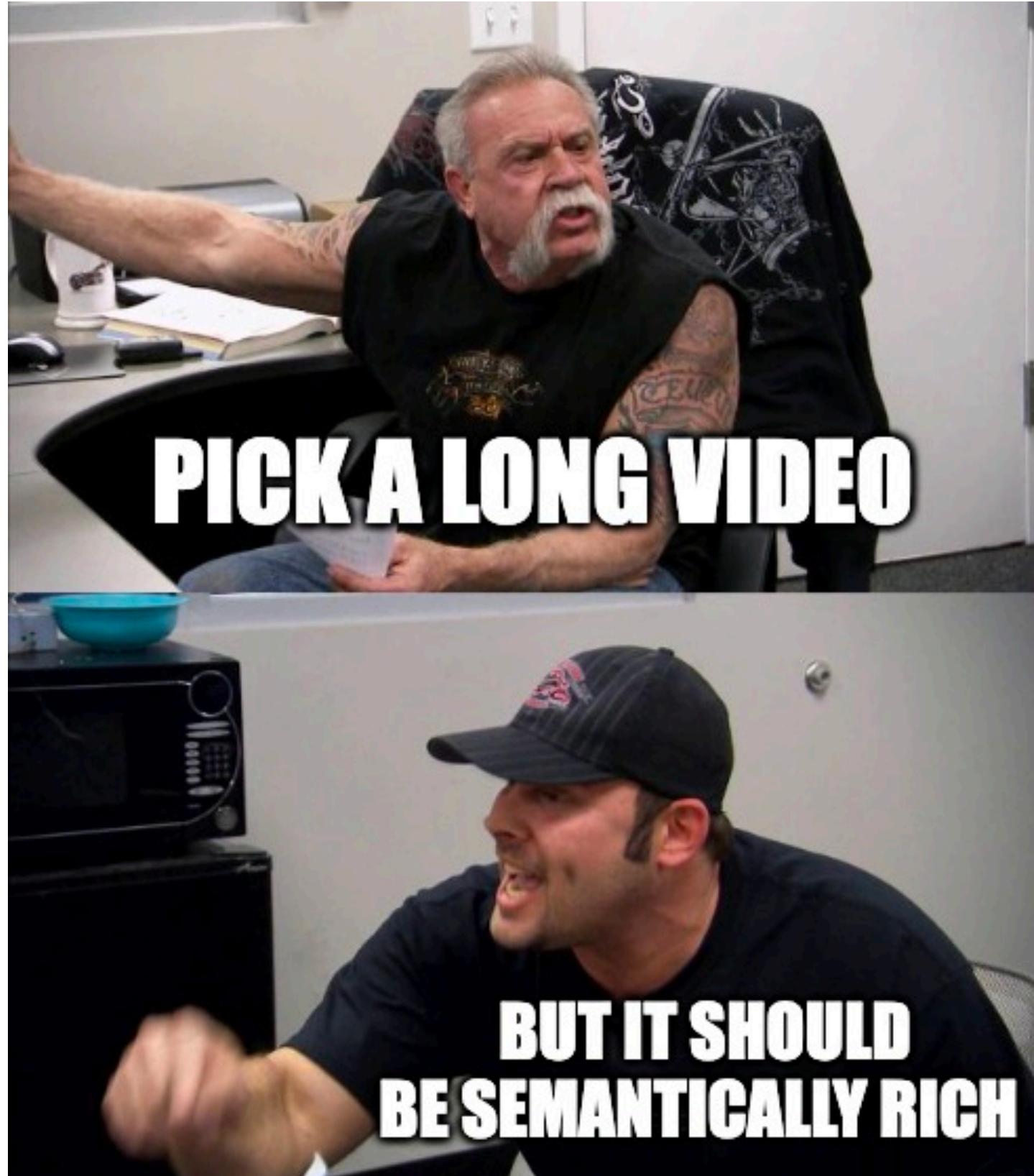
Study the extreme:
try to learn from a
single video,
from scratch.



Vermeer, The Milkmaid 1660

IS ALL WE NEED ONE
LONG VIDEO WITH
MANY DETAILS?

