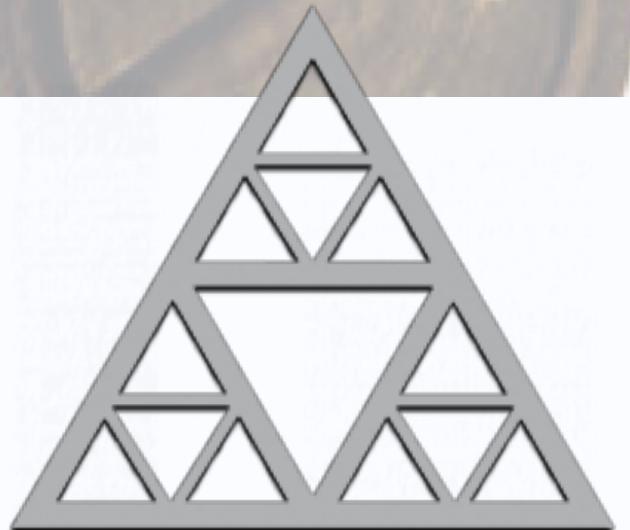




Beyond Action Recognition: Detailed Video Modeling

[youInc.com](#)



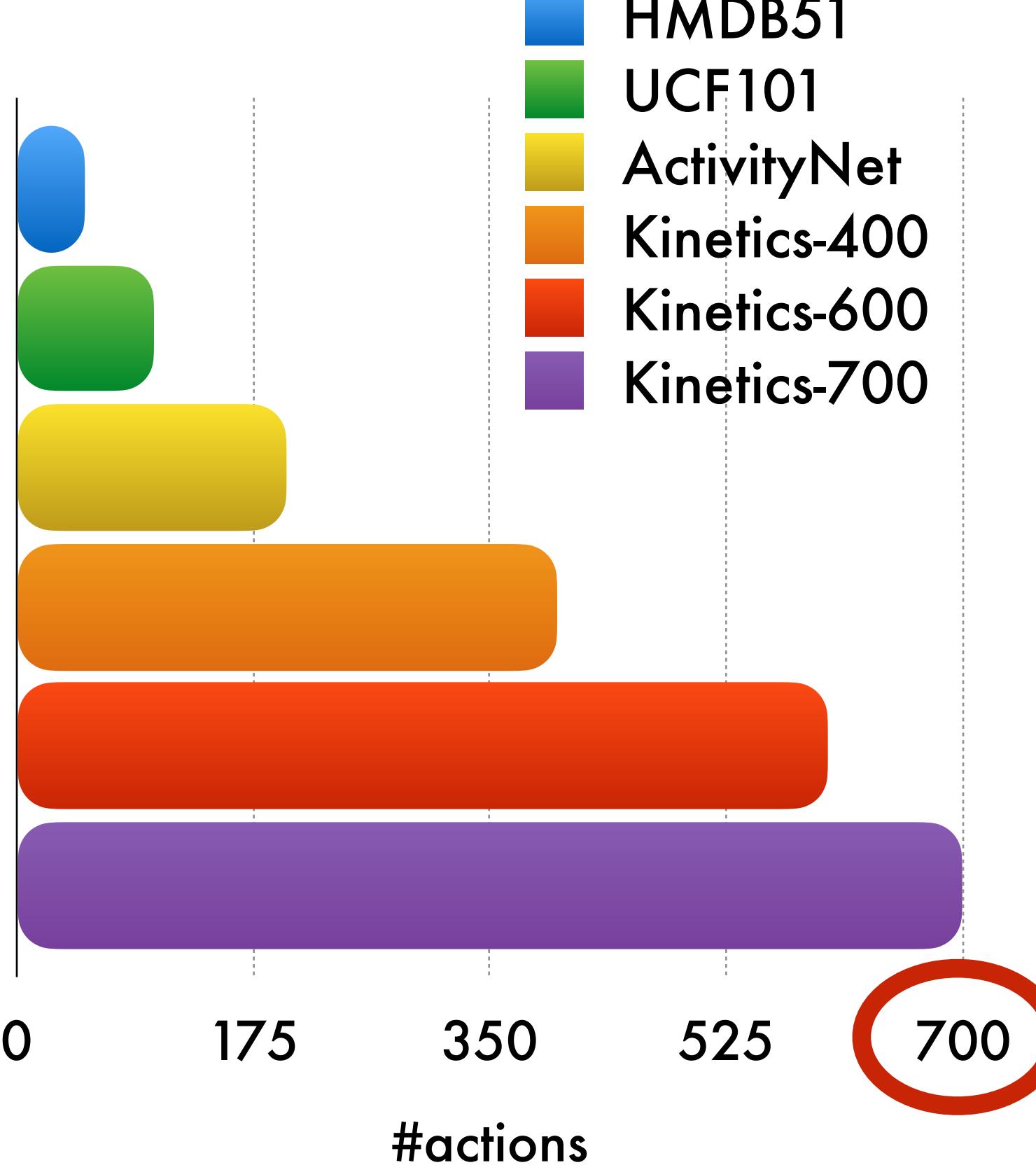
École des Ponts
ParisTech

Gül Varol

IMAGINE team, École des Ponts ParisTech

@ICCVW, 11.10.2021

What is wrong with action recognition?



14 dataset results for Action Classification AND Videos ×

Filter by Modality (clear)

- Videos** x
- Texts 2
- 3D 1
- Actions 1

Filter by Task (clear)

- Action Classification** x
- Action Recognition 50
- Temporal Action Localization 26
- Video Understanding 20

Filter by Language

- English 2

Kinetics (Kinetics Human Action Video Dataset)
The Kinetics dataset is a large-scale, high-quality dataset for human action recognition in videos. The dataset consists of around 500,000 video clips covering 600 human action...
552 PAPERS • 13 BENCHMARKS

ActivityNet
The ActivityNet dataset contains 200 different types of activities and a total of 849 hours of videos collected from YouTube. ActivityNet is the largest benchmark for temporal activity d...
328 PAPERS • 9 BENCHMARKS

Charades
The Charades dataset is composed of 9,848 videos of daily indoors activities with an average length of 30 seconds, involving interactions with 46 objects classes in 15 types ofindo...
219 PAPERS • 4 BENCHMARKS

THUMOS14 (THUMOS 2014)
The THUMOS14 dataset is a large-scale video dataset that includes 1,010 videos for validation and 1,574 videos for testing from 20 classes. Among all the videos, there are 220 and...
188 PAPERS • 11 BENCHMARKS

YouCook2
YouCook2 is the largest task-oriented, instructional video dataset in the vision community. It contains 2000 long untrimmed videos from 89 cooking recipes; on average, each distinct...
51 PAPERS • 4 BENCHMARKS

Moments in Time
Moments in Time is a large-scale dataset for recognizing and understanding action in videos. The dataset includes a collection of one million labeled 3 second videos, involving people,...
50 PAPERS • 2 BENCHMARKS

paperswithcode.com

Closed set, loss of information from categorisation



(video from Kinetics)

category: **playing ukulele**

Description: Two musicians playing ukulele and double bass on the stage.

Arbitrary level of details

e.g., Dozen categories for dancing, one category for sign language

Kinetics categories:

- Belly dancing
- Breakdancing
- Country line dancing
- Dancing ballet
- Dancing charleston
- Dancing gangnam style
- Dancing macarena
- Jumpstyle dancing
- Robot dancing
- Salsa dancing
- Swing dancing
- Tango dancing
- Tap dancing
- Zumba
- ...

category: **sign language interpreting**



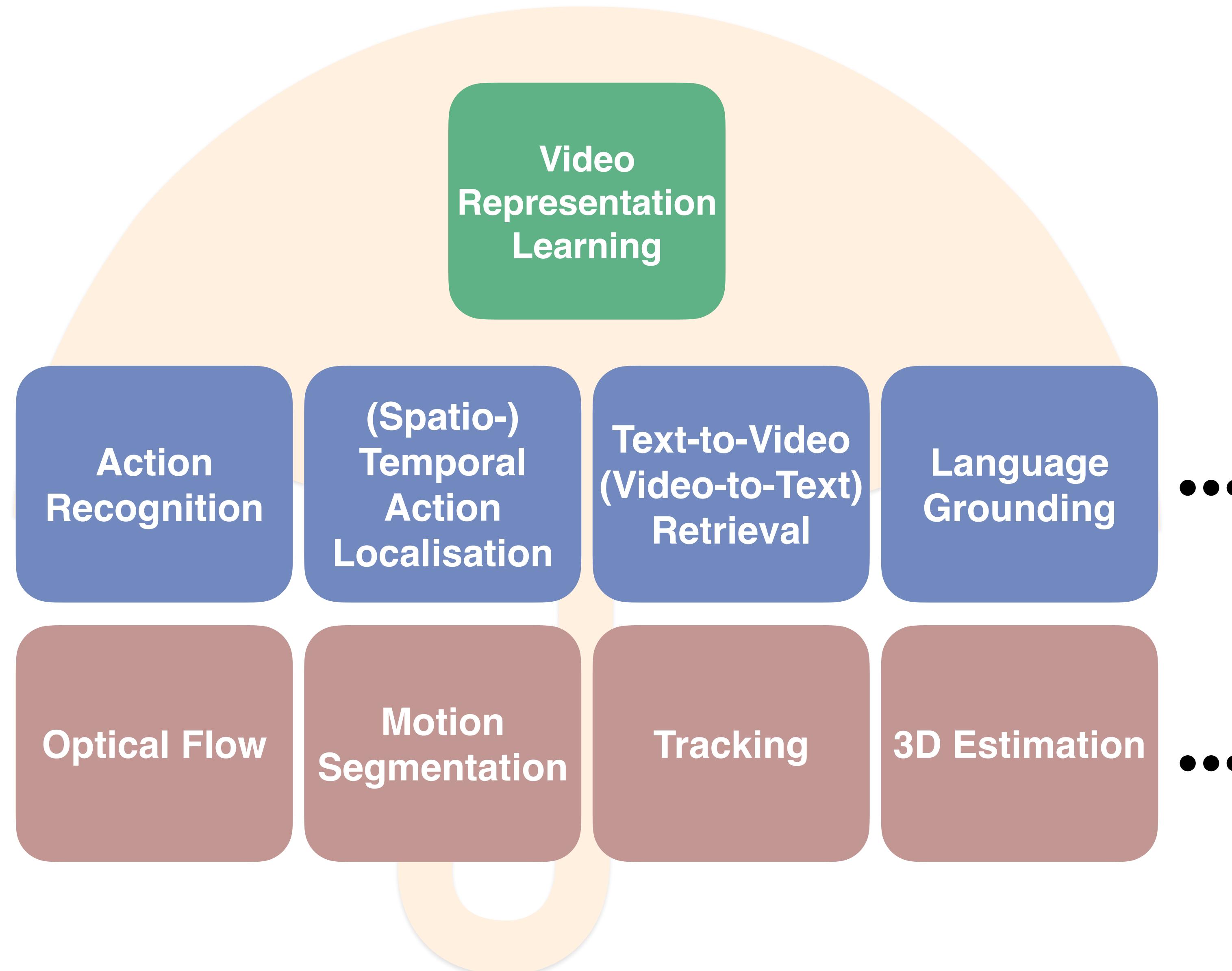
Beyond semantics

Robots learning from human demonstrations

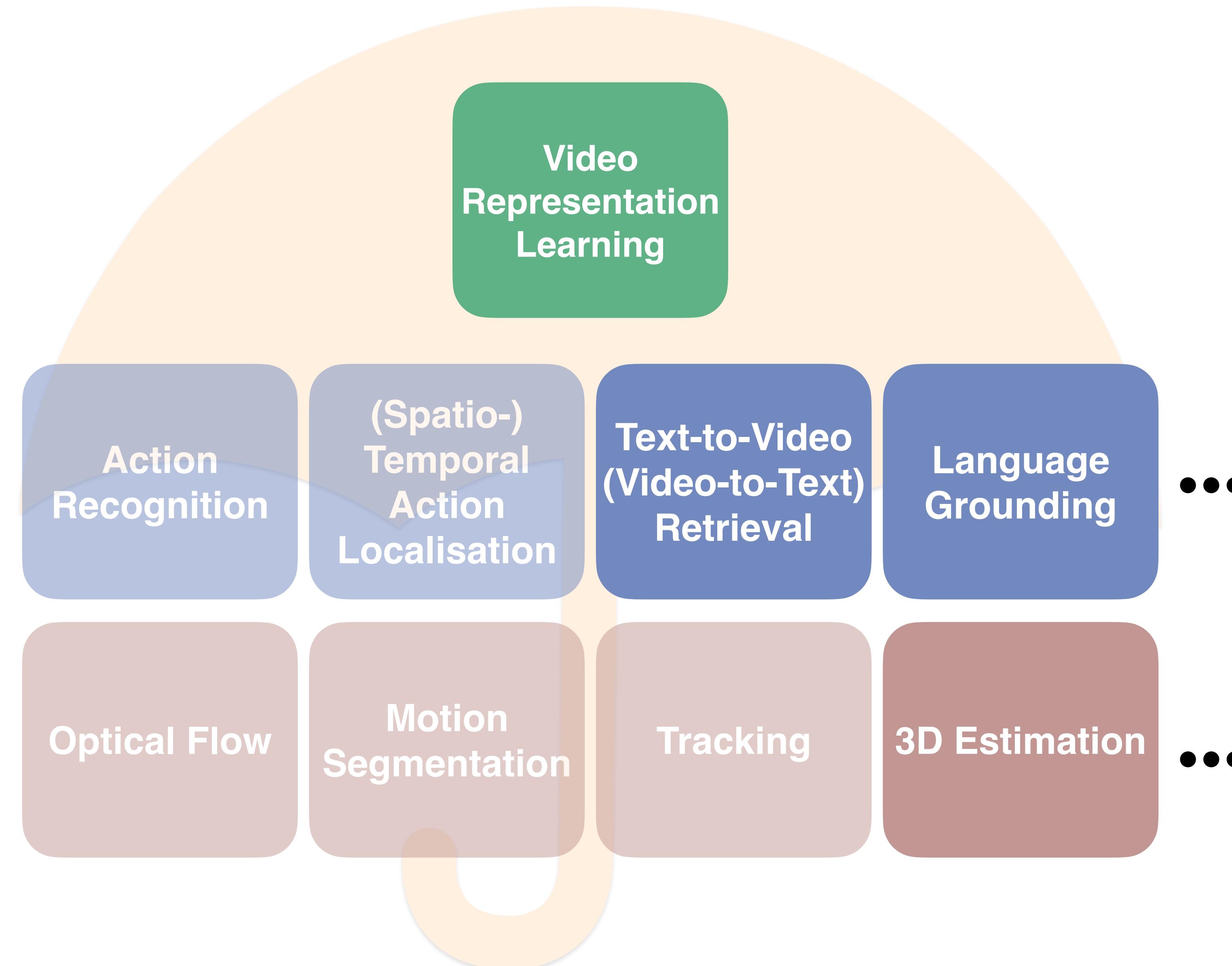


category: **washing dishes**

Video Modeling?



Video Modeling?