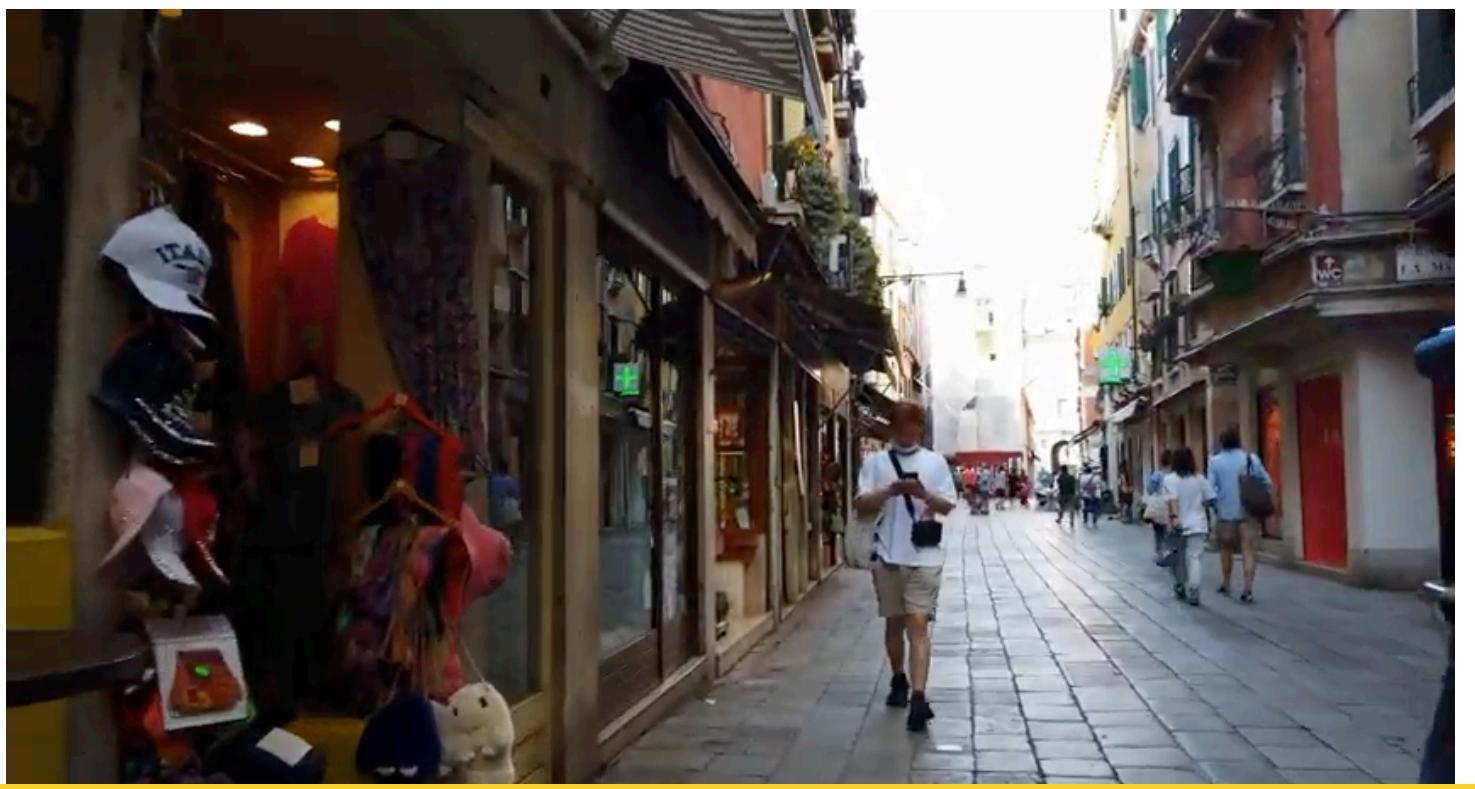
Us figuring out which video to use



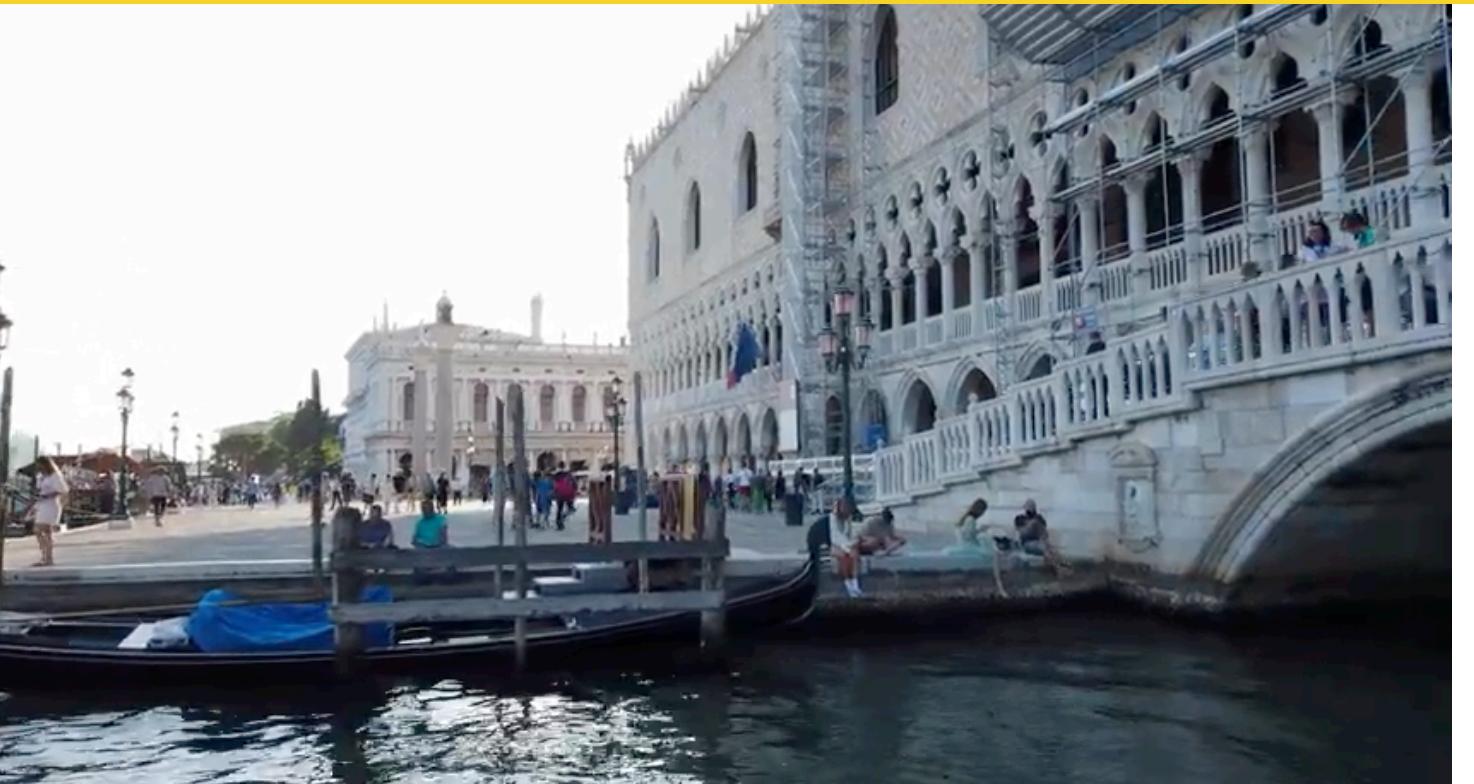
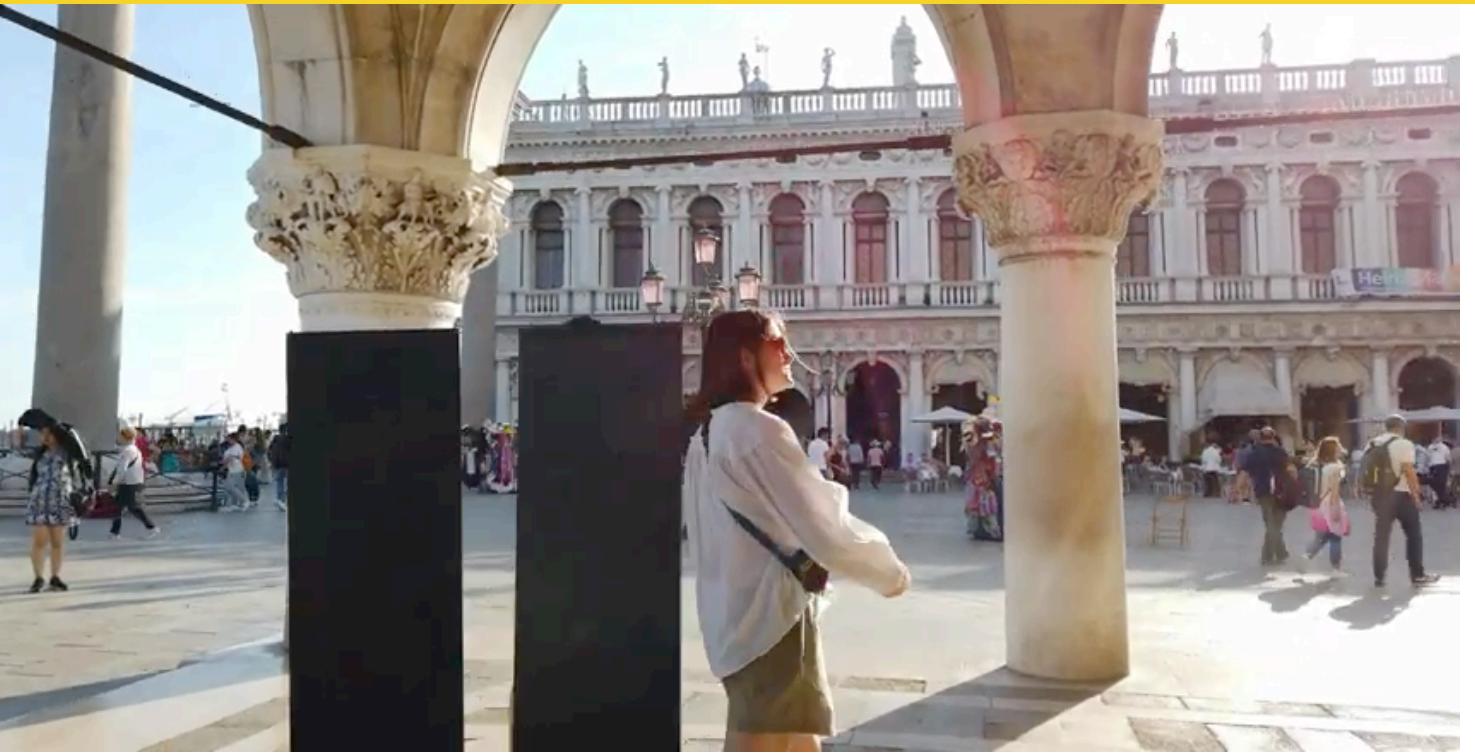
- ✓ Long
- ✓ High-res, smooth
- ✓ Semantically rich
- ✓ Scalable (we ❤ SSL)



Walking Tours



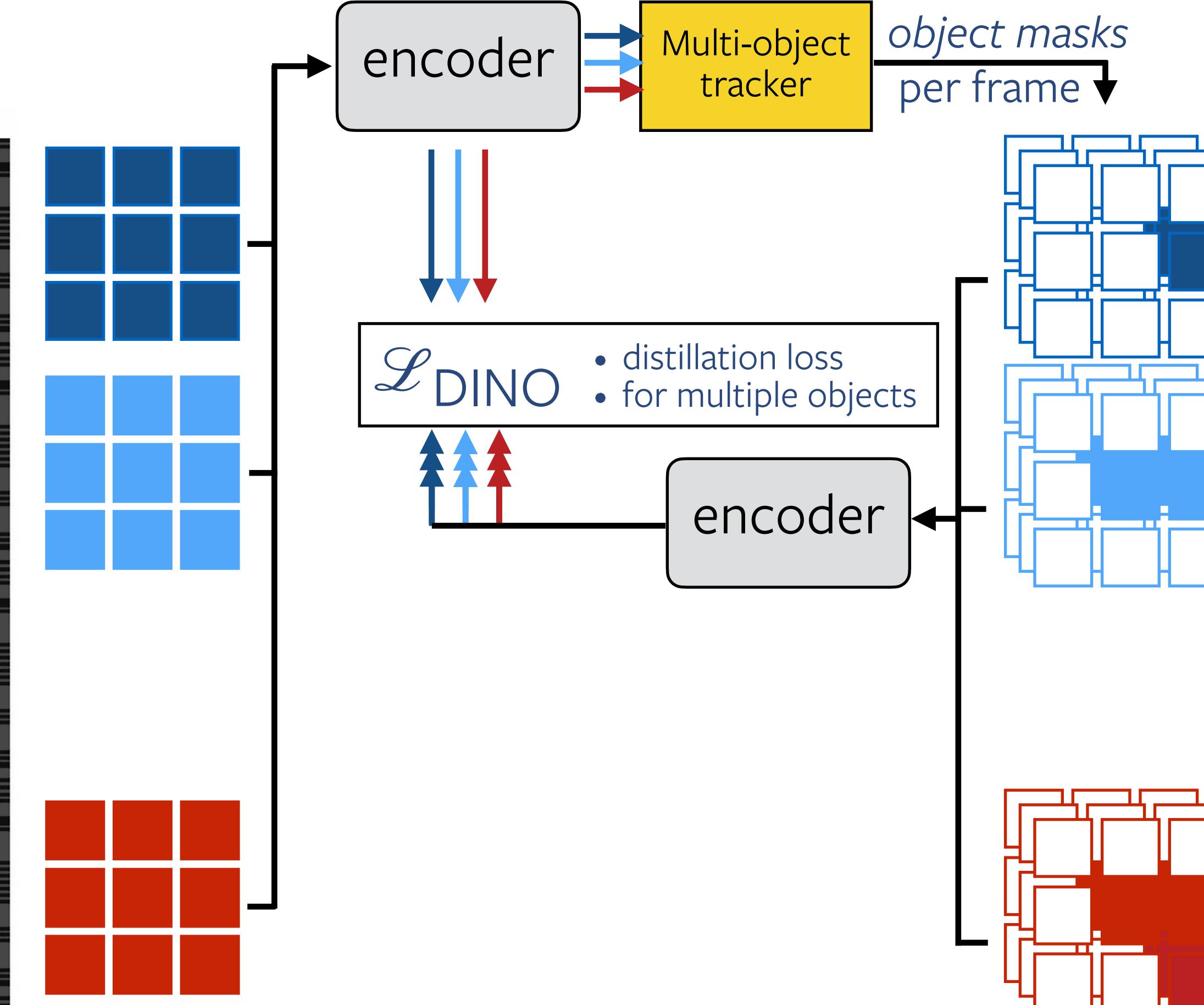
The dataset consists of 10x 4K videos of different cities' Walking Tours.



Dora: Discover and Track



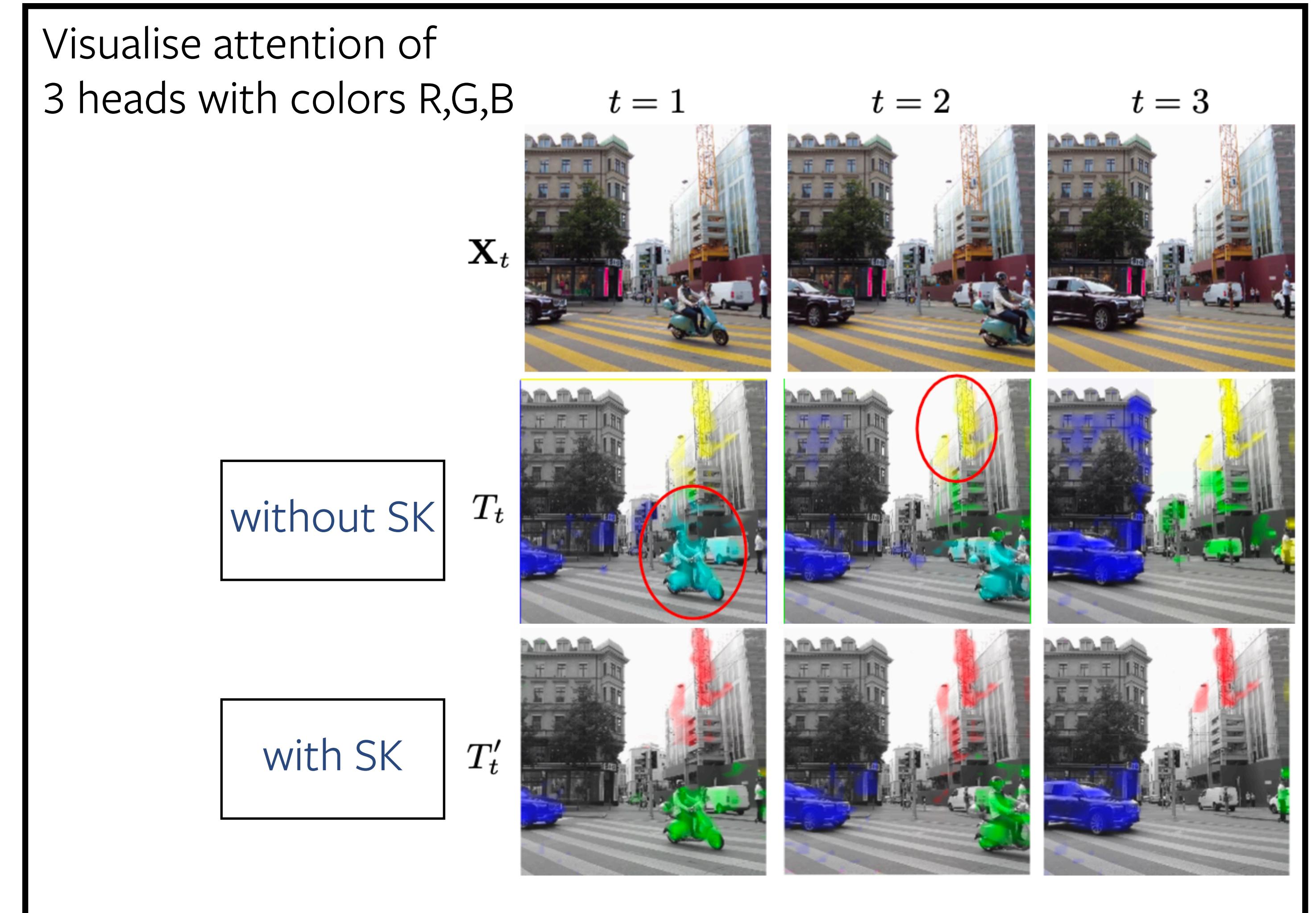
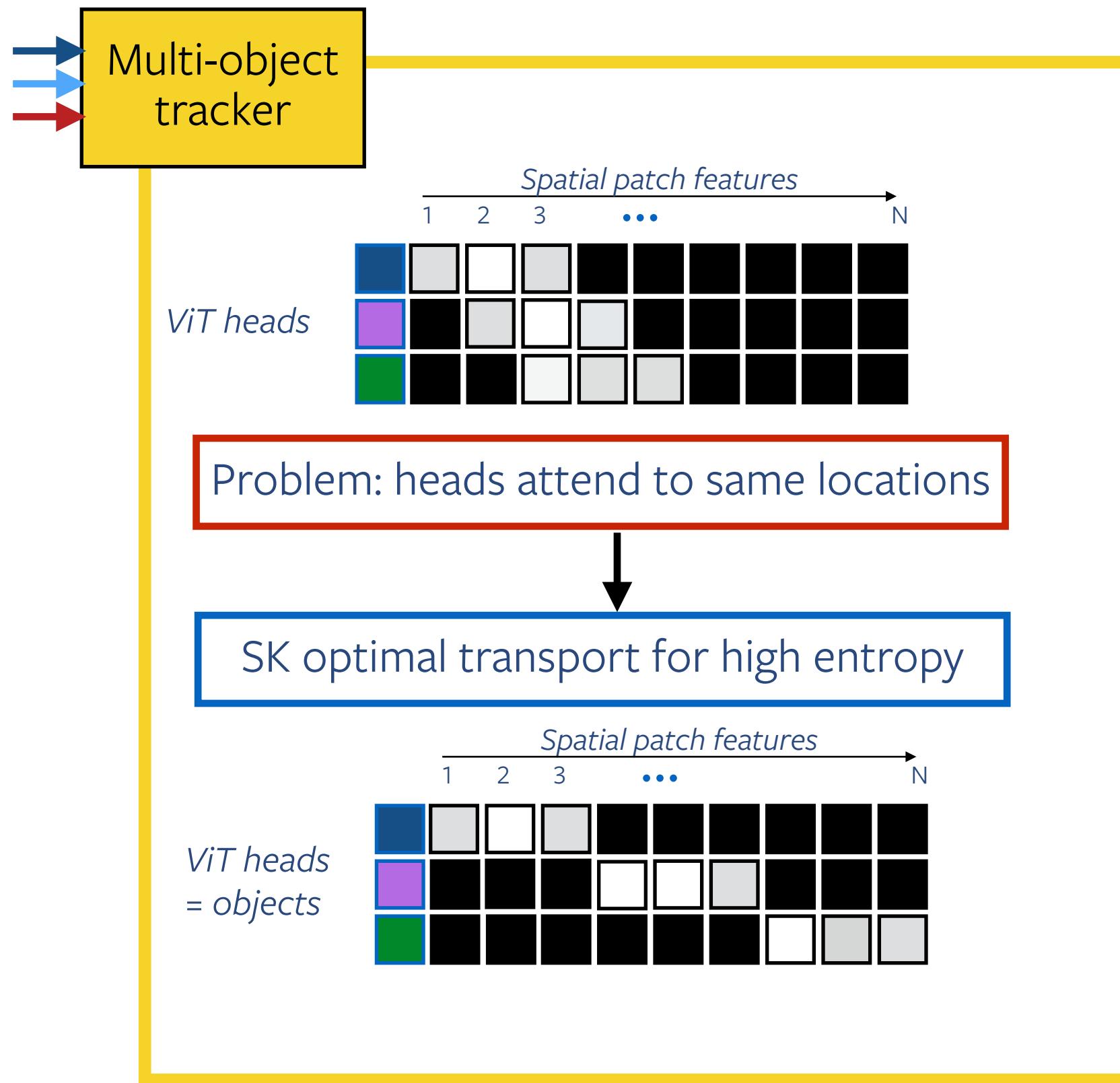
Much like Dora, we walk around and learn from what we see.



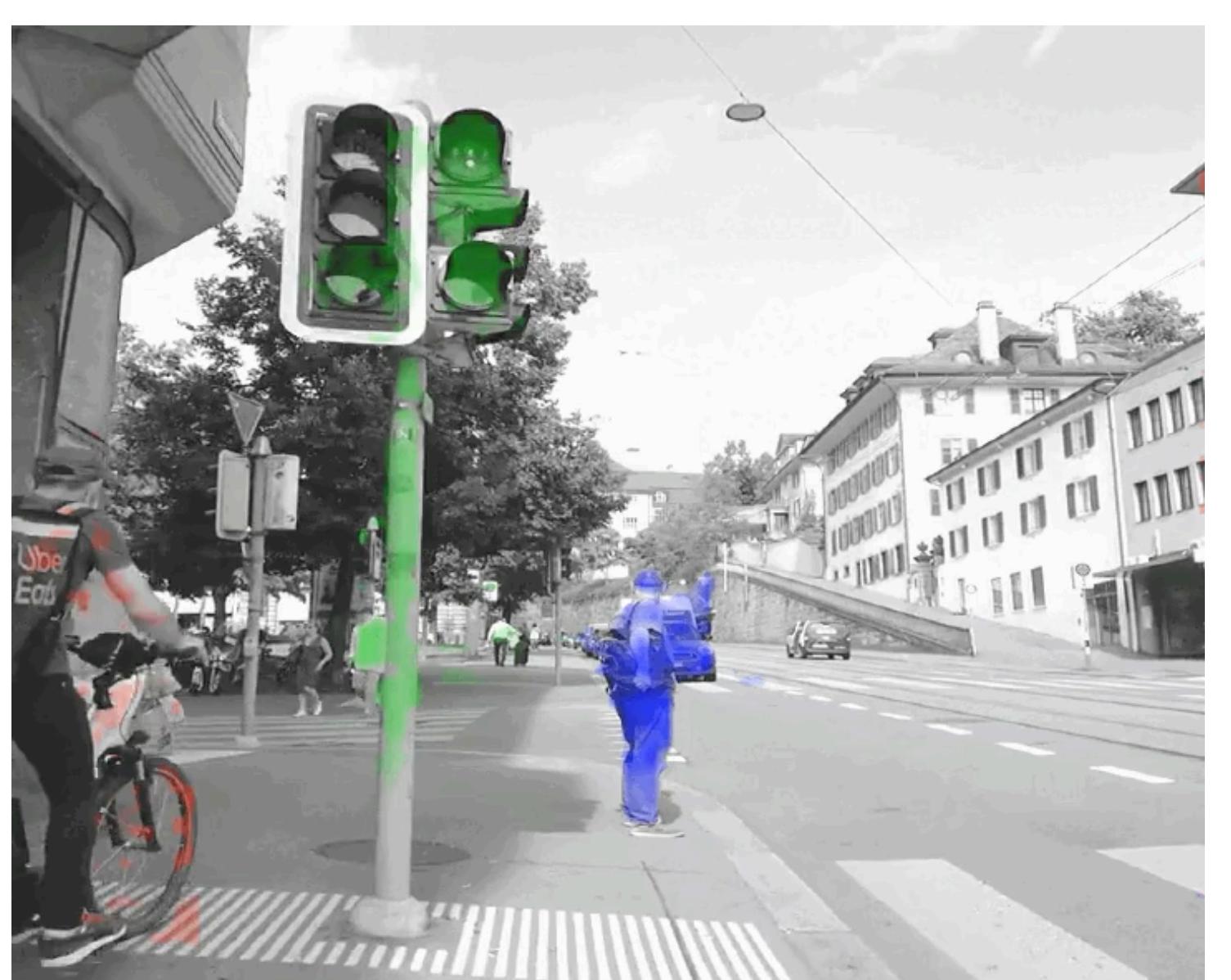
High-level idea:

- 1) track multiple objects across time
- 2) enforce invariance of features across time

Spreading attention with Sinkhorn-Knopp

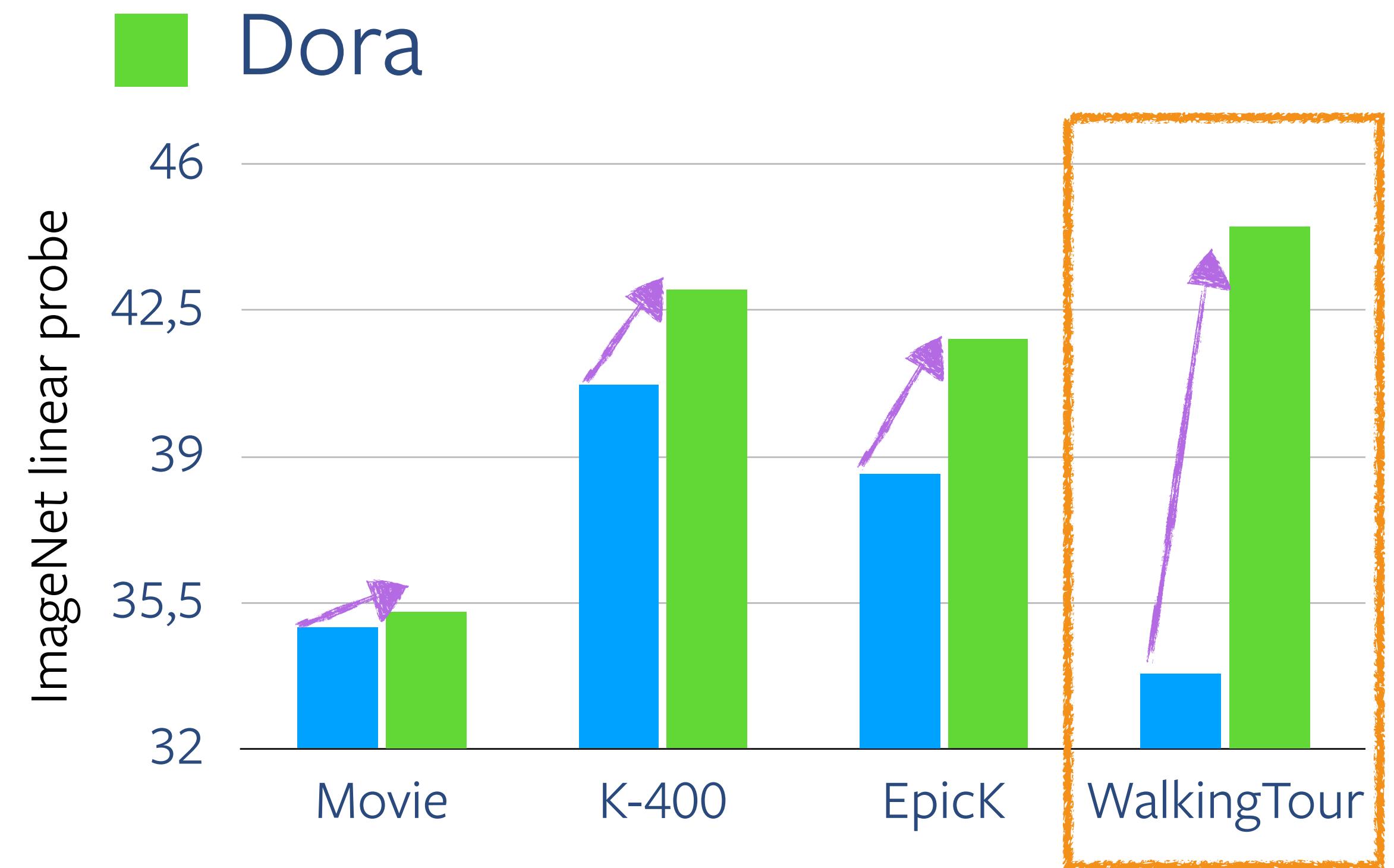
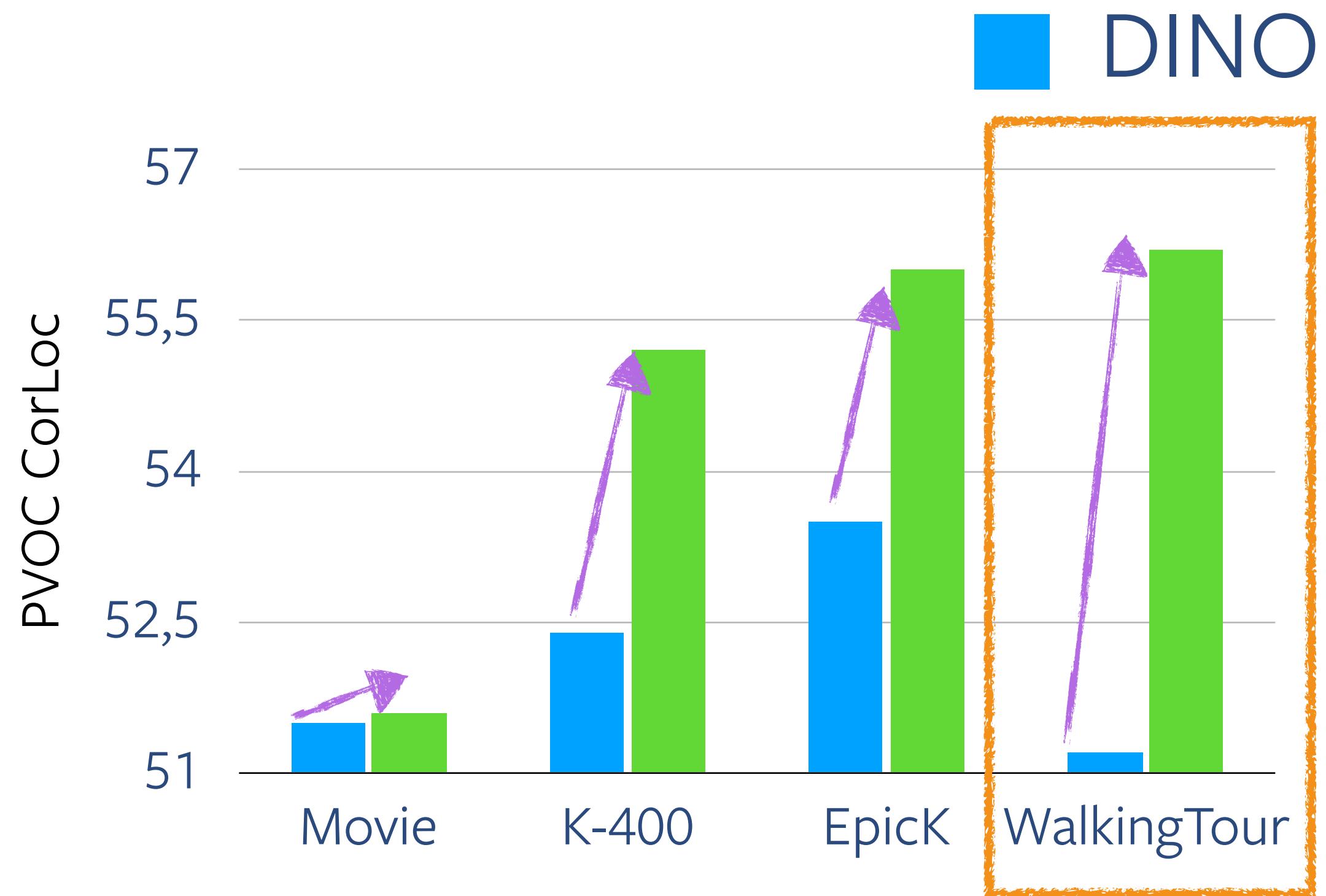