Talk Outline

Text-to-Video
Retrieval

◆ 1) Text-to-video retrieval

[Bain et al. ICCV 2021]



Sign Language
Localisation

◆ 2) Temporal localisation in sign language videos

[Varol et al. CVPR 2021] [Bull et al. ICCV 2021]



3D Estimation

◆ 3) Hand-object reconstruction from RGB videos

[Hasson et al. 3DV 2021]



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◆ 3) Hand-object reconstruction from RGB videos

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Frozen in Time: A Joint Video and Image Encoder For End-to-End Retrieval

ICCV 2021

<https://www.robots.ox.ac.uk/~vgg/research/frozen-in-time/>



**Max
Bain**



**Arsha
Nagrani**



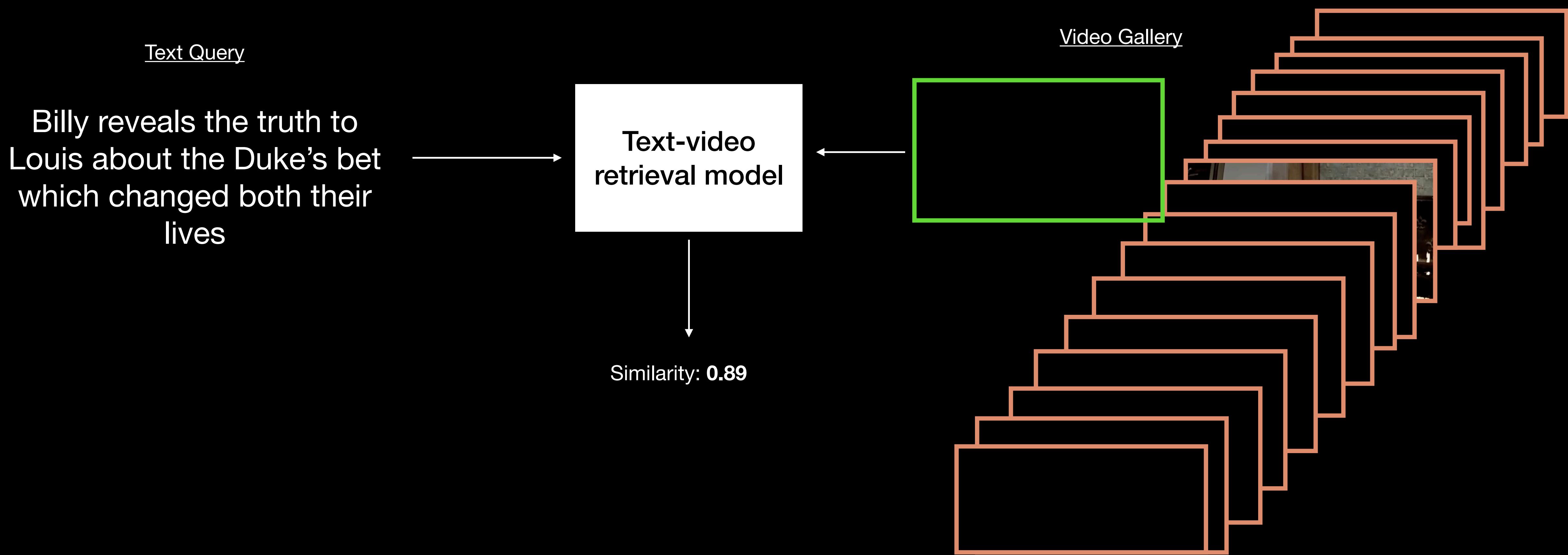
**Gül
Varol**



**Andrew
Zisserman**



Text-to-Video Retrieval



Demo:

❄️ Frozen in Time ⏳ 🔍 Video Search Demo 🎬

e.g. empty street in nepal

display:

Visual search of ~2.6M videos are based on research described in
[Frozen in time: A joint video and image encoder for end-to-end retrieval.](#)

State of the art in video retrieval:

✗ Image and video retrieval progress largely disjoint

✗ Not end-to-end

- Pre-extracted “expert” features, typically trained on other tasks (ImageNet, Kinetics...)
- Performance limited and strongly linked to quality of features
- Experts typically not trained for vision & language space (MoEE[1], CE[2], MMT[3])

✗ Lack of large scale text-video data

[1] Antoine Miech, Ivan Laptev, and Josef Sivic. Learning a text-video embedding from incomplete and heterogeneous data. arXiv, 2018

[2] Yang Liu, Samuel Albanie, Arsha Nagrani, and Andrew Zisserman. Use what you have: Video retrieval using representations from collaborative experts. BMVC, 2019.

[3] Valentin Gabeur, Chen Sun, Karteek Alahari, and Cordelia Schmid. Multi-modal transformer for video retrieval. ECCV, 2020.

State of the art in video retrieval:

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✓ End-to-end video representation

✗ Lack of large scale text-video data

✓ Introduces WebVid-2M data

[1] Antoine Miech, Ivan Laptev, and Josef Sivic. Learning a text-video embedding from incomplete and heterogeneous data. arXiv, 2018

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State of the art in video representations:

- ✗ Image and video representations progress largely disjoint
- ✗ 3D Spatio-temporal Convolutions (I3D, ResNet3D, S3D, X3D...)

Either:

- ✗ Trained for action classification on Kinetics dataset (e.g., X3D [1]) - **closed set of categories**
- ✗ Trained for retrieval on HowTo100M dataset (e.g., MIL-NCE [2]) - **noisy speech data, long training**
- ✗ Trained with “self-supervision” (e.g., [3]) - **requires audio or other modality**

[1] Christoph Feichtenhofer. X3D: Expanding architectures for efficient video recognition. CVPR, 2020.

[2] Antoine Miech, Jean-Baptiste Alayrac, Lucas Smaira, Ivan Laptev, Josef Sivic, and Andrew Zisserman. End-to-end learning of visual representations from uncurated instructional videos. CVPR, 2020.

[3] Yuki M. Asano*, Mandela Patrick*, Christian Rupprecht, Andrea Vedaldi. Labelling unlabelled videos from scratch with multi-modal self-supervision. NeurIPS , 2020.

State of the art in video representations:

This work:

- ✗ Image and video representations progress largely disjoint
- ✗ 3D Spatio-temporal Convolutions (I3D, ResNet3D, S3D, X3D...)



Joint image-video training via Transformer encoder

Either:

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- ✗ Trained for retrieval on HowTo100M dataset (e.g., MIL-NCE [2]) - **noisy speech data, long training**
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Trained for retrieval efficiently on WebVid-2M dataset

[1] Christoph Feichtenhofer. X3D: Expanding architectures for efficient video recognition. CVPR, 2020.

[2] Antoine Miech, Jean-Baptiste Alayrac, Lucas Smaira, Ivan Laptev, Josef Sivic, and Andrew Zisserman. End-to-end learning of visual representations from uncurated instructional videos. CVPR, 2020.

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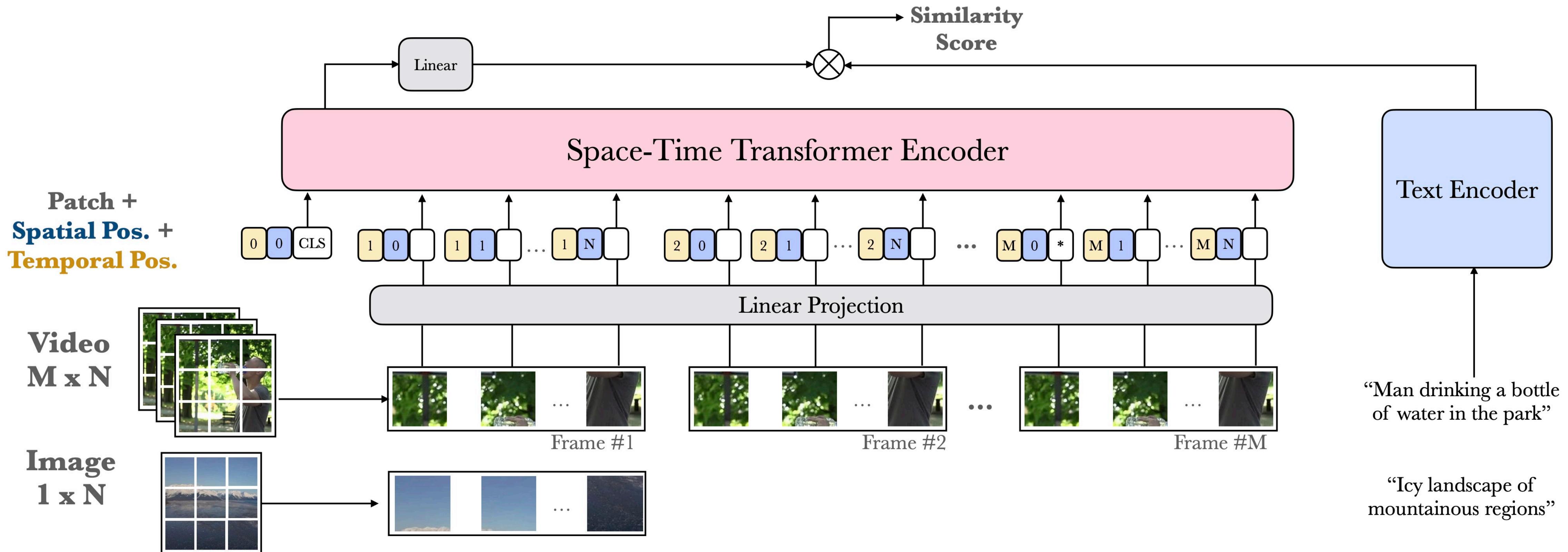
Frozen in Time

A Joint Video and Image Encoder

In this work aim to overcome these with:

- ✓ **End-to-end** retrieval model (from pixels)
- ✓ **Jointly training** on image-text and video-text pairs
 - Using a **Transformer** encoder that accepts a variable-length sequence
 - Treating images as 1-frame videos, *frozen in time*
- ✓ Collecting a **large-scale video-text dataset**, WebVid-2M, for pretraining

End-to-end retrieval

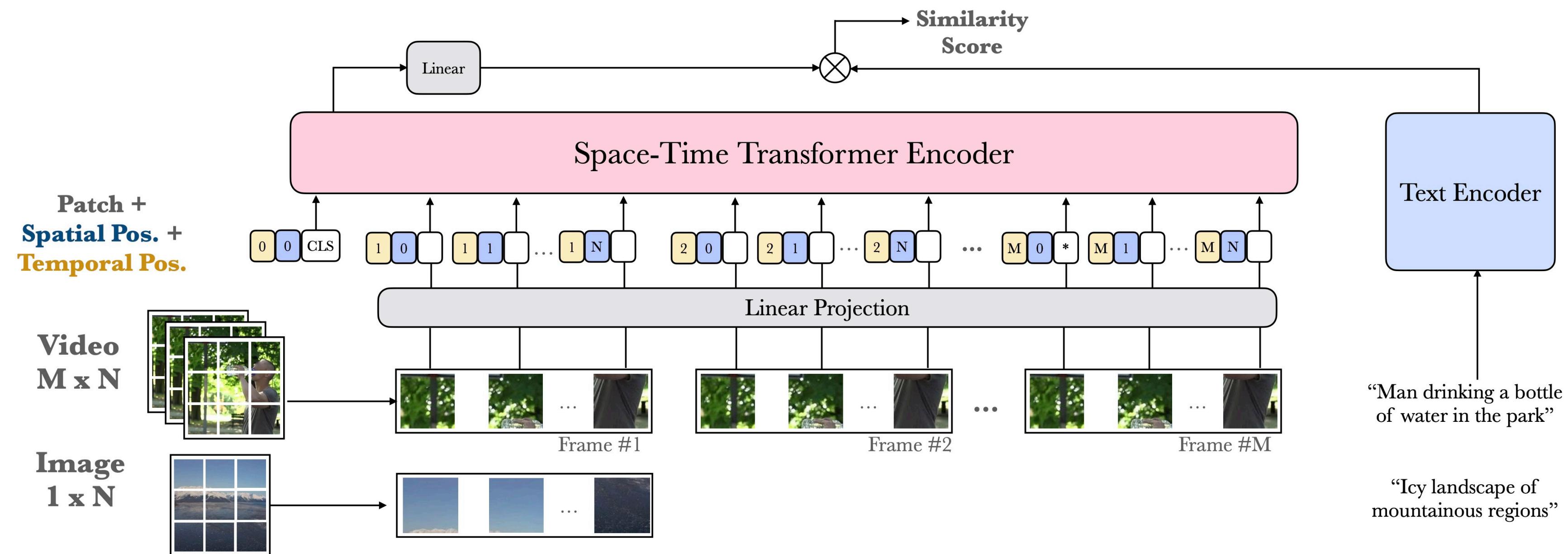


- Dual encoder for efficient retrieval

End-to-end retrieval

Video encoder:

- inspired from Timesformer [1]
- initialized from ViT [2] weights pretrained on ImageNet
 - Temporal embeddings zero-initialized



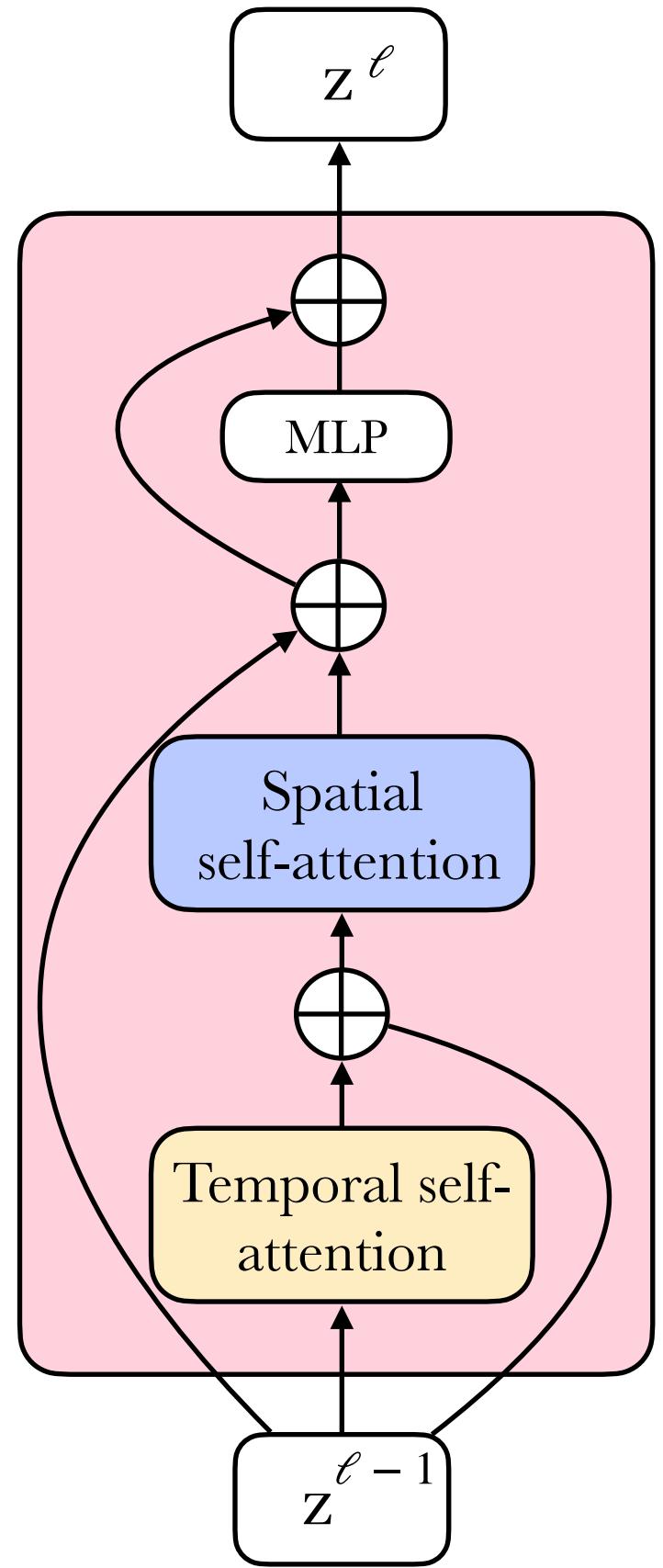
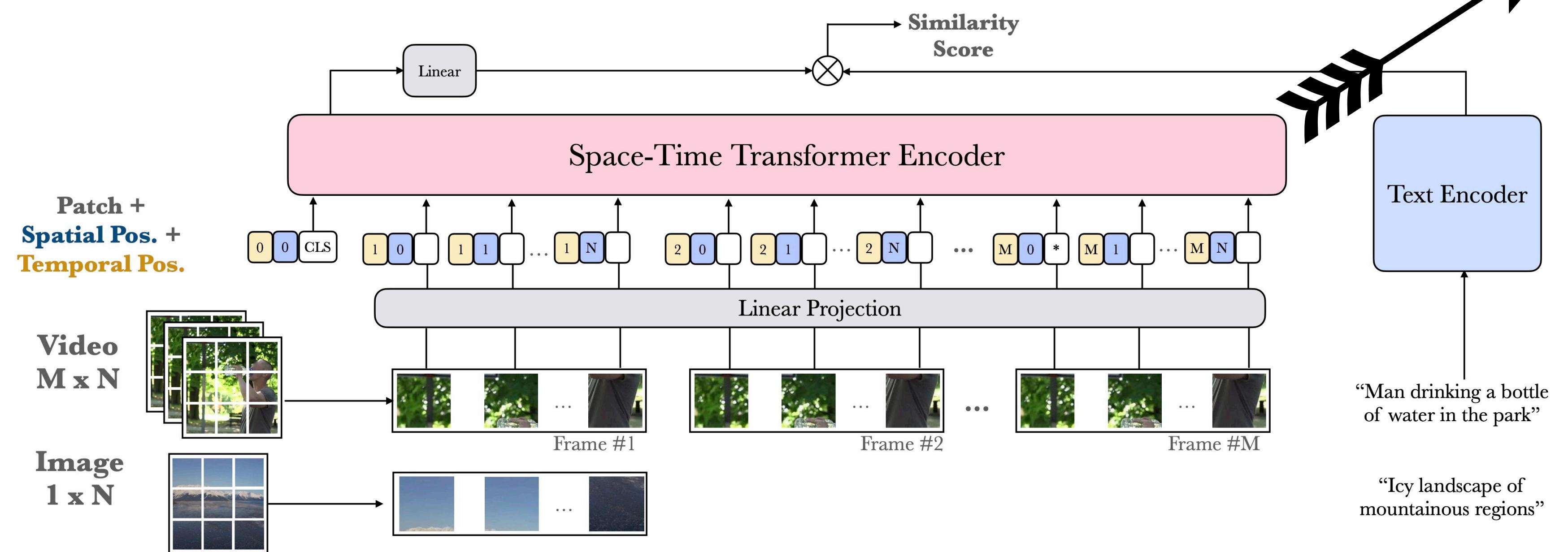
[1] Gedas Bertasius, Heng Wang, and Lorenzo Torresani. Is space-time attention all you need for video understanding? arXiv, 2021.

[2] Alexey Dosovitskiy et al. An image is worth 16x16 words: Transformers for image recognition at scale. ICLR, 2021.

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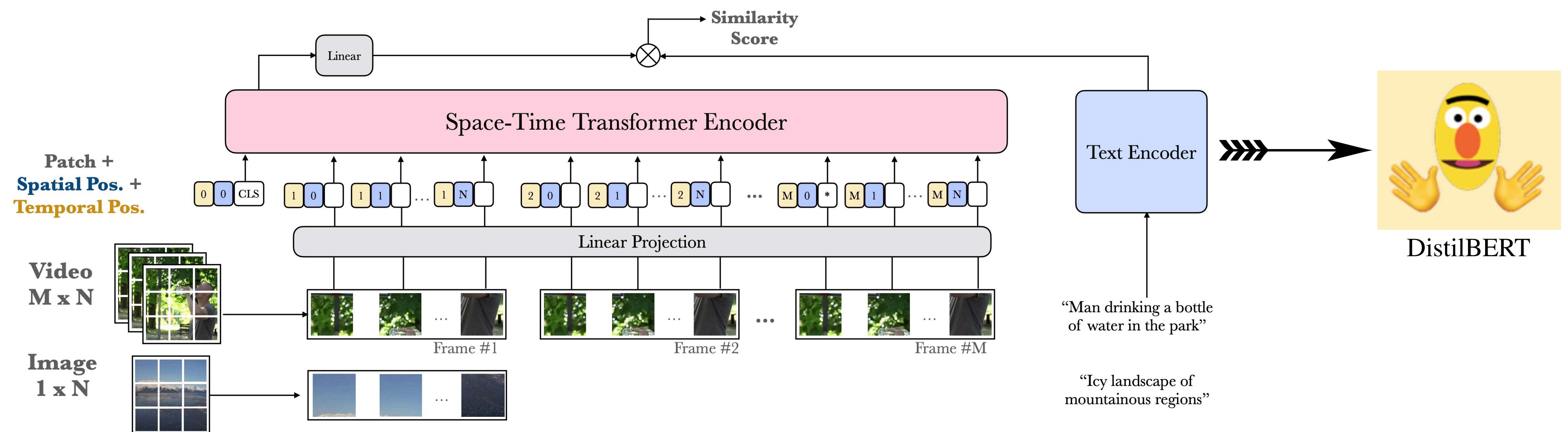
[1] Gedas Bertasius, Heng Wang, and Lorenzo Torresani. Is space-time attention all you need for video understanding? arXiv, 2021.

[2] Alexey Dosovitskiy et al. An image is worth 16x16 words: Transformers for image recognition at scale. ICLR, 2021.

End-to-end retrieval

Text encoder:

- initialized from DistilBERT [1]



WebVid-2M Dataset

2.5M video-text pairs scraped from the web



“Runners feet in a sneakers close up. realistic three dimensional animation.”



“Female cop talking on walkietalkie, responding emergency call, crime prevention”



“Billiards, concentrated young woman playing in club”



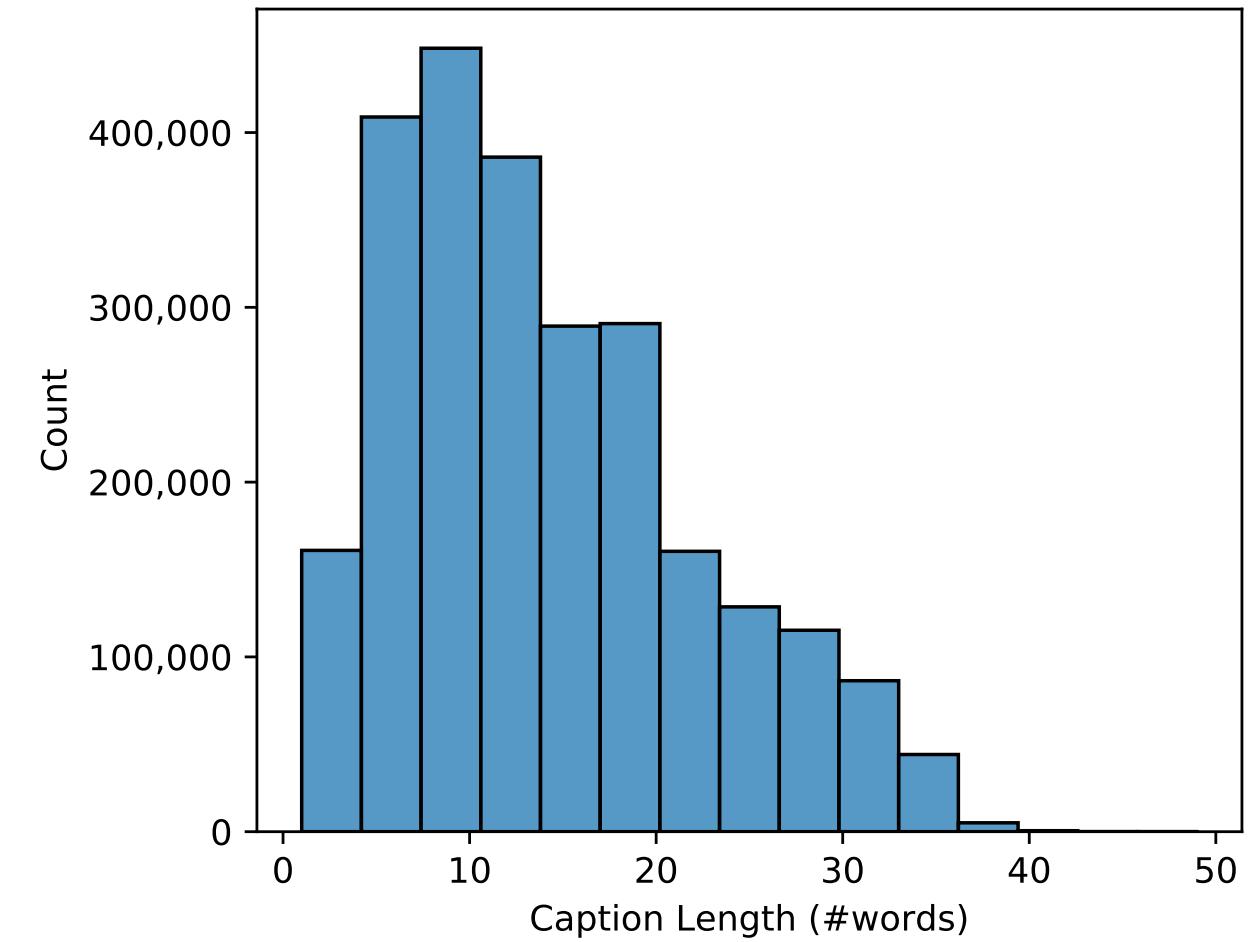
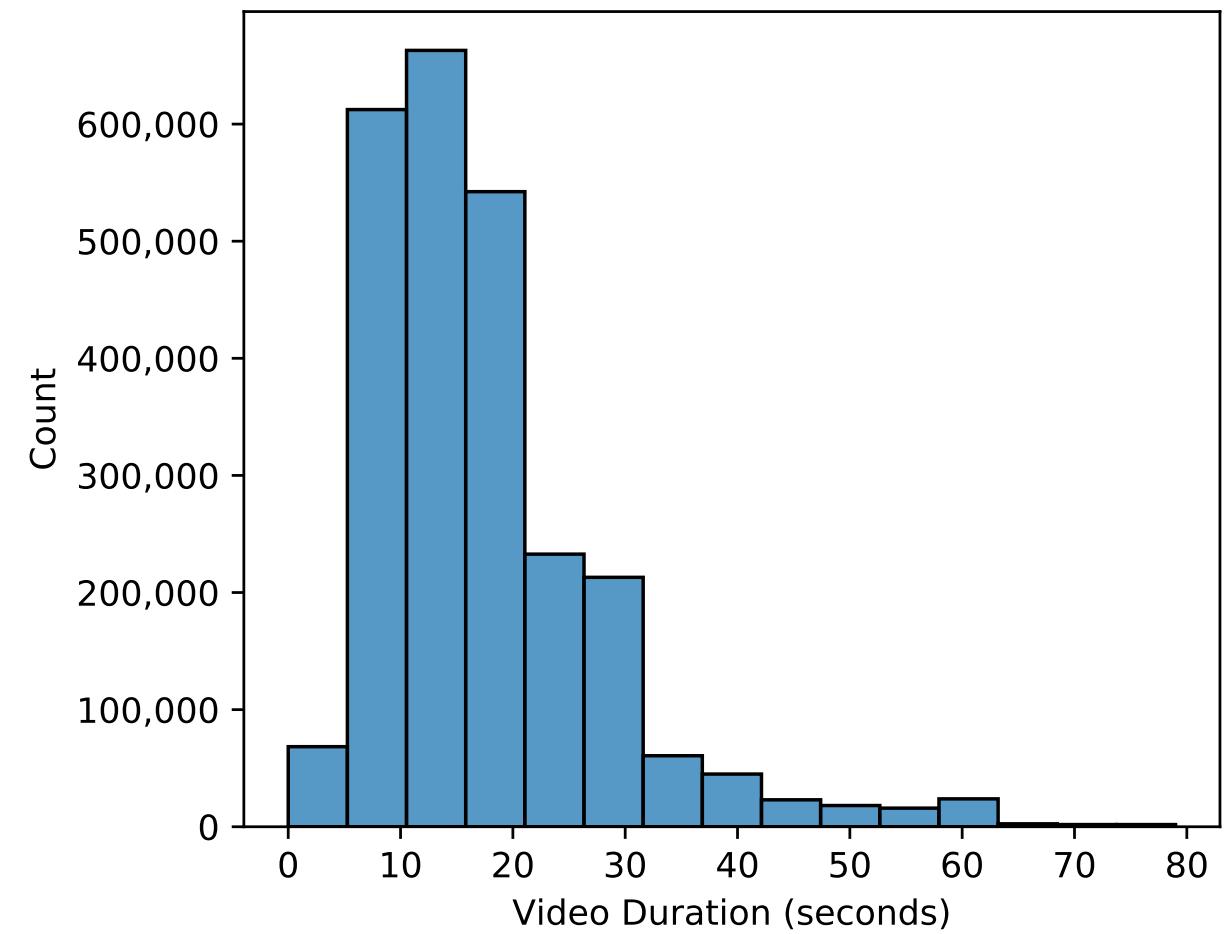
“Lonely beautiful woman sitting on the tent looking outside. wind on the hair and camping on the beach near the colors of water and shore. freedom and alternative tiny house for traveler lady drinking”



“Kherson, ukraine - 20 may 2016: open, free, rock music festival crowd partying at a rock concert. hands up, people, fans cheering clapping applauding in kherson, ukraine - 20 may 2016. band performing”



“Cabeza de toro, punta cana/ dominican republic - feb 20, 2020: 4k drone flight over coral reef with manta”



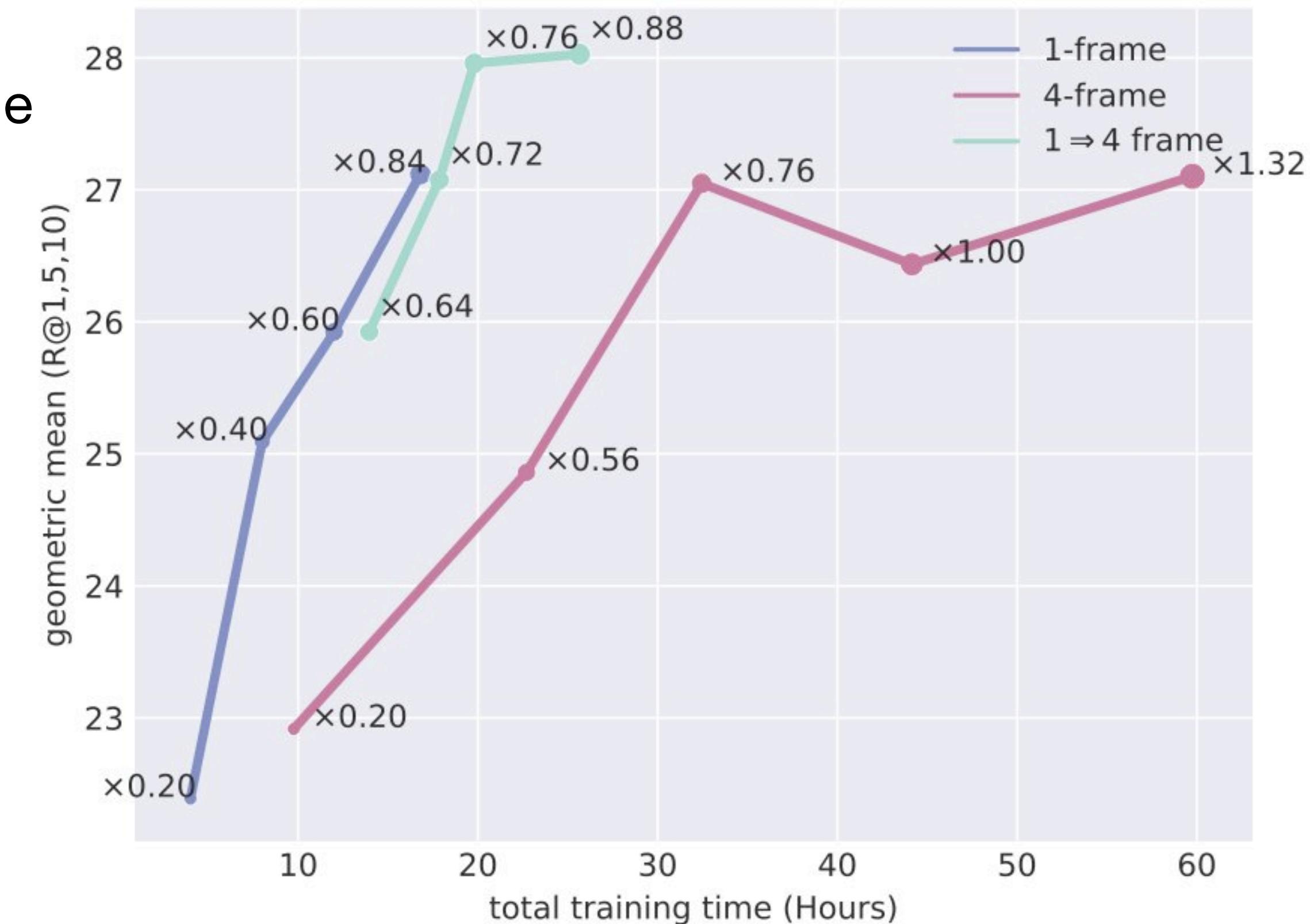
Effect of pretraining

Pre-training (for 1 epoch)	#pairs	↑R@1	↑R@10	↓MedR
-	-	5.6	22.3	55
ImageNet		15.2	54.4	9.0
HowTo-17M subset	17.1M	24.1	63.9	5.0
CC3M	3.0M	24.5	62.7	5.0
WebVid2M	2.5M	26.0	64.9	5.0
+ CC3M + WebVid2M	5.5M	27.3	68.1	4.0

MSRVTT Benchmark

Efficient training with curriculum learning

- Transformers are costly to train, and scale with the length of the sequence.
- We investigate curriculum learning:
 - Similar / better performance in much less training time
 - Initially train with only one frame
 - Gradually increase



Comparison to the state of the art

MSRVTT benchmark

Method	E2E†	Vis Enc. Init.	Visual-Text PT	#pairs PT	R@1	R@5	R@10	MedR
JSFusion [62]	✓	-	-	-	10.2	31.2	43.2	13.0
HT MIL-NCE [35]	✓	-	HowTo100M	100M	14.9	40.2	52.8	9.0
ActBERT [67]	✓	VisGenome	HowTo100M	100M	16.3	42.8	56.9	10.0
HERO [27]	✓	ImageNet, Kinetics	HowTo100M	100M	16.8	43.4	57.7	-
VidTranslate [22]	✓	IG65M	HowTo100M	100M	14.7	-	52.8	
NoiseEstimation [2]	✗	ImageNet, Kinetics	HowTo100M	100M	17.4	41.6	53.6	8.0
CE [29]	✗	Numerous experts†	-		20.9	48.8	62.4	6.0
UniVL [31]	✗	-	HowTo100M	100M	21.2	49.6	63.1	6.0
ClipBERT [25]	✓	-	COCO, VisGenome	5.6M	22.0	46.8	59.9	6.0
AVLnet [44]	✗	ImageNet, Kinetics	HowTo100M	100M	27.1	55.6	66.6	4.0
MMT [15]	✗	Numerous experts†	HowTo100M	100M	26.6	57.1	69.6	4.0
Support Set [39]	✗	IG65M, ImageNet	-	-	27.4	56.3	67.7	3.0
Support Set [39]	✗	IG65M, ImageNet	HowTo100M	100M	30.1	58.5	69.3	3.0
Ours	✓	ImageNet	CC3M	3M	25.5	54.5	66.1	4.0
Ours	✓	ImageNet	CC3M, WebVid-2M	5.5M	31.0	59.5	70.5	3.0
Zero-shot								
HT MIL-NCE [35]	✓	-	HowTo100M	100M	7.5	21.2	29.6	38.0
Ours	✓	ImageNet	CC3M, WebVid-2M	5.5M	18.7	39.5	51.6	10.0

Take-home messages

- An **end-to-end** trained video retrieval model can outperform “expert” feature models, even without multiple modalities such as audio.
- Video Transformers, with their flexible input sequence sizes, can benefit from **joint image-video** training, exploiting cheaper image-text datasets.
- **Curriculum** in sequence length (time) achieves competitive performance with far less compute.