More examples: multi-object tracking in a ViT emerges



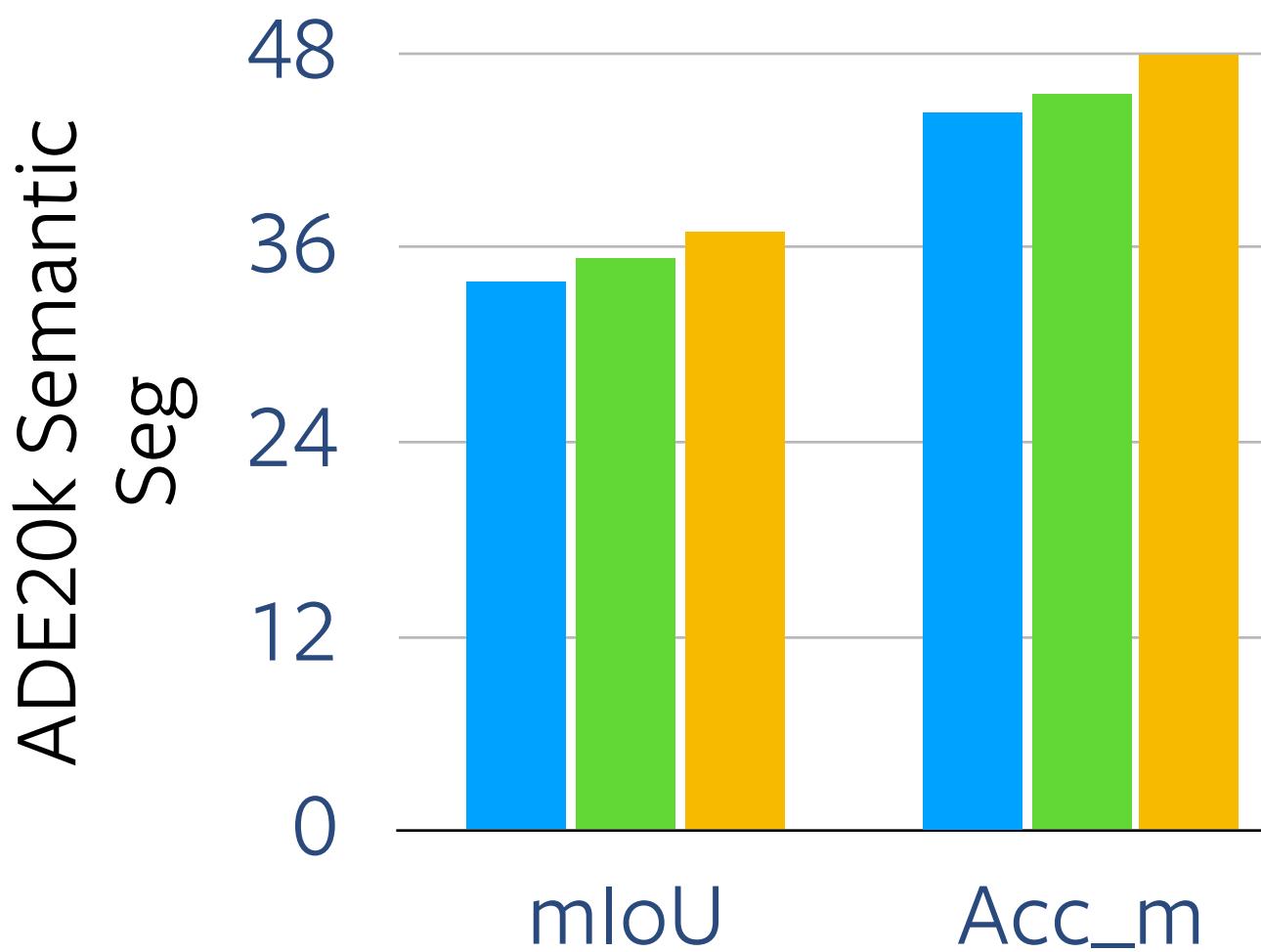
Dora better than DINO

WT+ Dora: great match

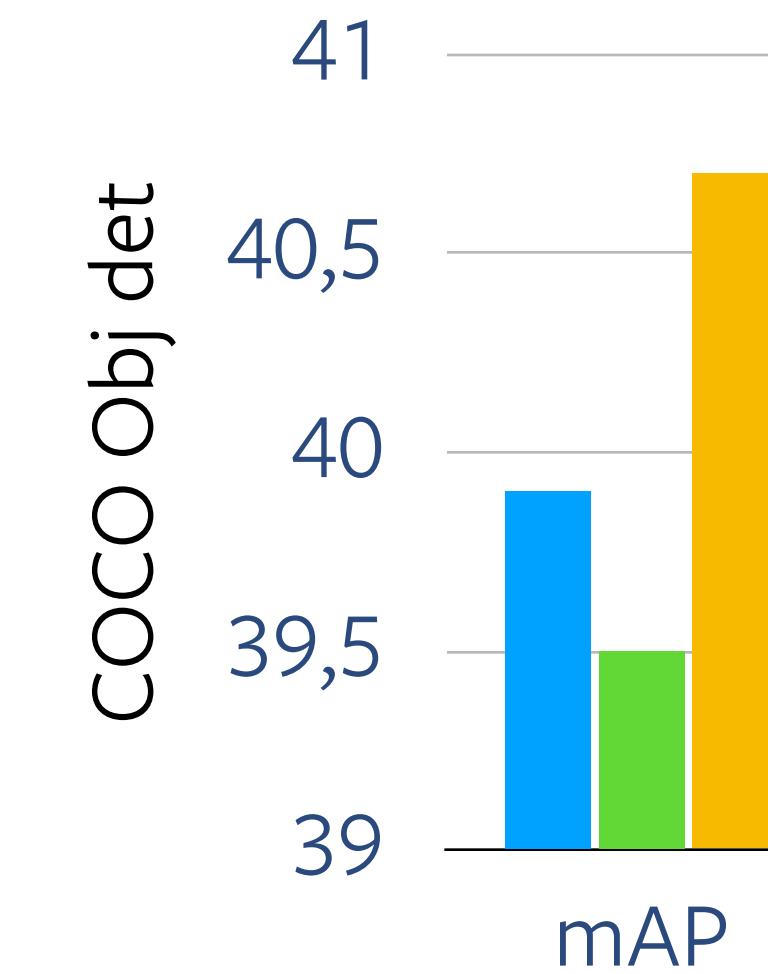


But how does it compare against ImageNet pretraining?

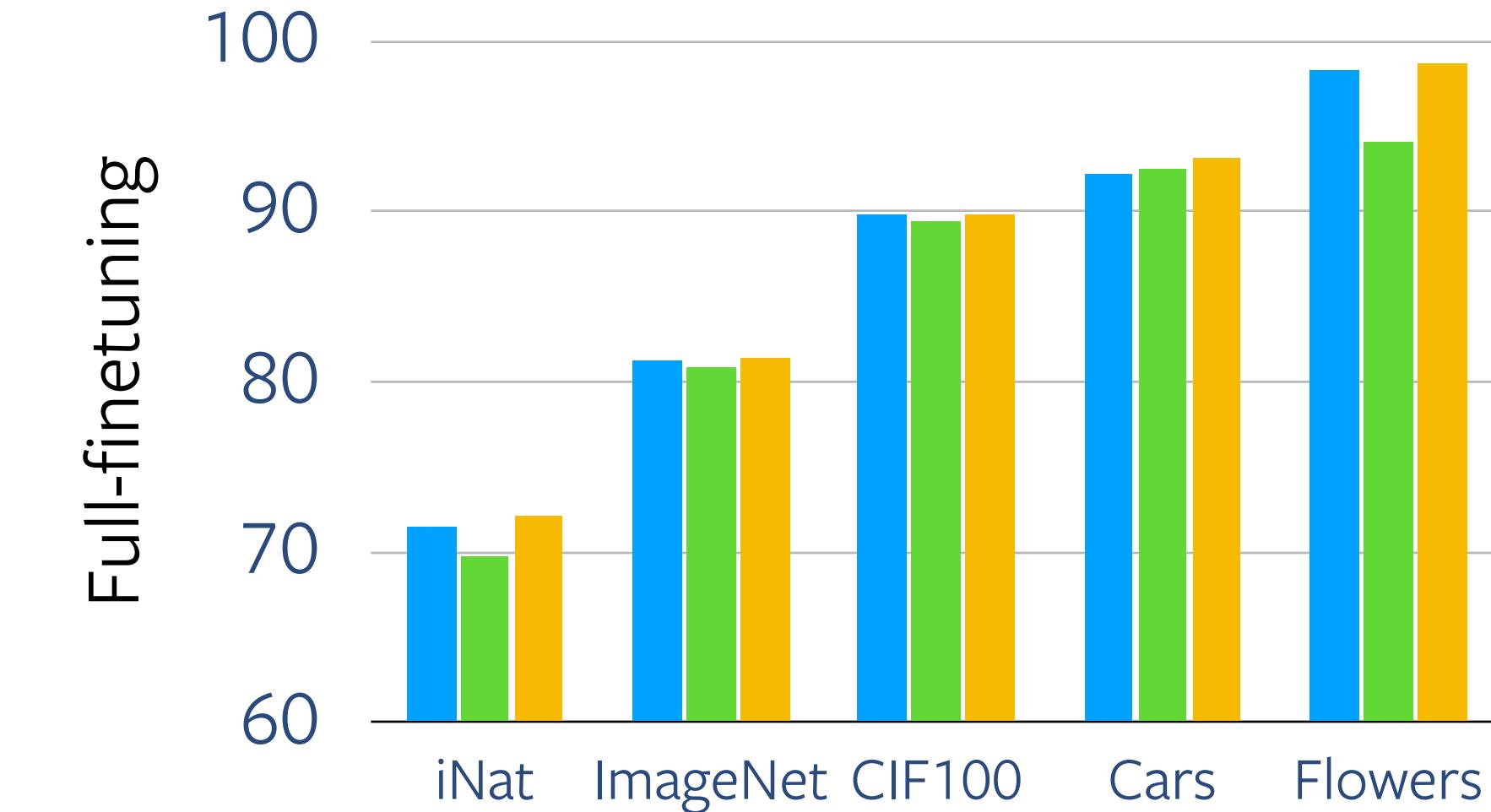
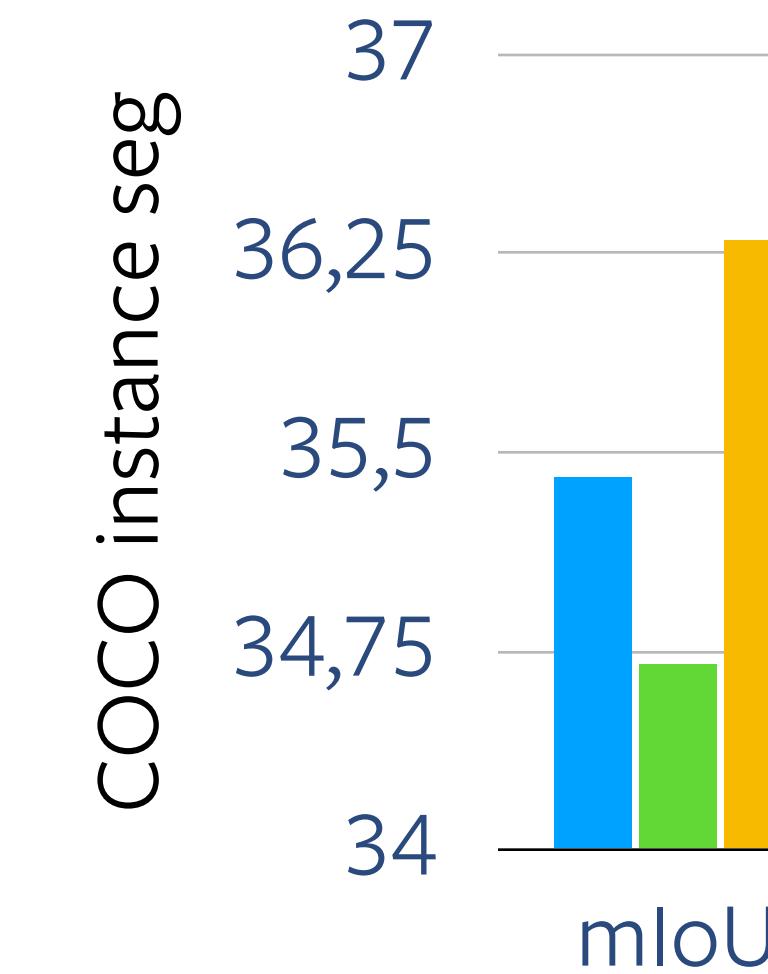
DINO (IN-1k)



Dora (1 WT)



Dora (10 WT)



Dora (1WT) ~ on par with DINO (IN-1k)
Dora (10WT) > DINO (IN-1k) everywhere

Summary

**CLUSTERING
WITH
SINKHORN-KNOPP**

[Asano et al. ICLR 2020]

**CLUSTERING
IN THE
SPATIAL DIMENSION**

[Ziegler & Asano. CVPR 2022]



**CLUSTERING
IN
SPACE AND TIME**

[Salehi et al.. ICCV 2023]

**HAVING
MULTI-OBJECT
TRACKING EMERGE**

[Vekataraman et al. Arxiv 2023]

imgflip.com



1 TimeTuning:

DINO as init & use temporal info of videos.