Talk Outline

Text-to-Video
Retrieval

Sign Language
Localisation

3D Estimation

- ◆ 1) **Text-to-video retrieval**
[Bain et al. ICCV 2021]
- ◆ 2) **Temporal localisation in sign language videos**
[Varol et al. CVPR 2021] [Bull et al. ICCV 2021]
- ◆ 3) **Hand-object reconstruction from RGB videos**
[Hasson et al. 3DV 2021]



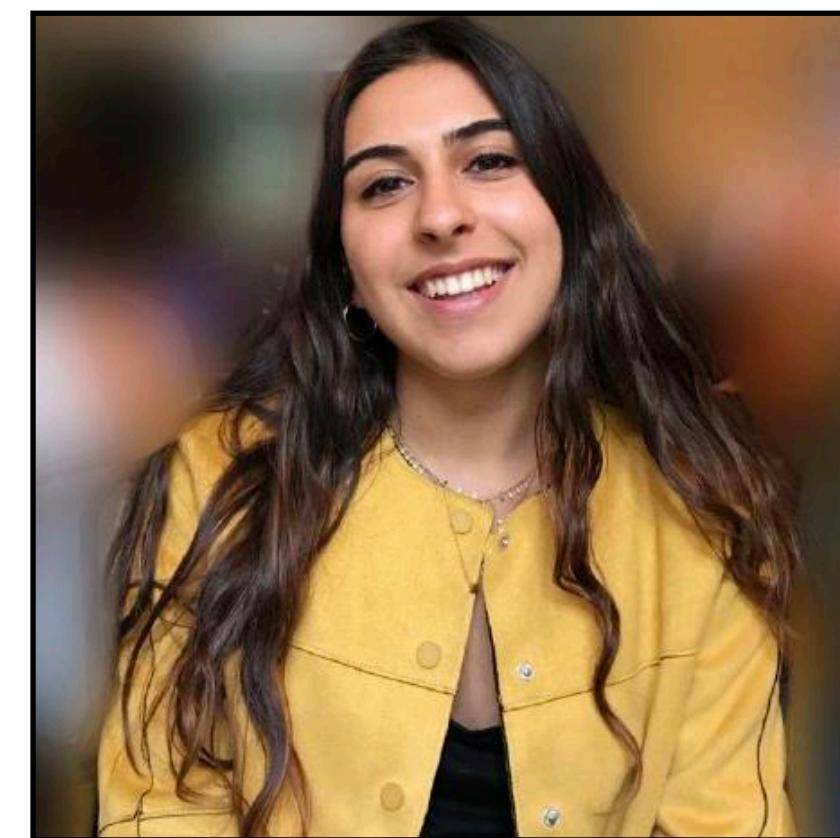
Read and Attend: Temporal Localisation in Sign Language Videos

CVPR 2021

<https://www.robots.ox.ac.uk/~vgg/research/blattend/>



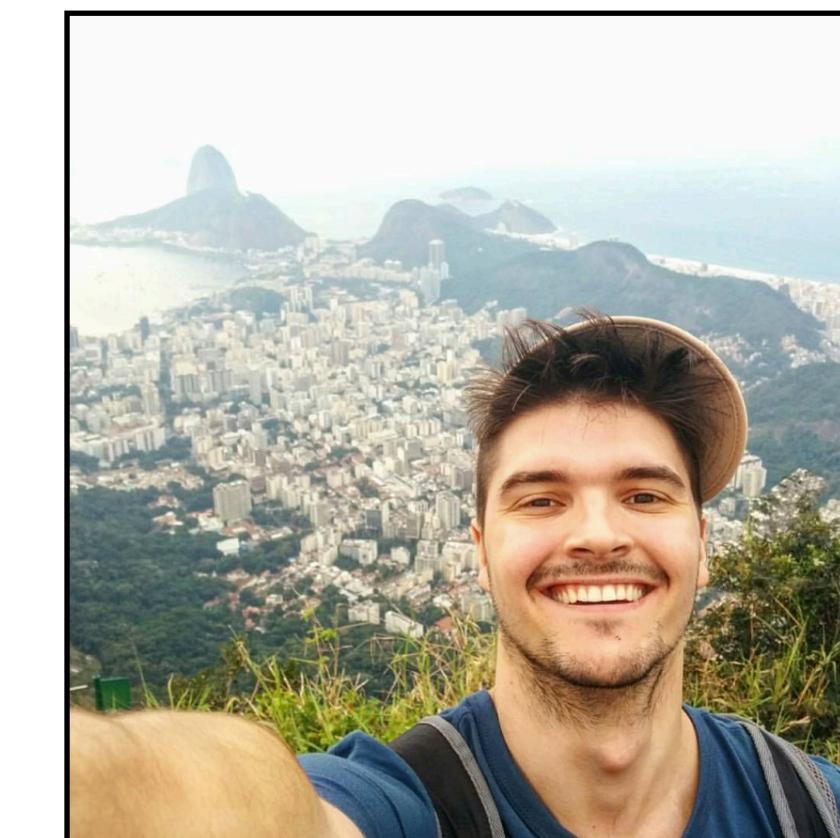
Gül Varol*



Liliane Momeni*



Samuel Albanie*



Triantafyllos Afouras*

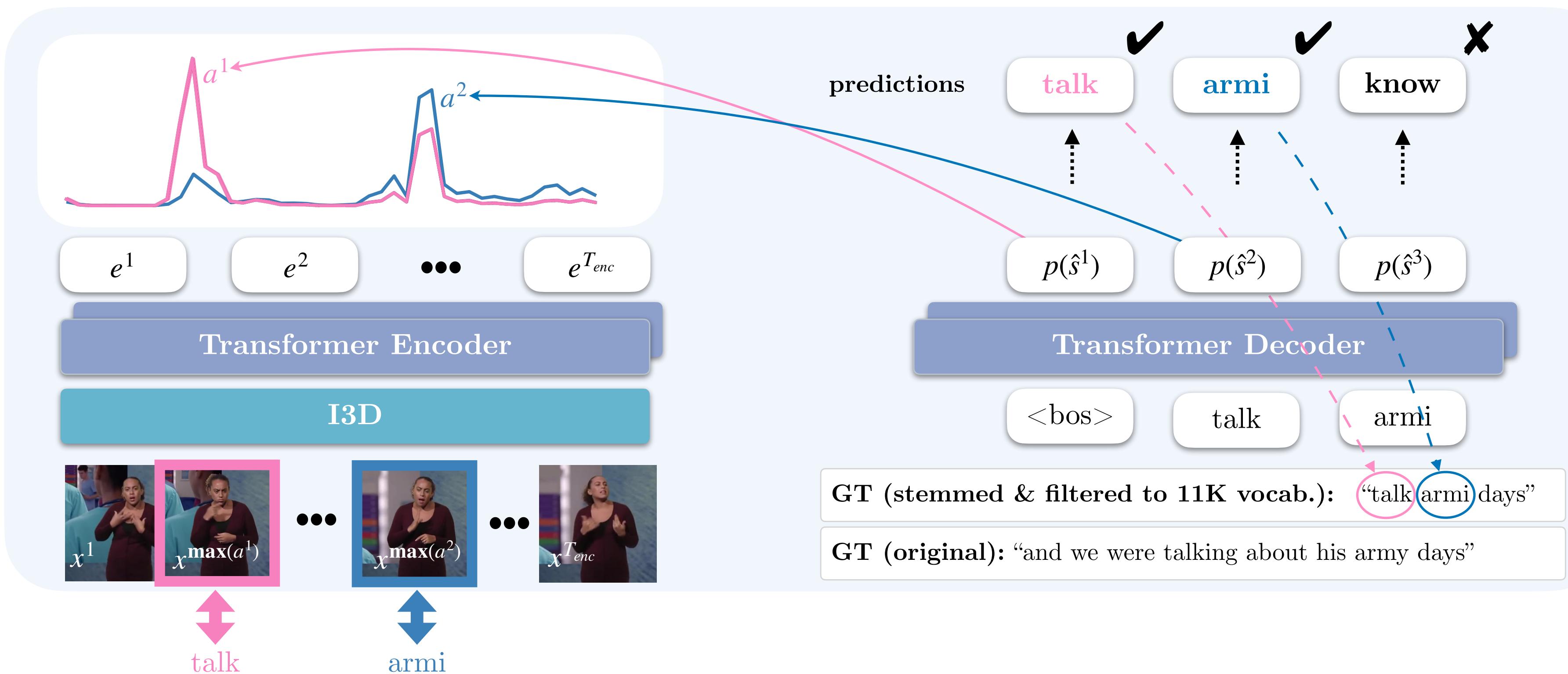


Andrew Zisserman

*equal contribution

Localising Words

- We train a **large-vocabulary** video-to-text Transformer model.
- **Translation** performance of this sequence prediction task is **low** (~20% recall).
- However, a **localisation** ability emerges from the **attention** mechanism.

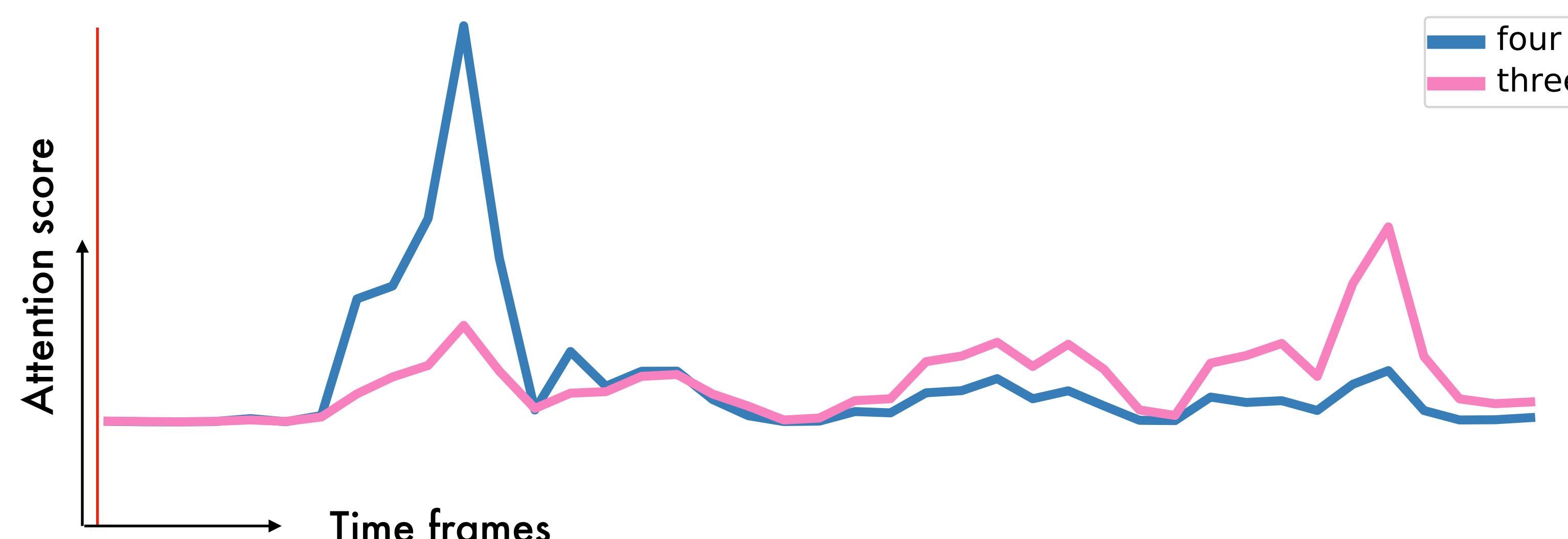
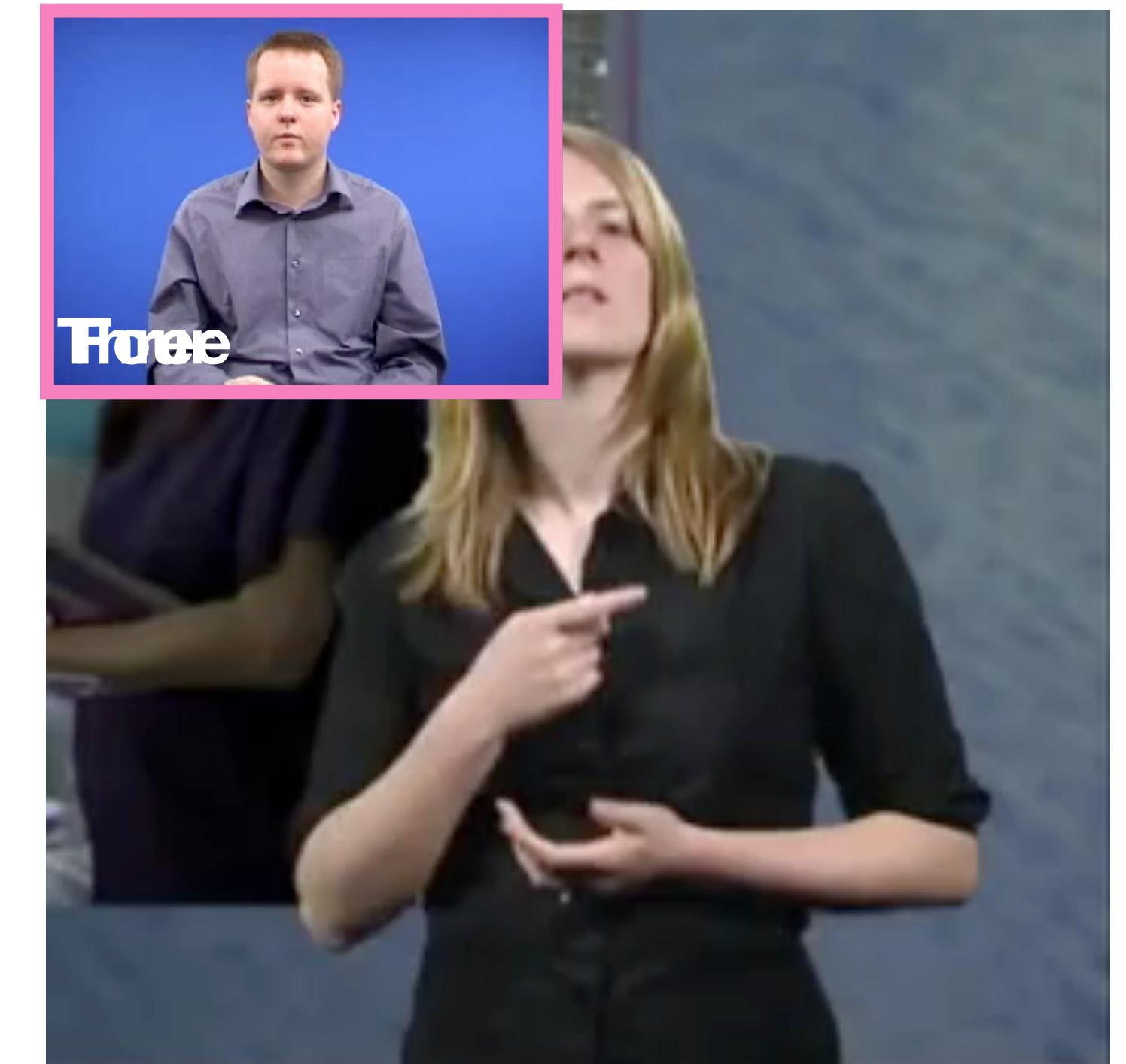


Attention visualisations

GT (original) : "Mr Hanssen said three you gave him four"

GT (processed): "mr said **three** gave **four**"

Prediction : "**four** week ago **three**"



*We show an example of the ground-truth sign from a dictionary to aid visual assessment.

Mining automatic annotations for sign recognition

Sign: “World”



Localising Sentences

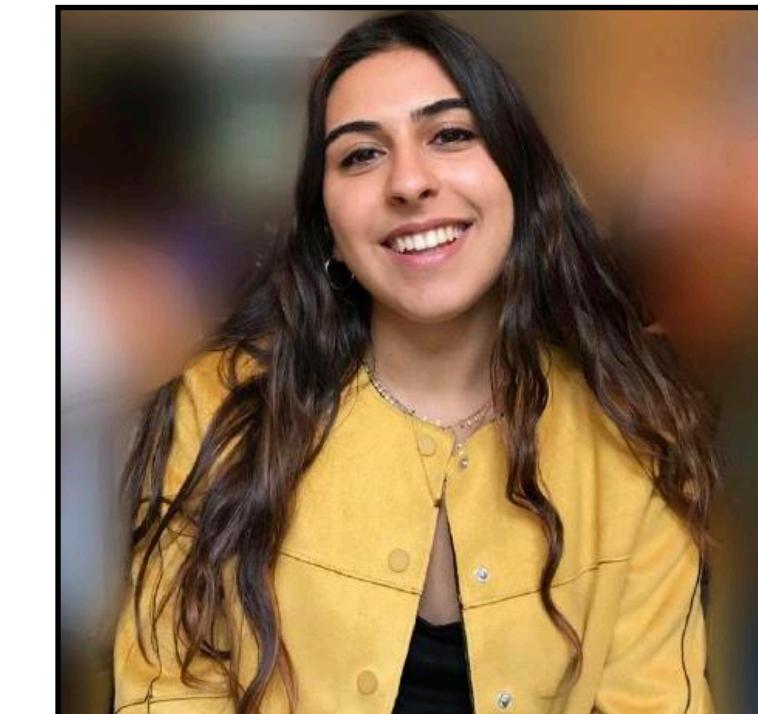
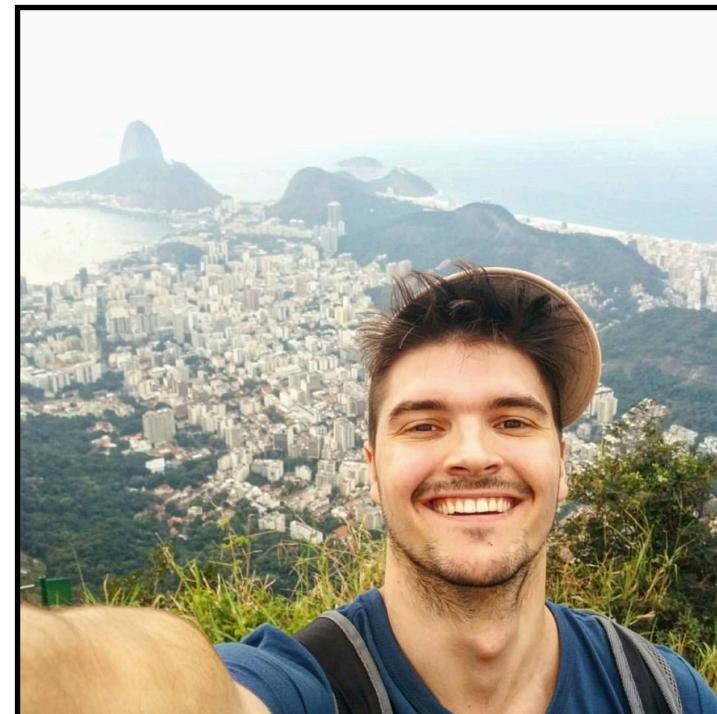
- We localised **individual** words that correspond to signs in the videos.
- Can we localise **multiple** words, i.e., phrases/sentences?



Aligning Subtitles in Sign Language Videos

ICCV 2021

<https://www.robots.ox.ac.uk/~vgg/research/bslalign/>



Hannah Bull*

Triantafyllos Afouras*

Gül Varol

Samuel Albanie

Liliane Momeni

Andrew Zisserman

*equal contribution

Problem formulation: Subtitle alignment



S_{audio}

Overlooked by a small hill known as Leopard Rock.

To keep her cubs alive in this dangerous neighbourhood,

the mother must make sure they stay hidden.

S_{gt}

Overlooked by a small hill known as Leopard Rock.

the mother must make sure they stay hidden.

To keep her cubs alive in this dangerous neighbourhood,

14:12

14:14

14:16

14:18

14:20

14:22

14:24

14:26

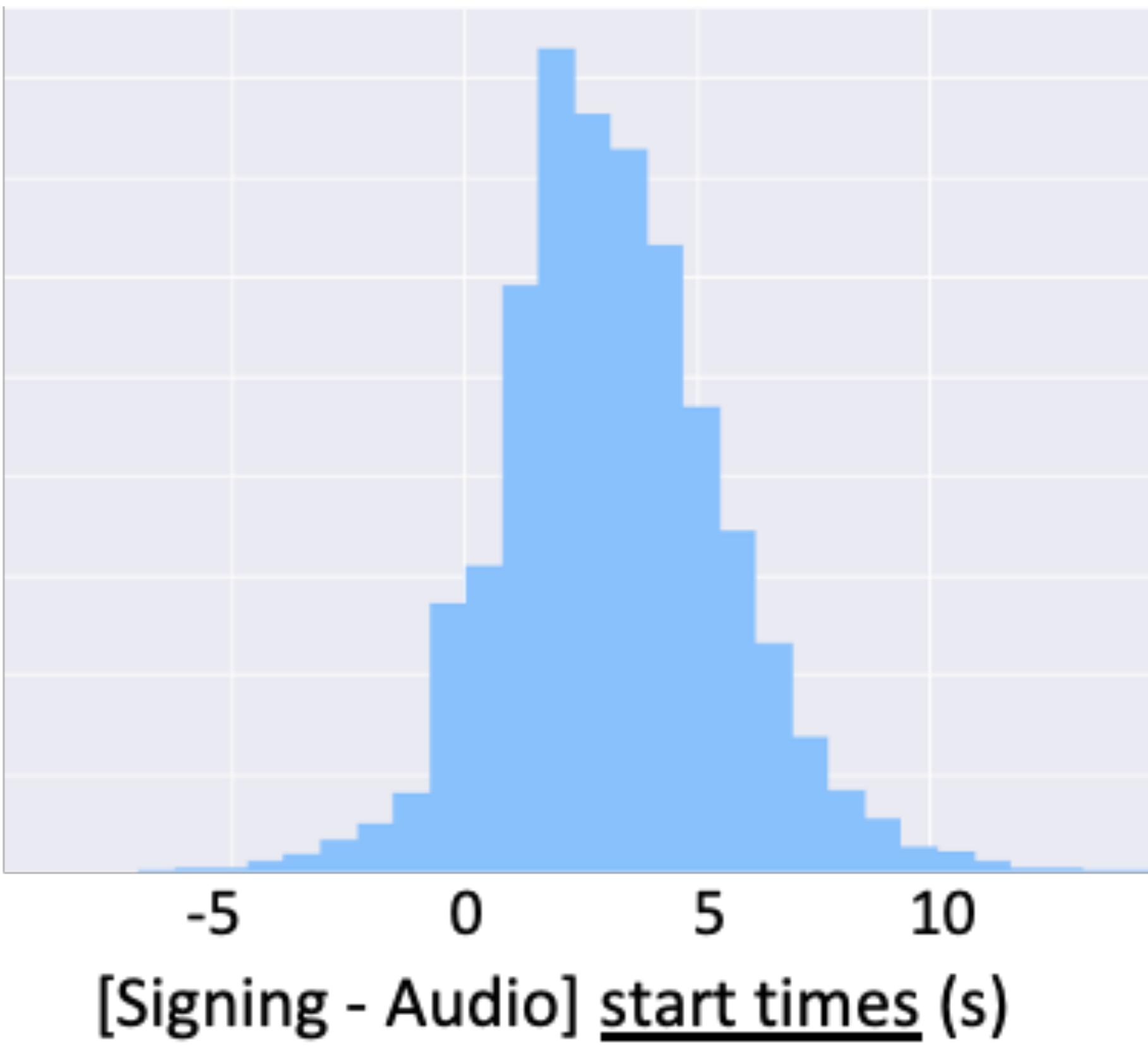
14:28

14:30

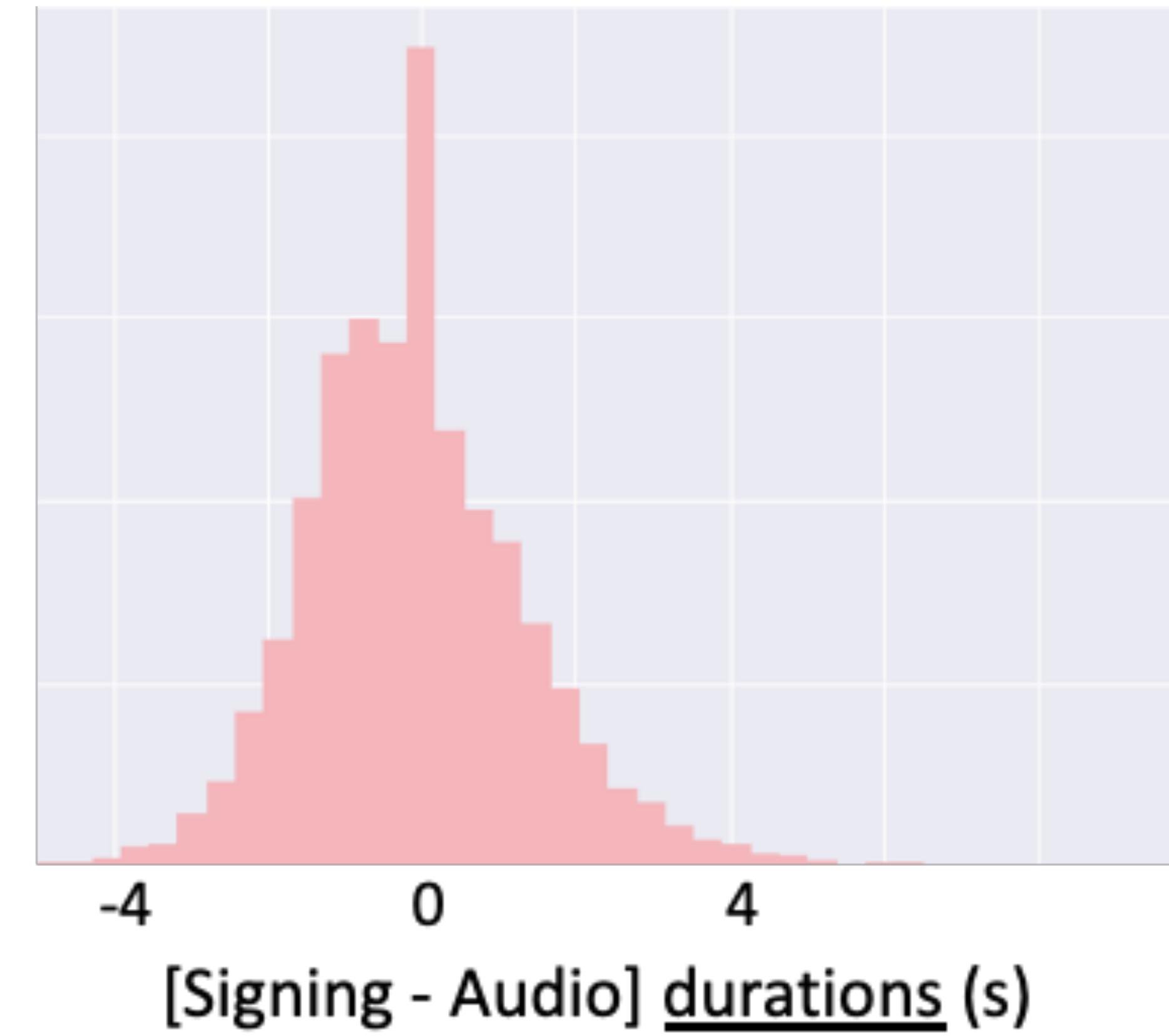
Time

Difference between speech- and sign-aligned subtitles

Shift

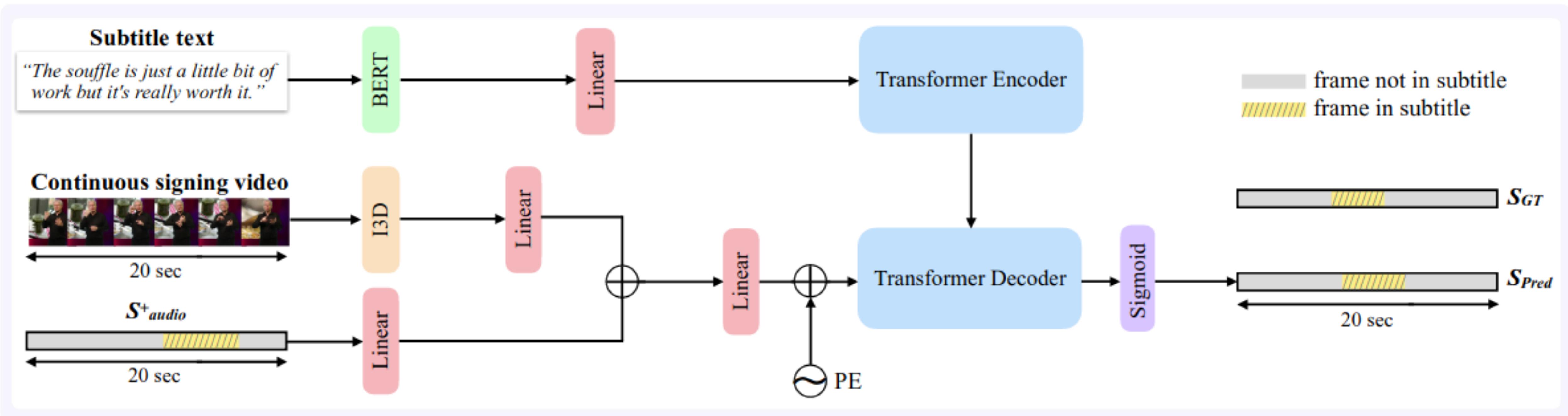


Duration



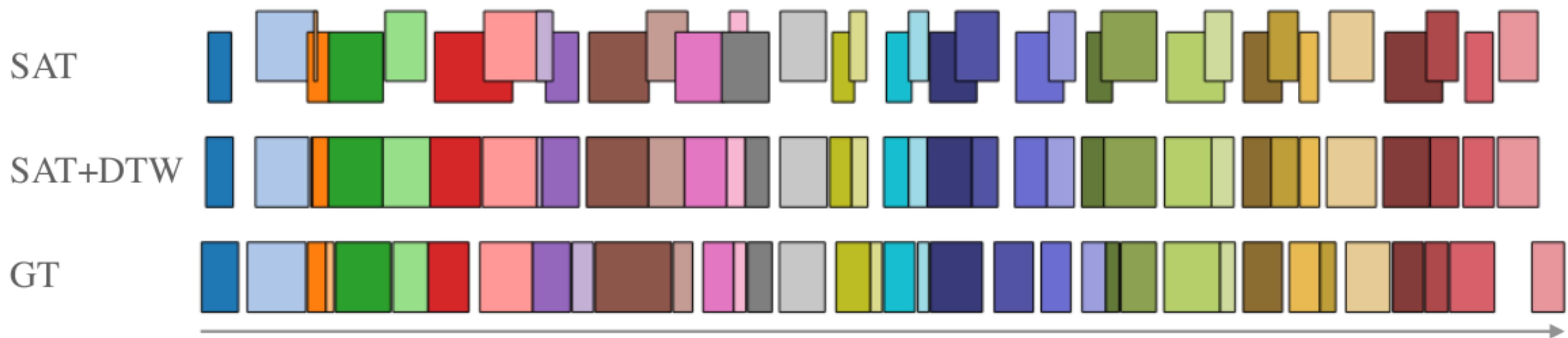
Subtitle Aligner Transformer (SAT)