How powerful is time without
image-pretraining?

2 Study the extreme:
try to learn from a
single video,
from scratch.



Videos allow for strong self-supervised learning

VLMs?

Can we reduce the need for paired data?

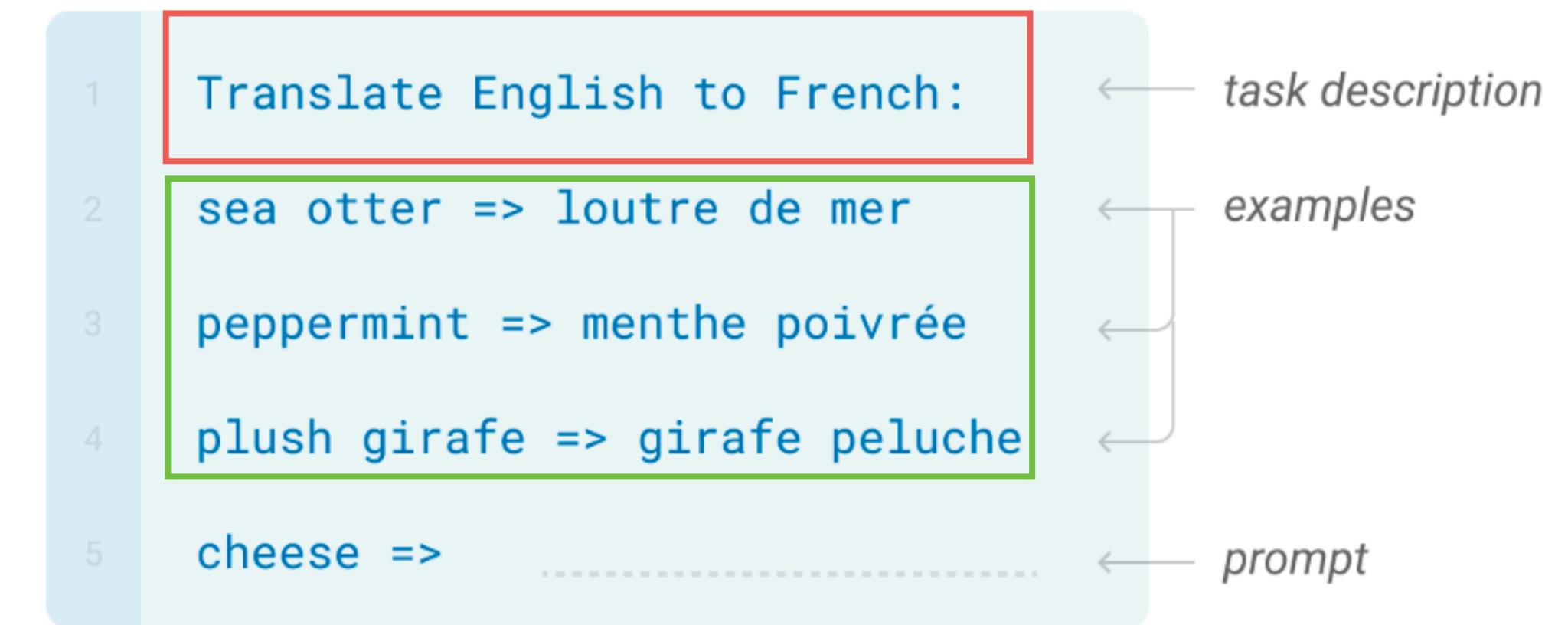
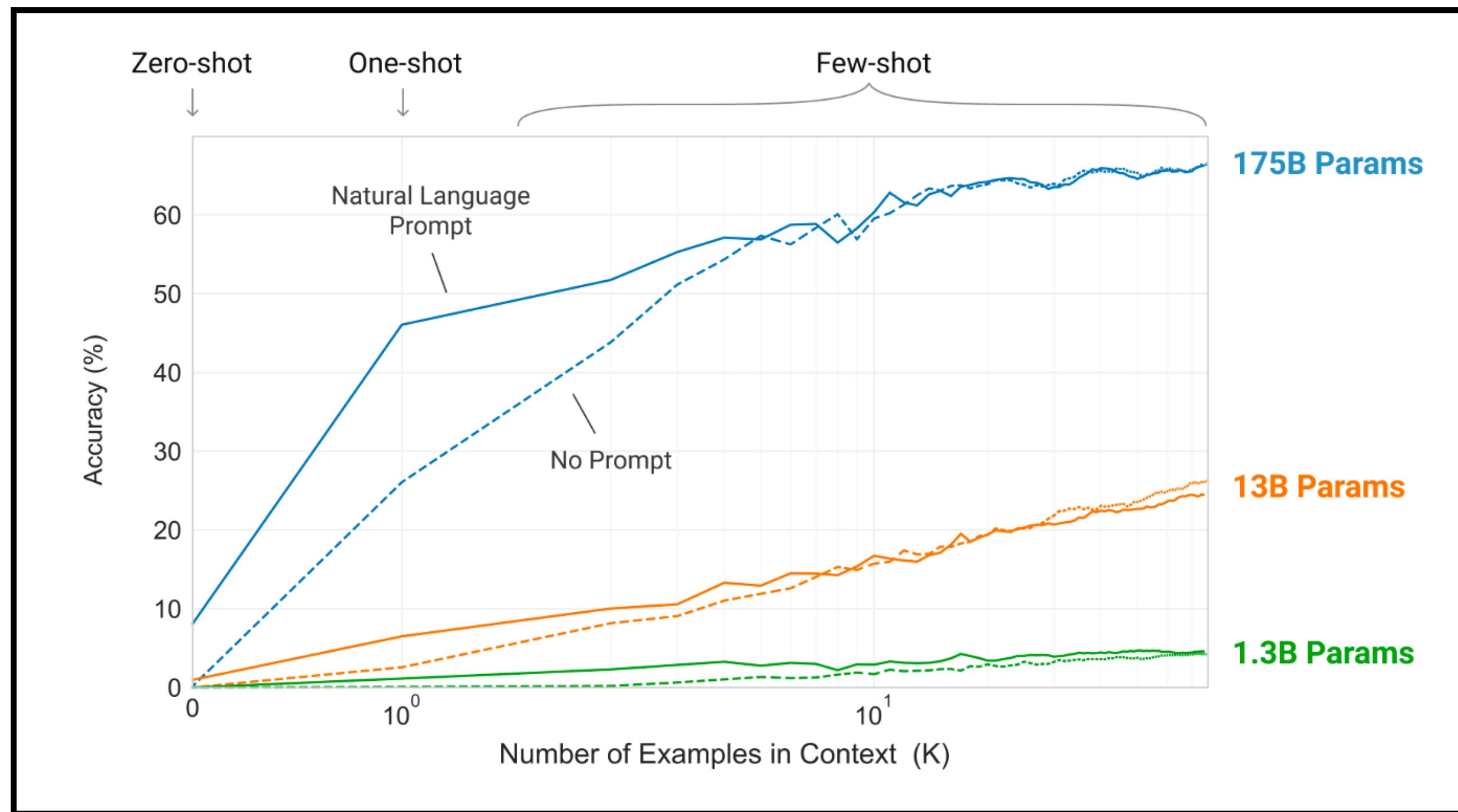
3 Use self-supervised features
to create noisily paired data.



Dirk Jacobsz, Painting a Portrait of His Wife, 1550

REDUCING THE NEED
FOR PAIRED
TEXT-IMAGE DATA

Why are LLMs so sexy? a) scaling behavior, b) In-context Learning!