- Single subtitle
- “Inverted” Transformer

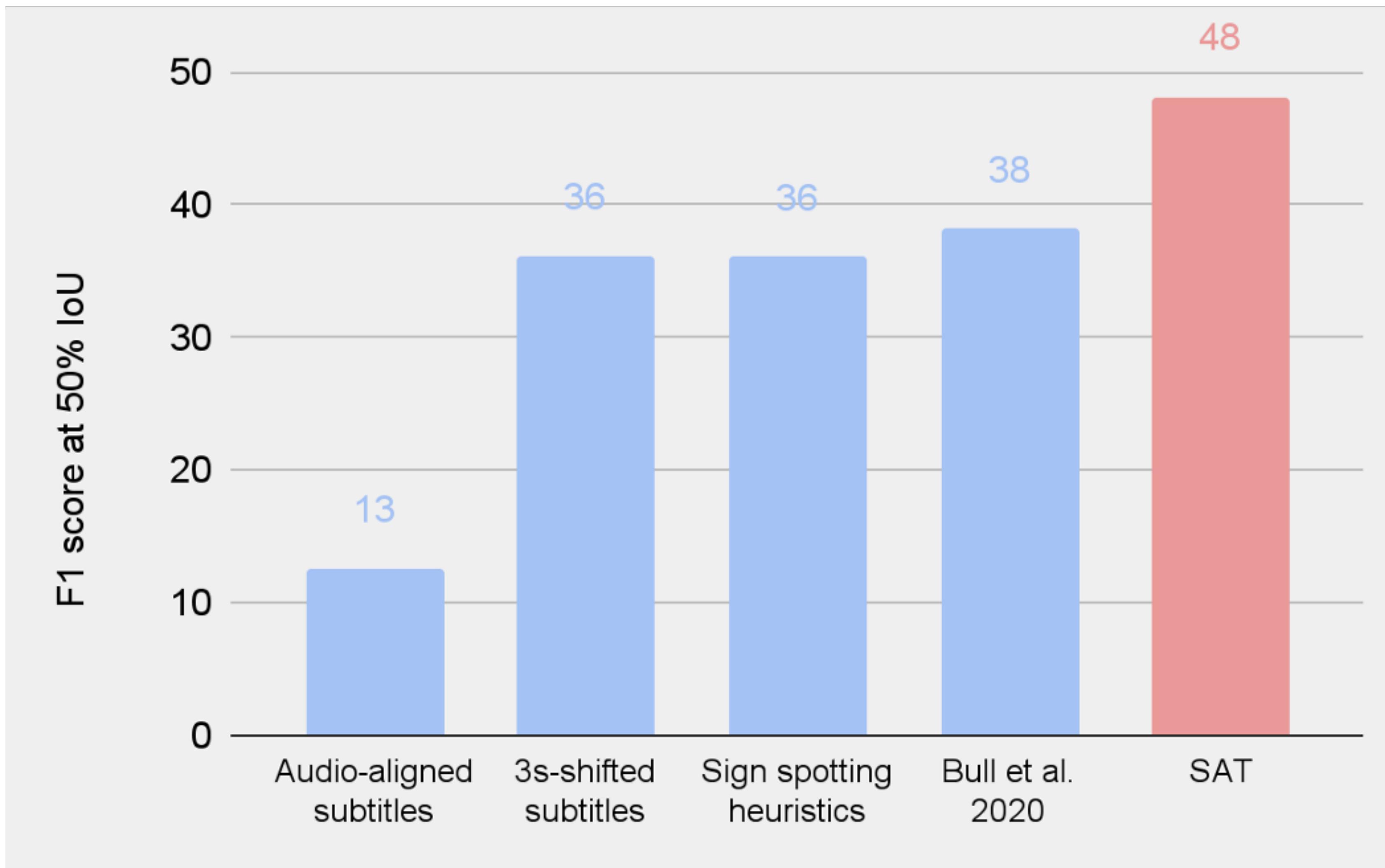


Global alignment with DTW

- Multiple subtitles

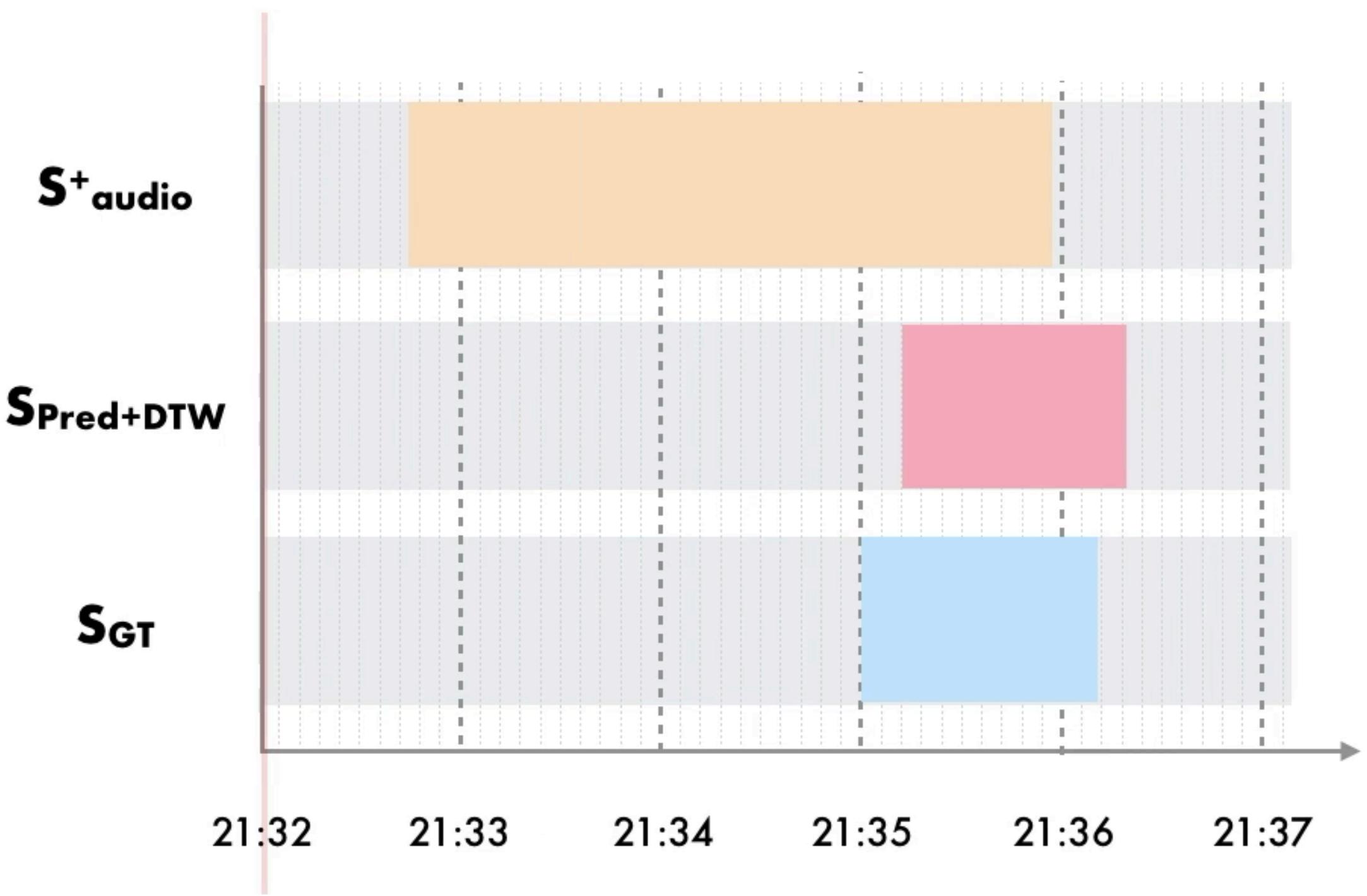


Main results



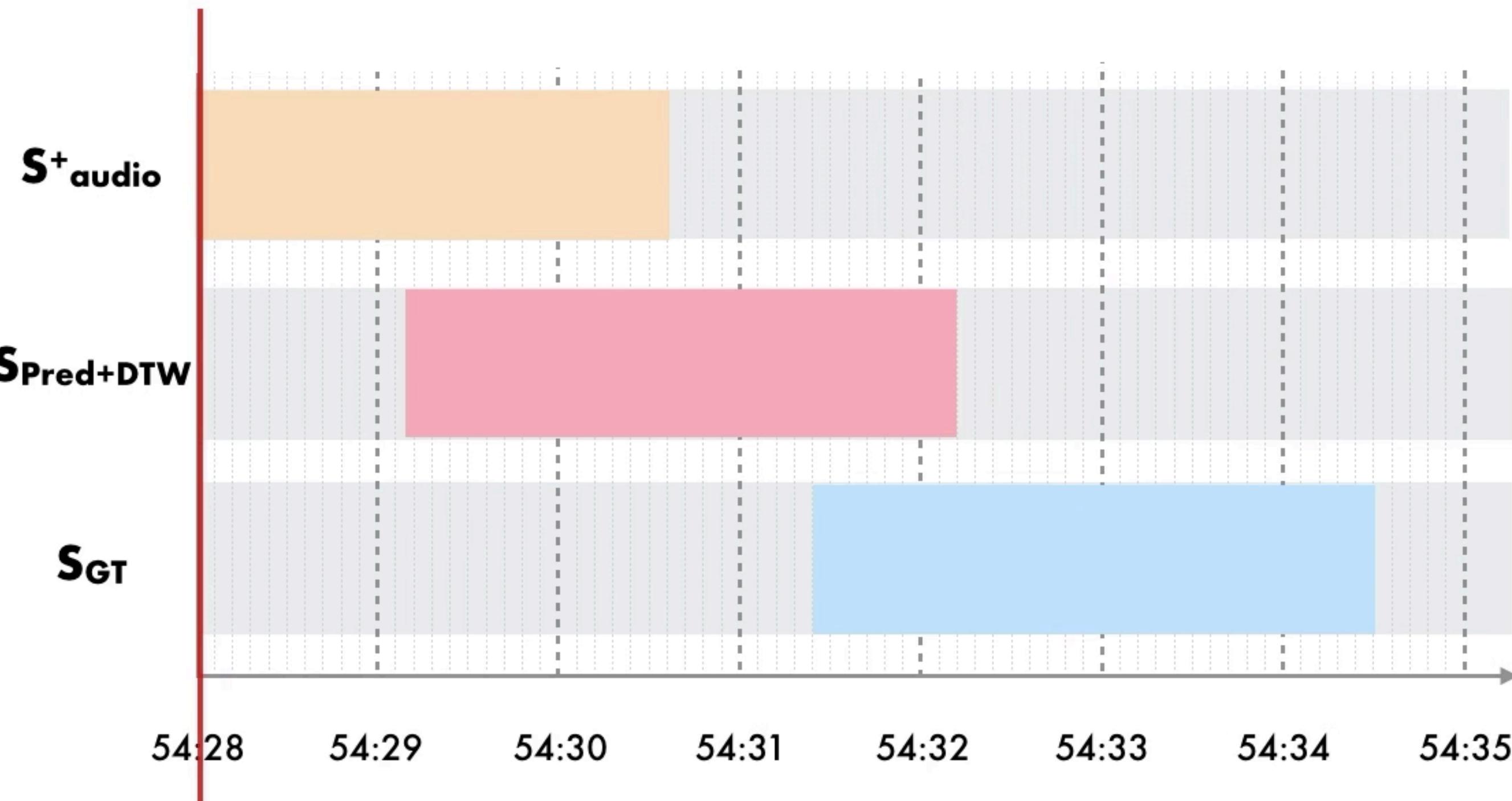
Qualitative results

Subtitle text: "But when it tastes this good, who cares?"



Qualitative results

Subtitle text: "It's the fate of the weakening daughter."



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◆ 1) Text-to-video retrieval

[Bain et al. ICCV 2021]



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◆ 2) Temporal localisation in sign language videos

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3D Estimation

◆ 3) Hand-object reconstruction from RGB videos

[Hasson et al. 3DV 2021]



Towards unconstrained hand-object reconstruction from RGB videos



Yana
Hasson



Gül
Varol



Cordelia
Schmid



Ivan
Laptev

Towards unconstrained reconstruction from RGB videos



In-the-wild hand-object interactions

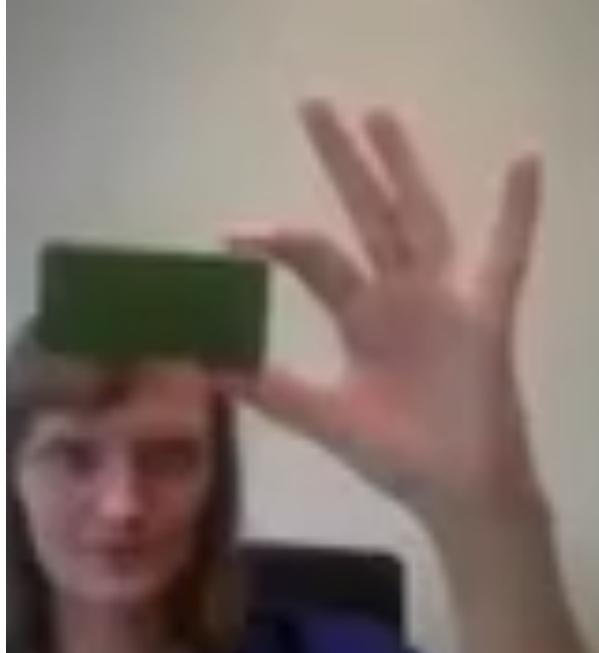


Limited datasets with 3D annotations

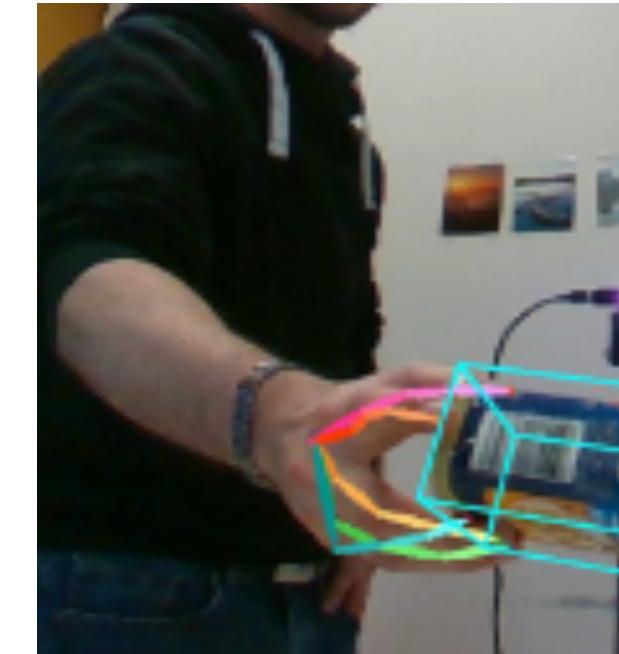
Hands In Action
ICCV 2015



Dexter+O
ECCV 2016



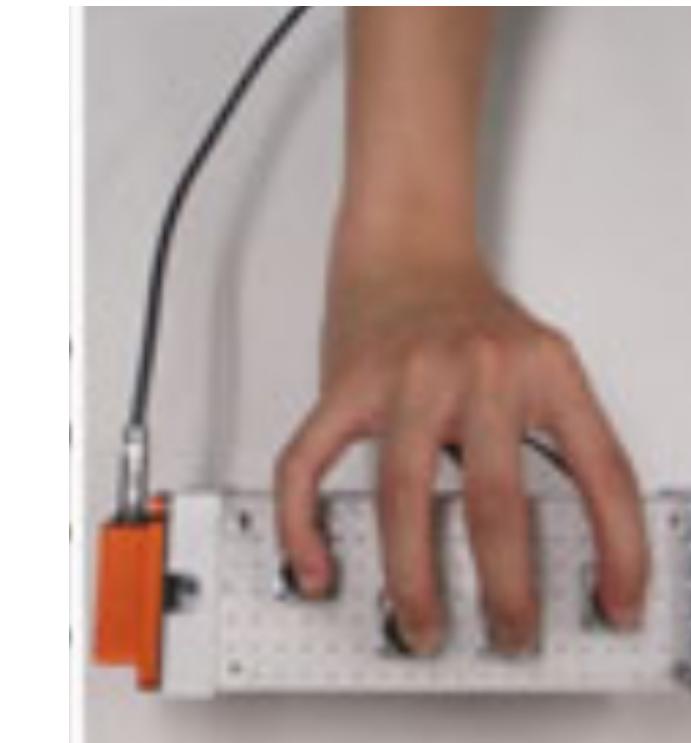
HO-3D
CVPR 2020



ContactPose
ECCV 2020



Contact Force
TPAMI 2018



FPHAB
CVPR 2018



Learning-based methods fail on different domains

Seen object,
Same domain
[HO-3D]