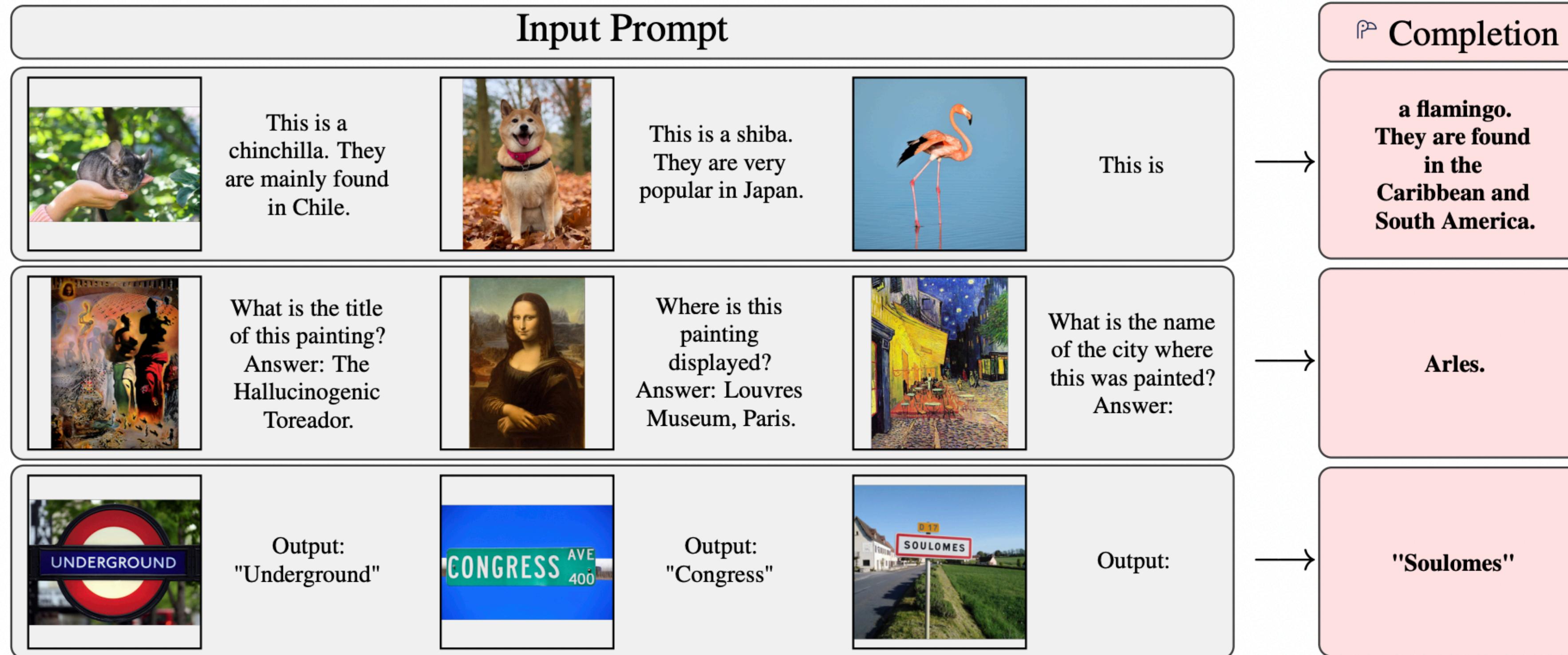


The possibility to

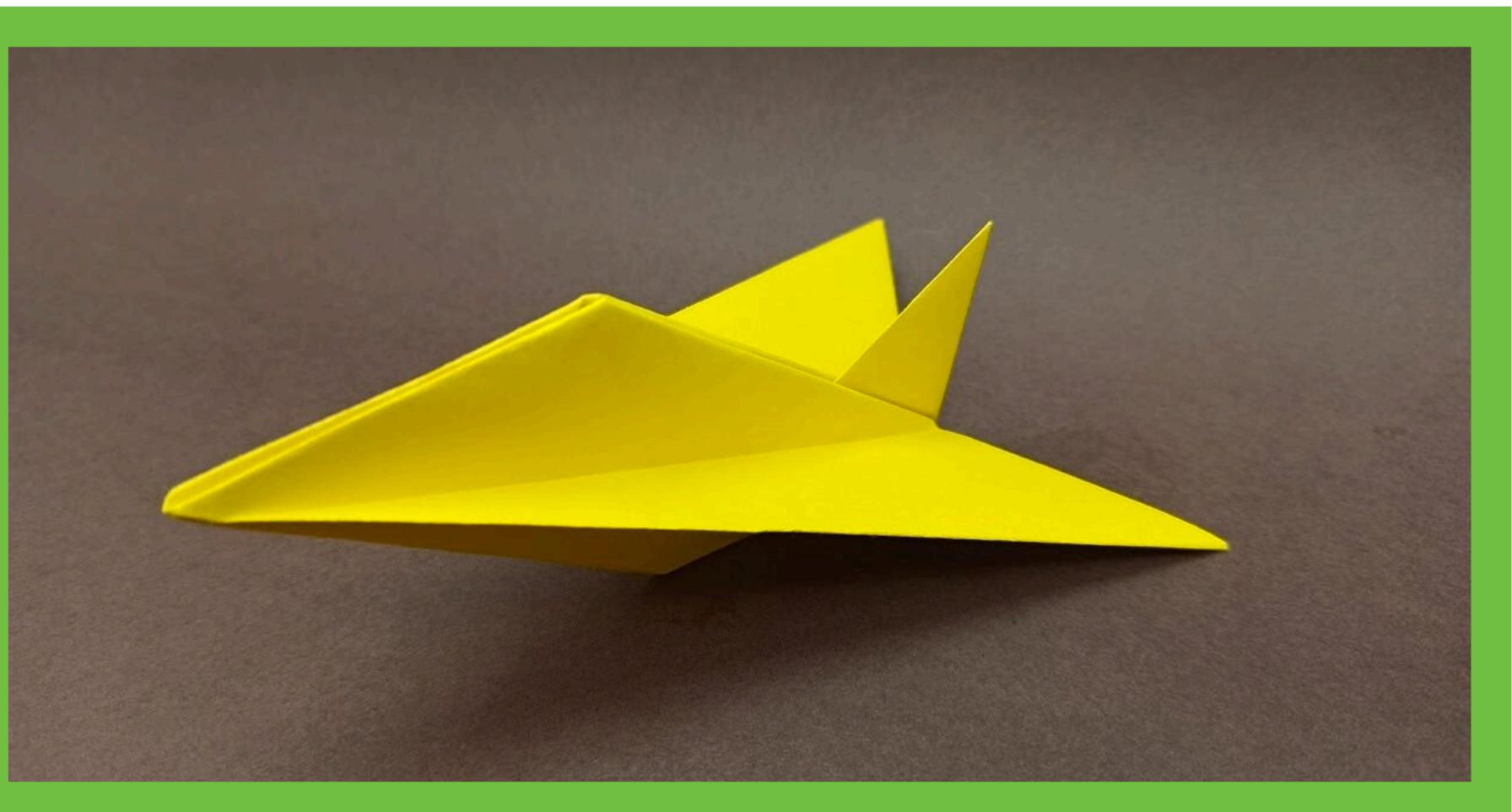
- *define a task* and the
- *learning-like* behaviour via few-shot examples
- with a *frozen model*

allows big scaling

In-context Learning emerges also for Visual Language Models

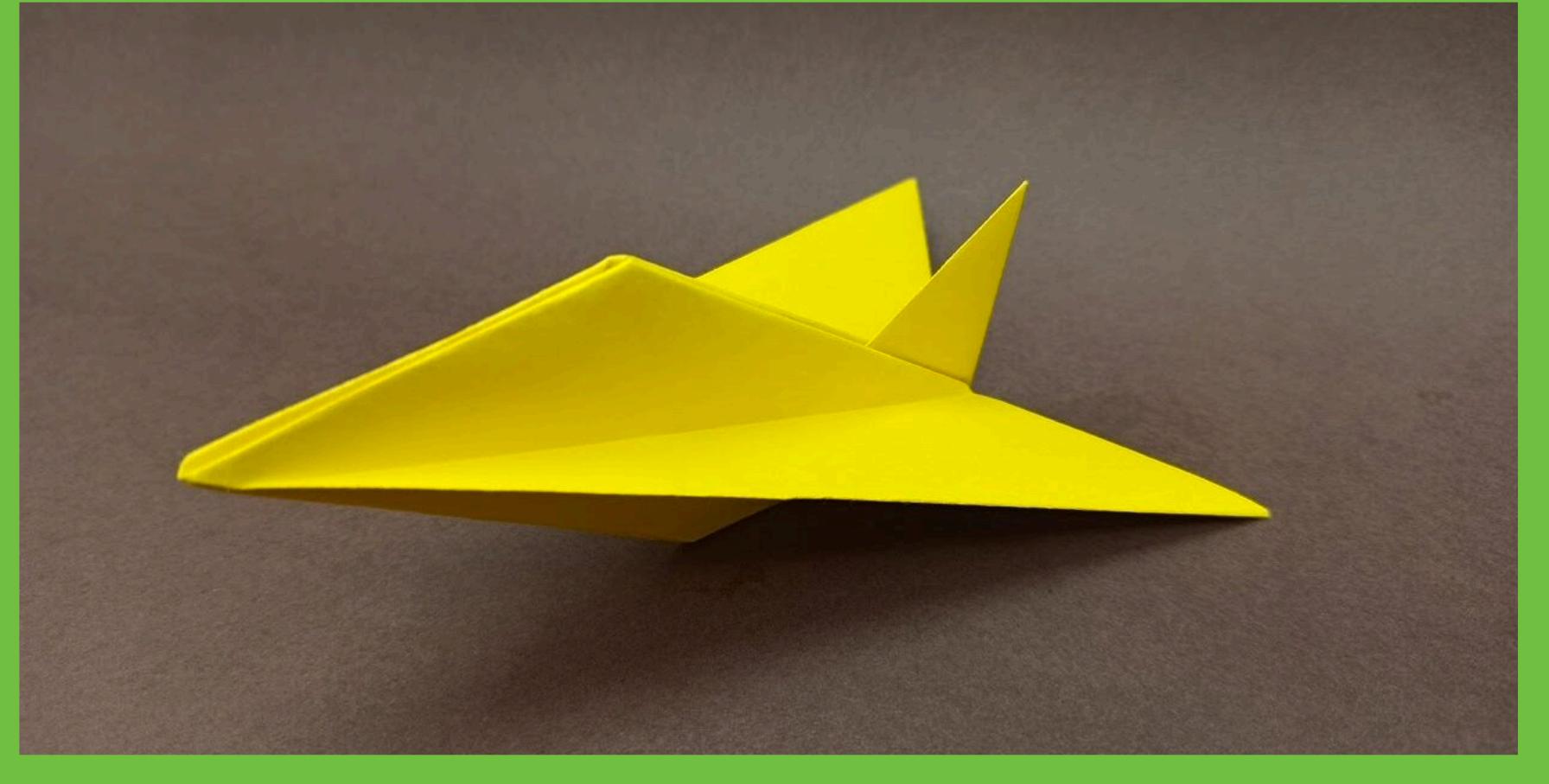


But just because it emerges
for **6B+ sized models**, does it
mean we cannot do this with
more **light-weight ones**?