Seen object,
Different domain
[Dex-YCB]



Unseen object,
Different domain
[Core50]



Learning

[Hasson 2019]

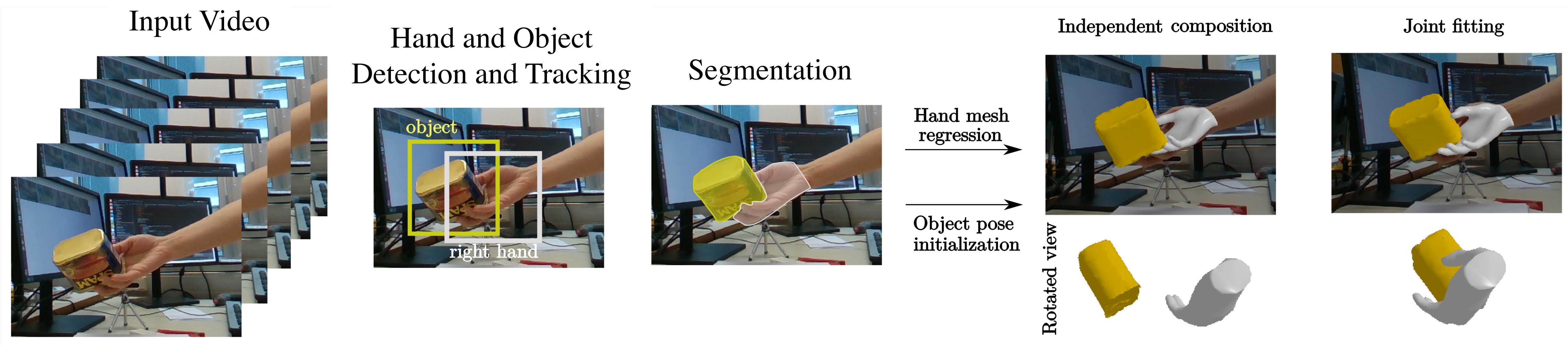


Fitting

[Hasson 2021]



Towards unconstrained joint hand-object reconstruction from RGB videos



Known object model

Input clip



Object model



Joint fitting

Camera view

Rotated views



Input clip



Object model



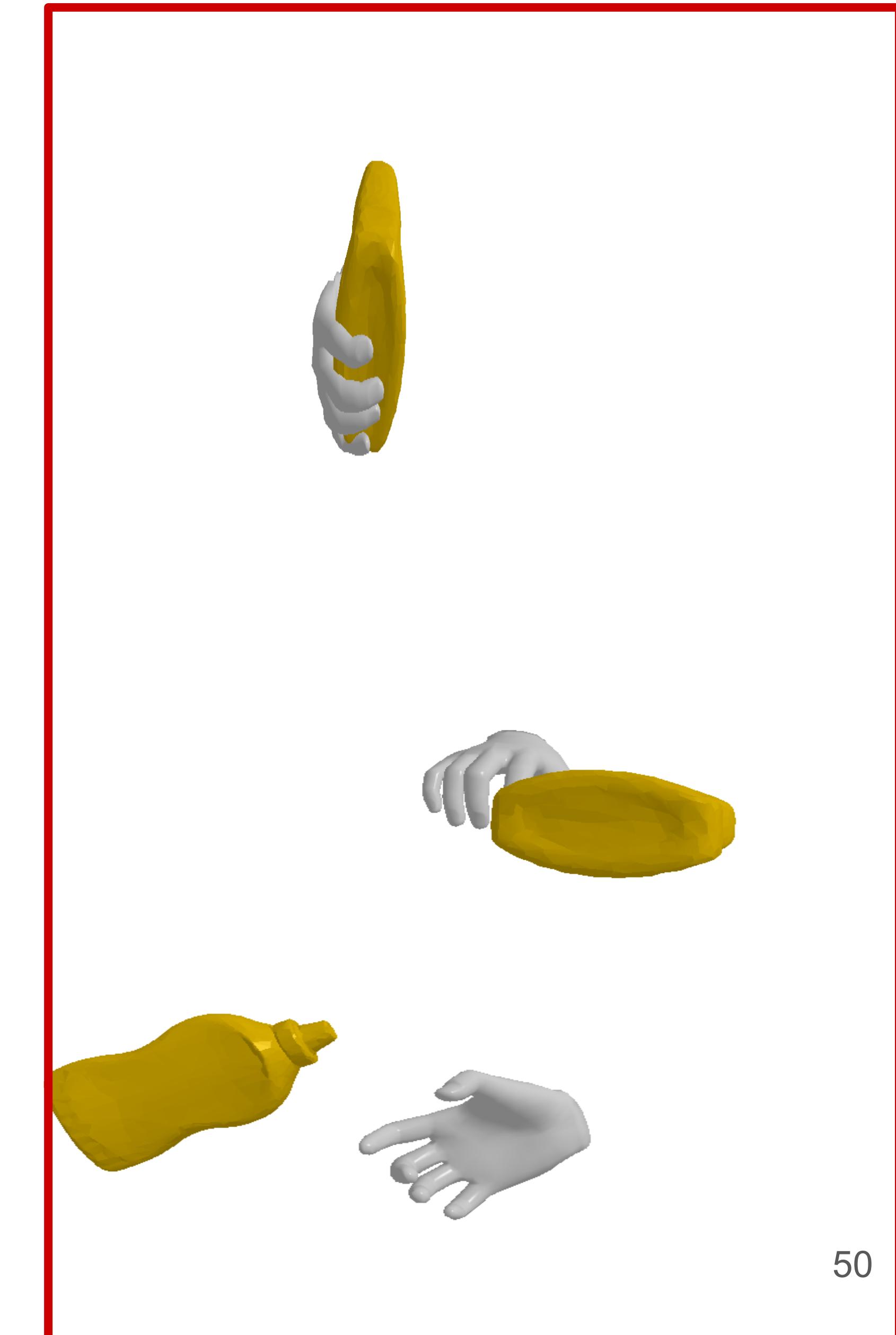
Joint fitting

Camera view

Rotated views



Independent composition



Input clip



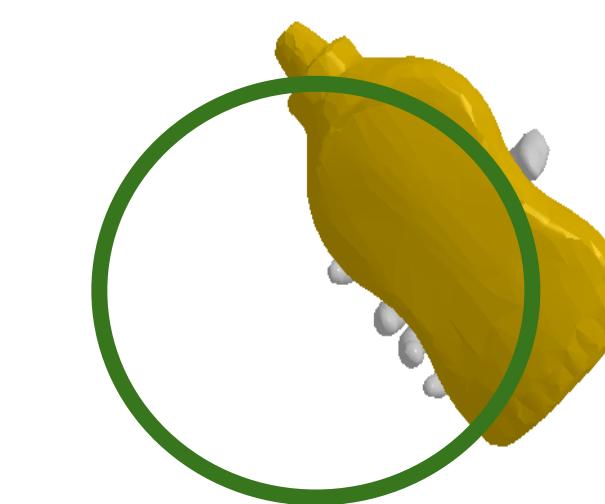
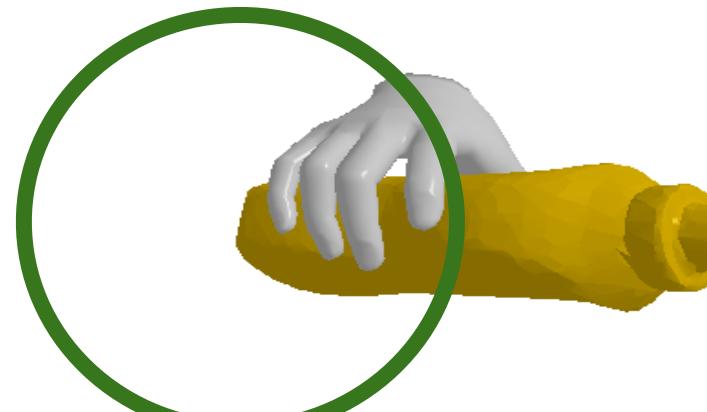
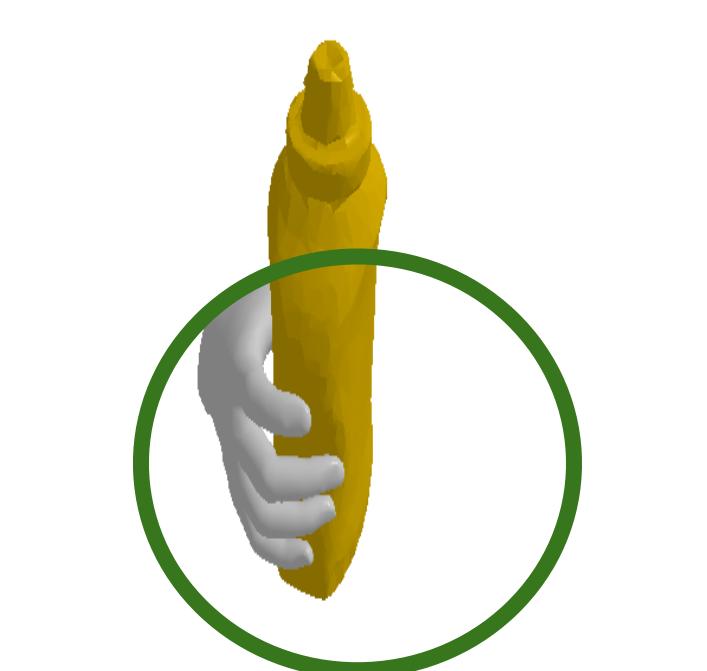
Object model



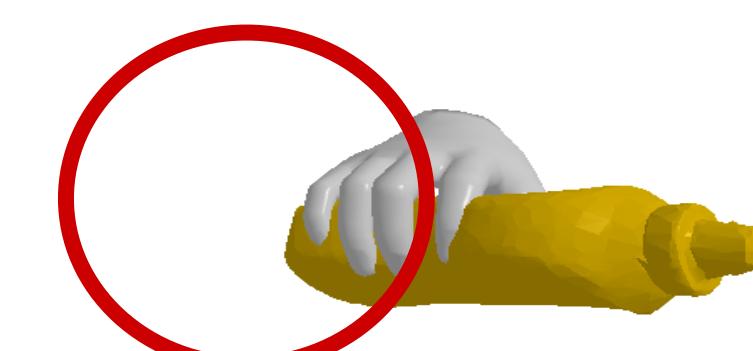
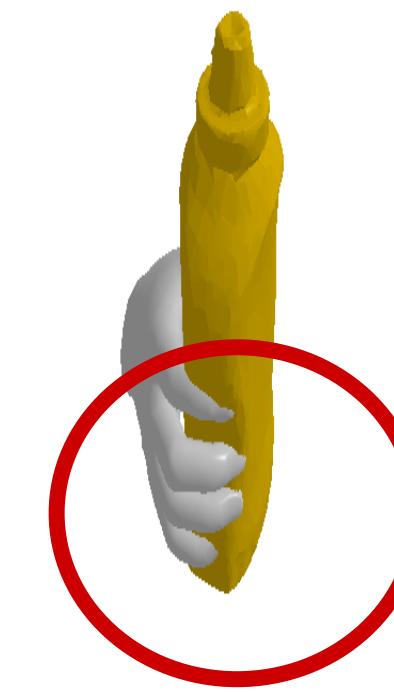
Joint fitting

Camera view

Rotated views



Without collision
penalization \mathcal{L}_{col}



interpenetration

Input clip



Object model



Joint fitting

Camera view

Rotated views



Without local
interactions

\mathcal{L}_{local}



Results on HO-3D

Input clip



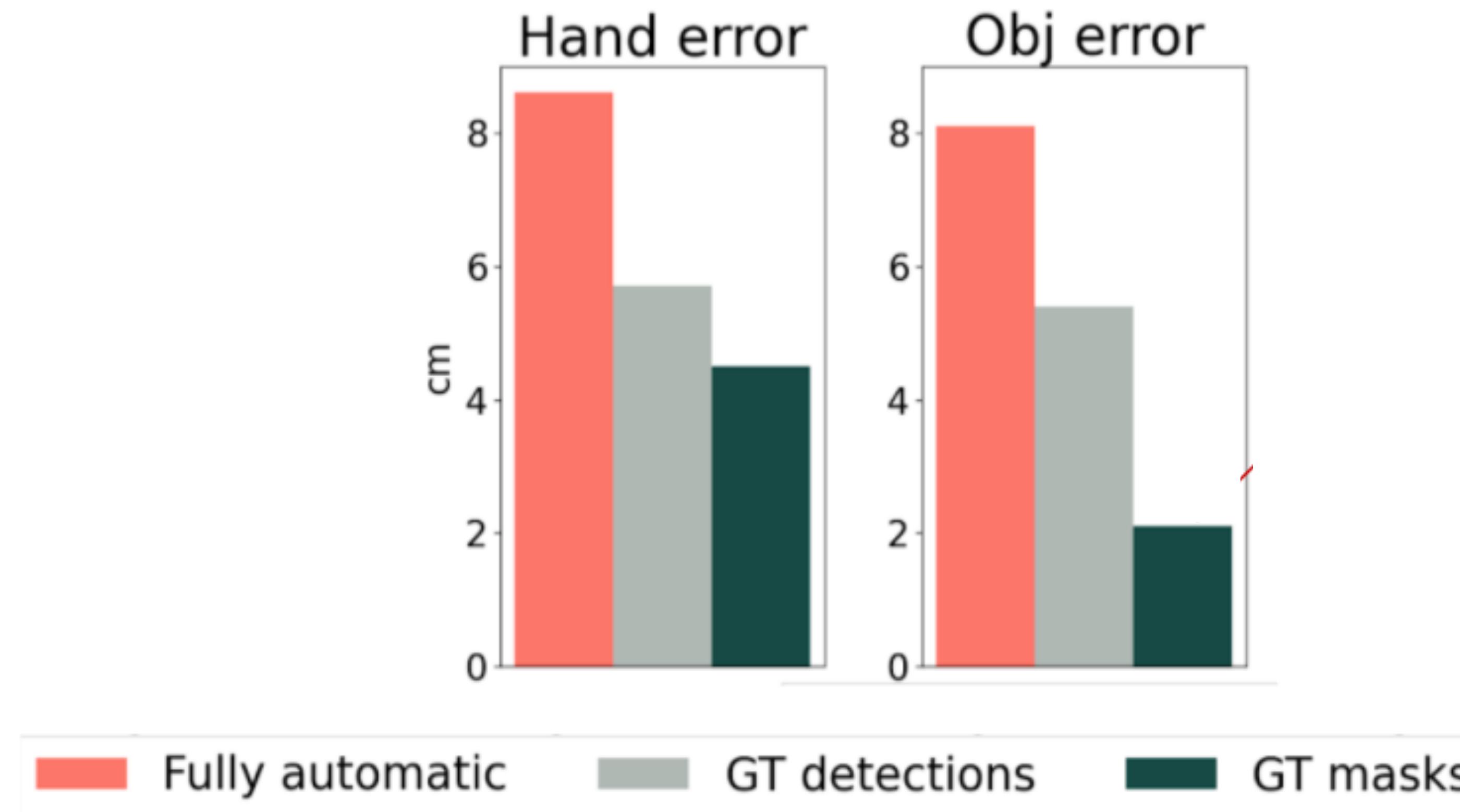
2D segmentations



Reconstruction



Ablation study for effect of 2D noise in pseudo-labels for HO-3D dataset

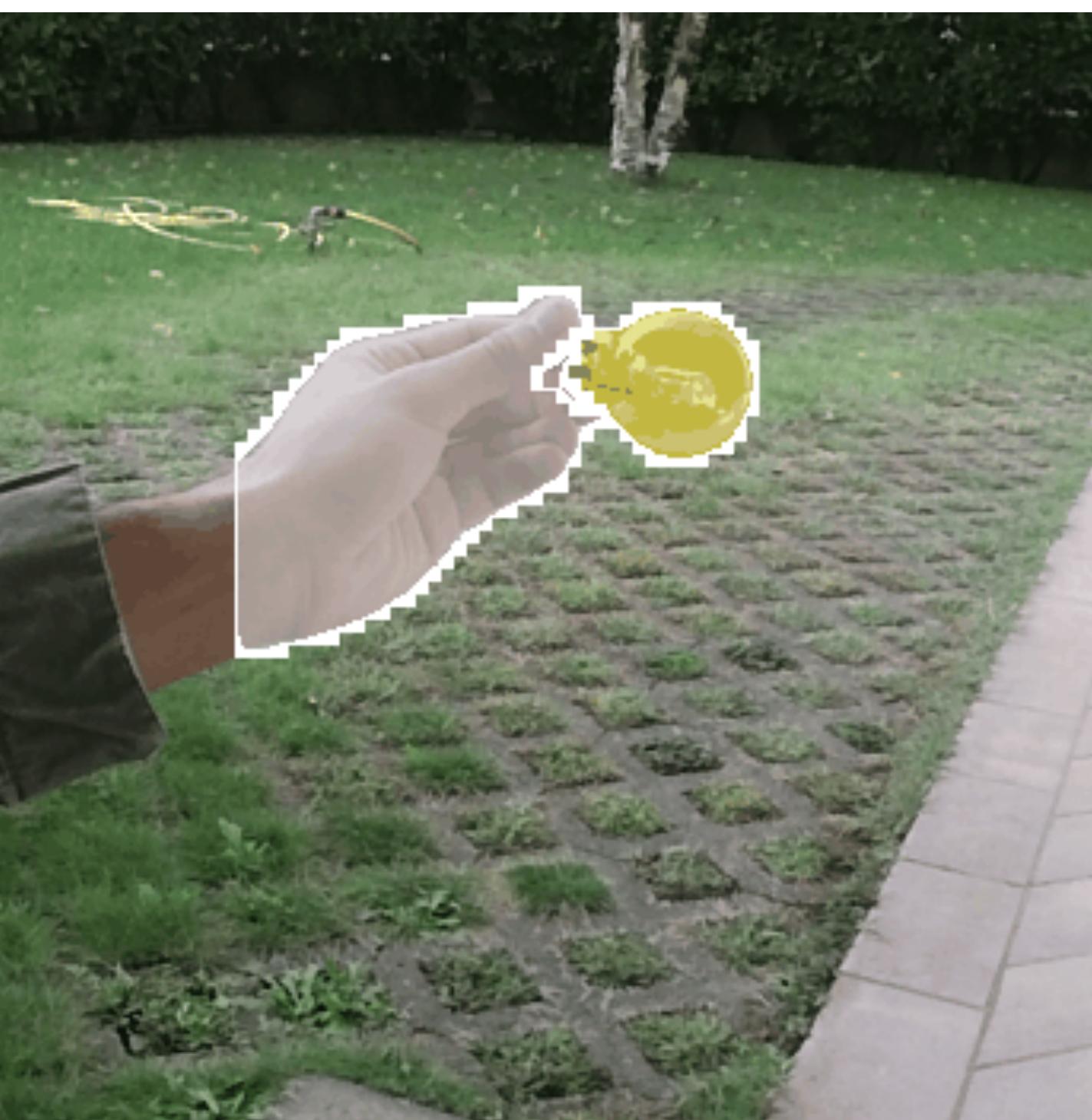


Results on Core50

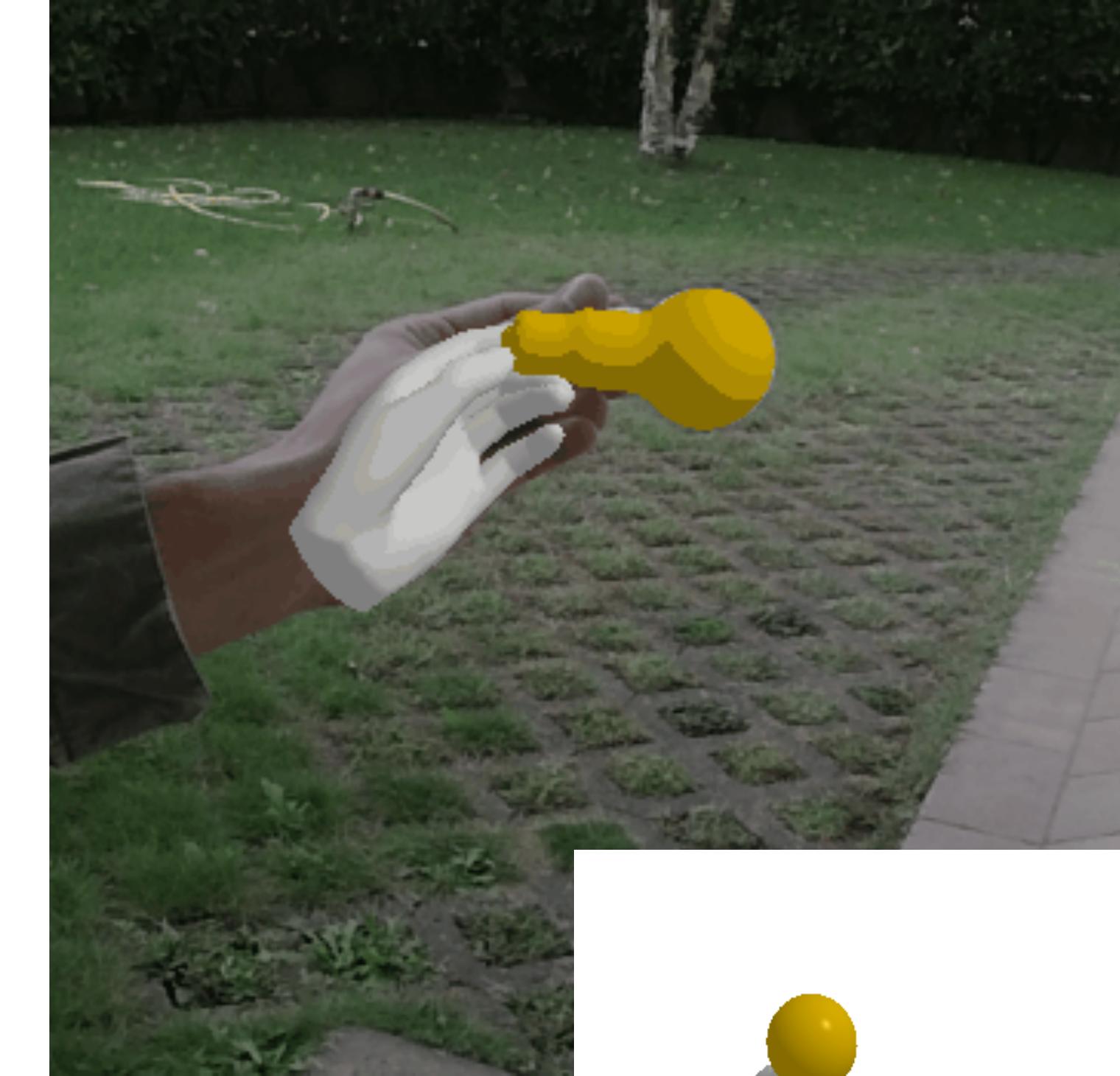
Input clip



2D segmentations



Reconstruction



Results on Epic-Kitchens

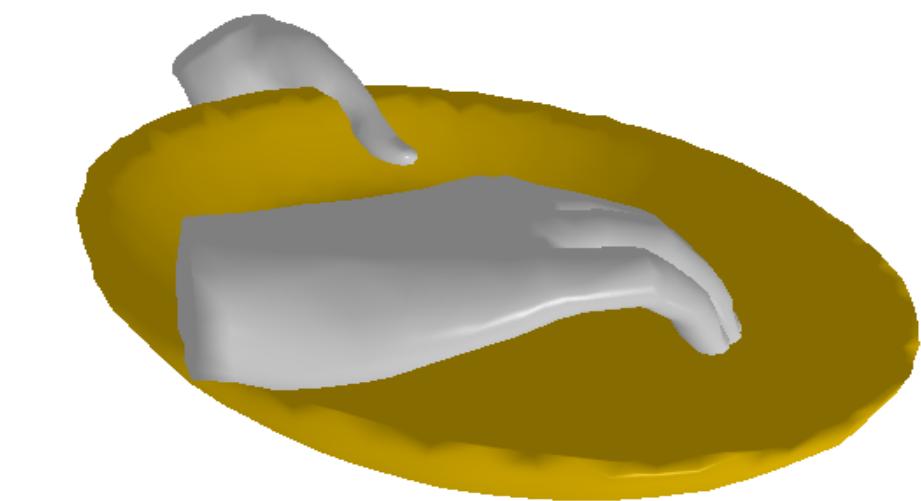
Input clip



2D segmentations



Reconstruction



Summary

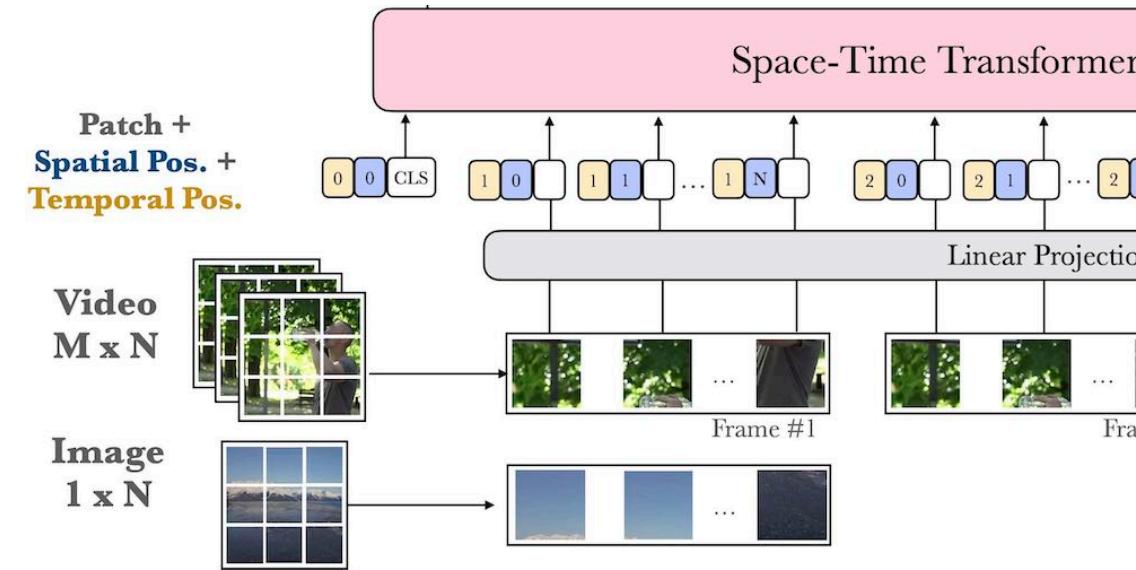
This talk:

- ◆ 1) Text-to-video retrieval
- ◆ 2) Temporal localisation in sign language videos
- ◆ 3) Hand-object reconstruction from RGB videos

What next? Open problems?

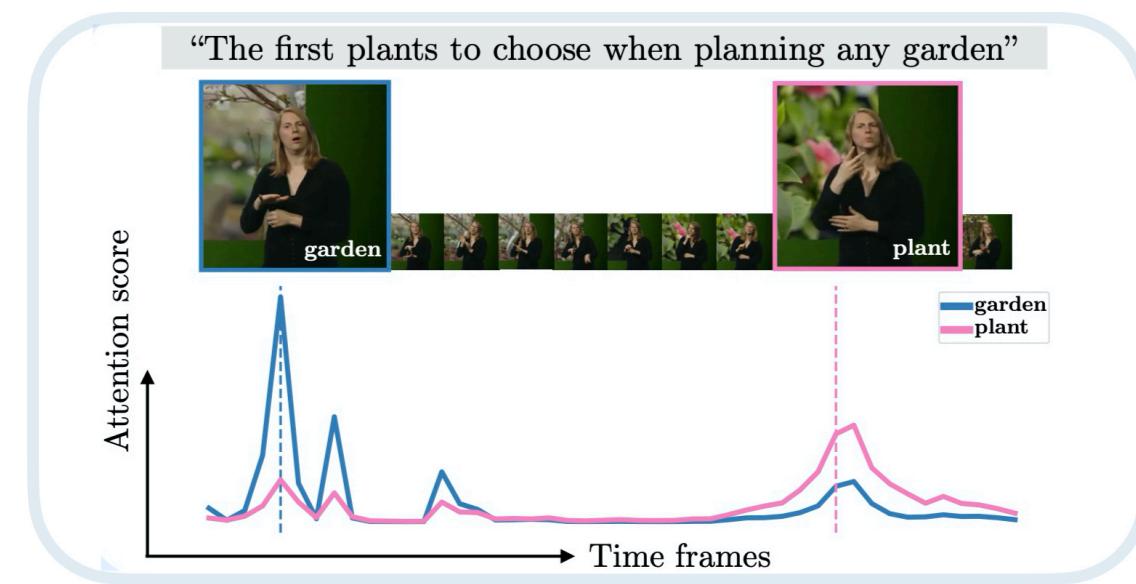
- Long-term video modeling
- Using more knowledge from image models for video modeling
- Sign language translation
- Bridging the gap between 3D and semantics

Summary



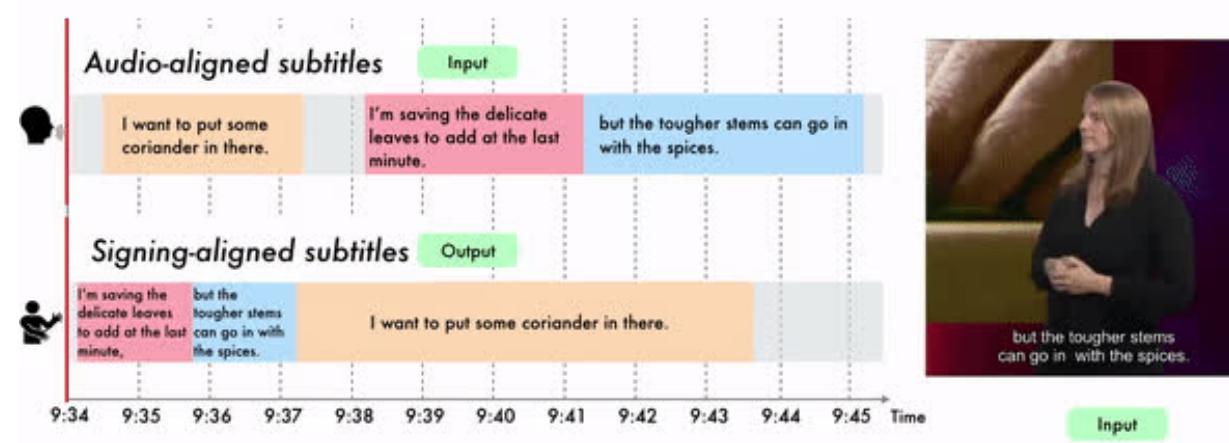
Frozen in Time: A Joint Video and Image Encoder for End-to-End Retrieval

Max Bain, Arsha Nagrani, GÜl Varol and Andrew Zisserman
ICCV 2021.



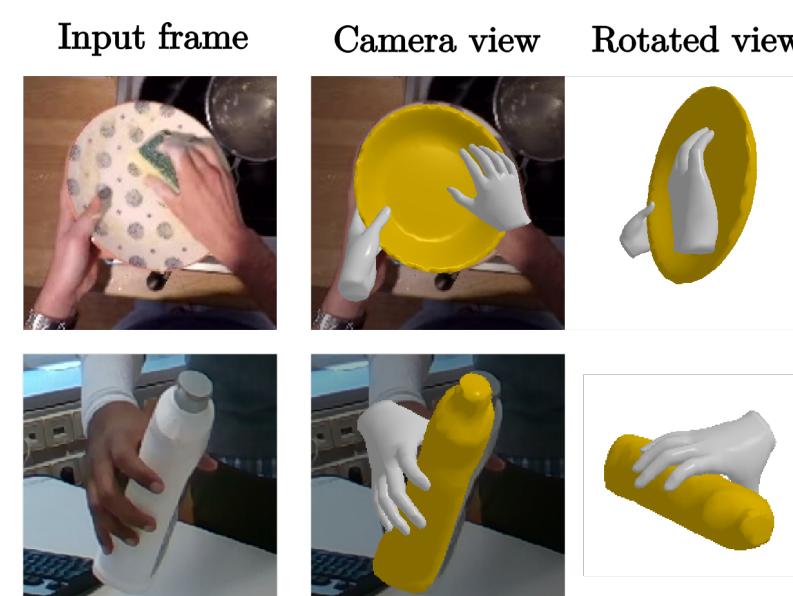
Read and Attend: Temporal Localisation in Sign Language Videos

GÜl Varol*, Liliane Momeni*, Samuel Albanie*, Triantafyllos Afouras* and Andrew Zisserman
CVPR 2021.



Aligning Subtitles in Sign Language Videos

Hannah Bull*, Triantafyllos Afouras*, GÜl Varol, Samuel Albanie, Liliane Momeni and Andrew Zisserman
ICCV 2021.



Towards unconstrained joint hand-object reconstruction from RGB videos

Yana Hasson, GÜl Varol, Cordelia Schmid and Ivan Laptev
3DV 2021.