Our goal

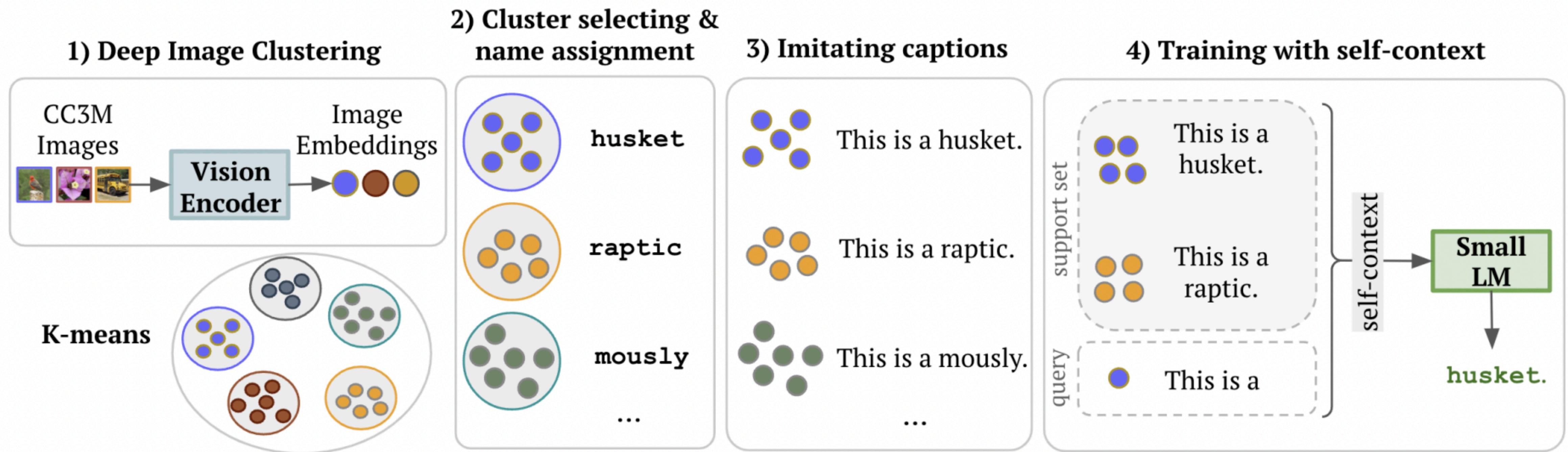
open-ended multi-modal ICL
with small VLMs
without using supervised data.



Why?

- Ultimately, paired data is rare
- ICL as algorithm: symbols replaceable
- As an existence-proof

How? Our method simply *mimics* supervised data by using SSL



Where are we?



We train with fake names, but evaluation works just fine!



This is a
scoreboard.



This is a
school bus.

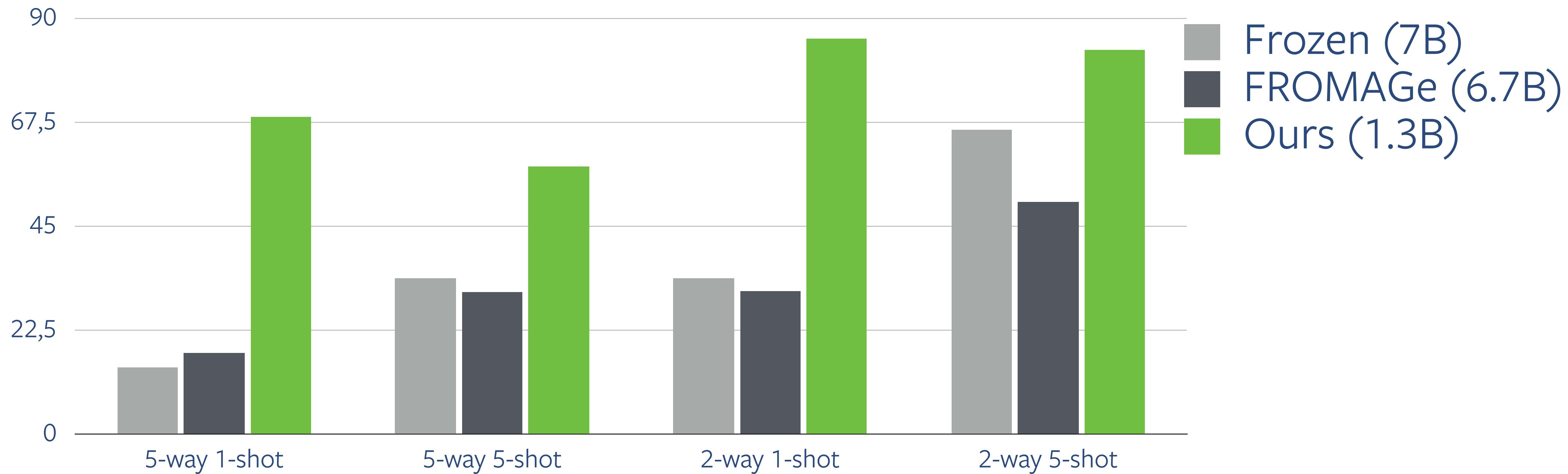


This is a <?>

- ✗ **ClipCap**: distinguished from all other by its long slender torso.
- ✗ **FROMAGe**: school bus that is parked in the school yard.
- ✓ **SeCAt (Ours)**: school bus.

Simple-as-that; beats 6B-sized models on open-ended multi-modal classif.

Open-ended mini-ImageNet ICL evaluation



Team for the works presented

TimeTuning



Mohammadreza Salehi



Efstratios Gavves



Cees G. M. Snoek



Yuki M. Asano

WTour Dora



Shashanka Venkataraman



Mamshad N Rizve



Joao Carreira



Yuki M. Asano*



Yannis Avrithis*

SeCAT



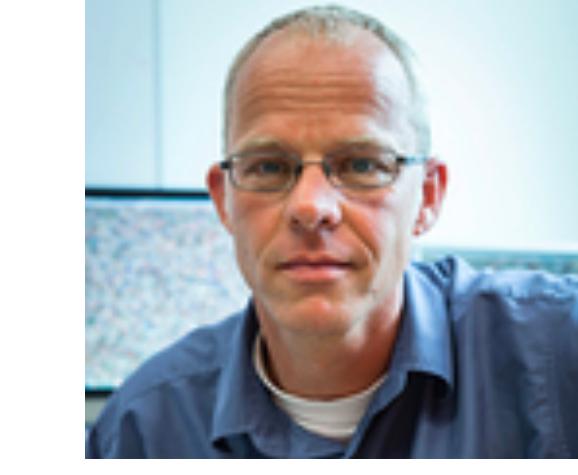
Mohammad M Derakhshani¹



Ivona Najdenkoska¹



Cees G. M. Snoek*



Marcel Worring*



Yuki M. Asano*

Especially videos open exiting new directions



Visual development for AI

Bonus: insan

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Solution is obvious

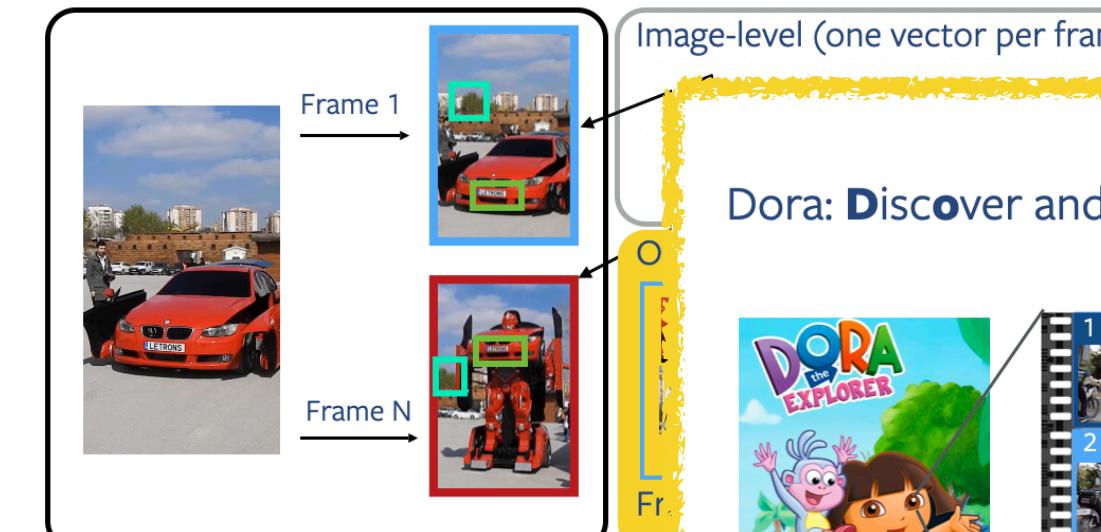


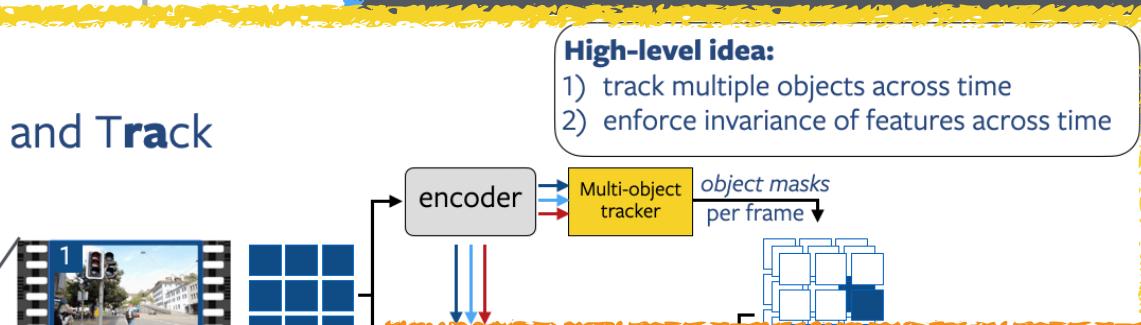
Image-level (one vector per frame)

Dora: Discover and Track



Much like Dora, we walk around and learn from what we see.

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We train with fake names, but evaluation works just fine in-context



This is a scoreboard. This is a school bus. This is a <?>

ClipCap: distinguished from all other by its long slender torso.
FROMAGE: school bus that is parked in the school yard.
SeCat (Ours): school bus.



This is a desert-rose. This is a gray kingbird. This is a <?>

ClipCap: close up of a alpine sea holly.
FROMAGE: bird that is native to the United States and Canada.
SeCat (Ours): gray kingbird.



This is a russian blue. This is a egyptian mau. This is a <?>

ClipCap: daffodil in my garden.
FROMAGE: russian blue cat.
SeCat (Ours): egyptian mau.

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Future Foundation Models will be massively pretrained with videos.
Current multi-modal training will become only the cherry on top.