



Human-Centric Object Interactions: A Fine-Grained Perspective from Egocentric Videos

Fine(r)-grained?



put garlic down

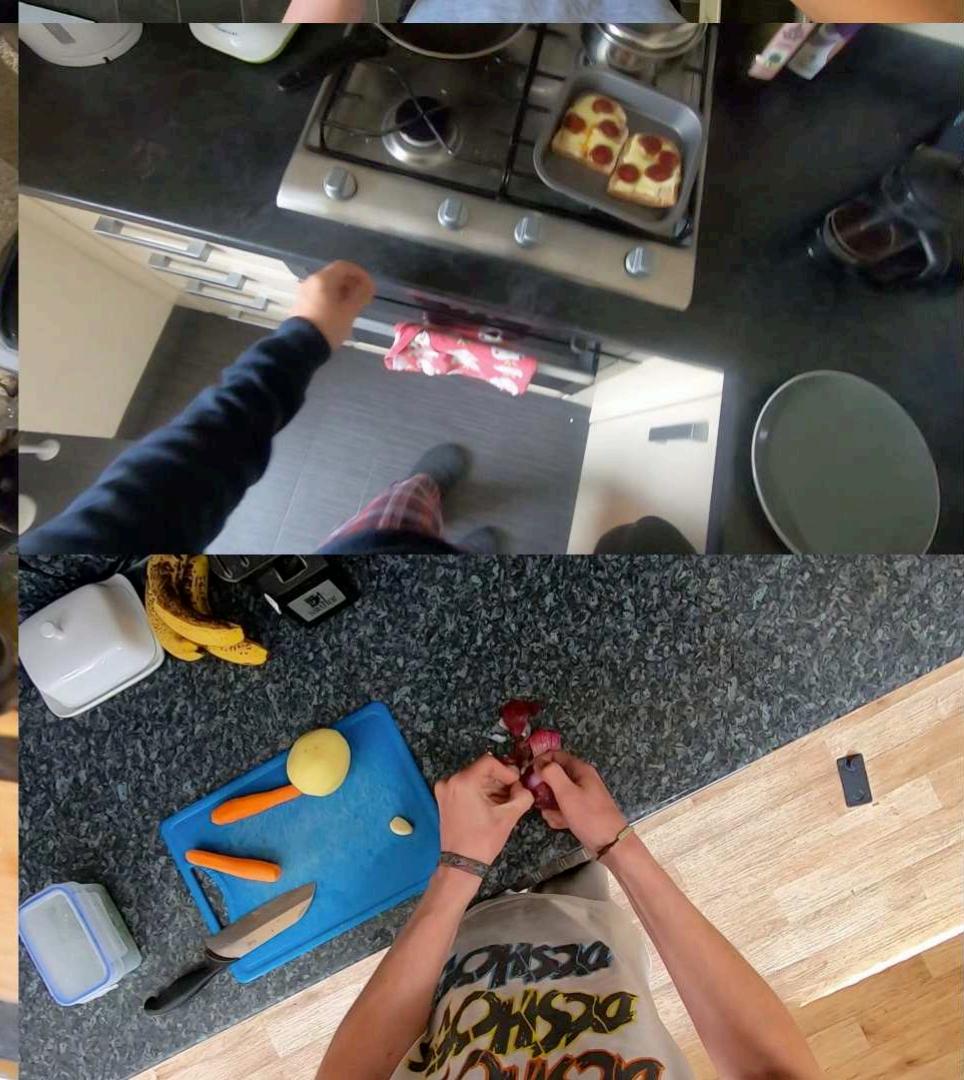
Fine(r)-grained?



- Coarse-grained: Cooking
- Fine-grained: add garlic
- Fine(r)-grained: smash garlic
 - When was the garlic smashed?
 - How was the garlic smashed?
 - Why was the garlic smashed?
 - How skilled was this person in smashing garlic?
 - Has garlic now been fully smashed?
- What information to make these decisions
 - Change in appearance
 - Motion
 - Audio
 - ??

Natural Object Interactions...







Scaling and Rescaling Egocentric Vision: The EPIC-KITCHENS Dataset



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Jonathan Munro



Toby Perrett



Will Price



Michael Wray

Scaling and Rescaling Egocentric Vision



EPIC-KITCHENS-55
Avg actions per video
91.3 188.6

EPIC-KITCHENS-100
Avg actions per minute
13 20

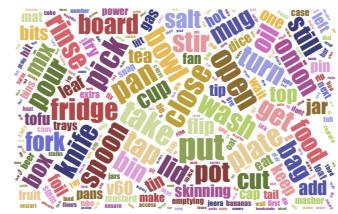


EPIC-KITCHENS-100

Data Collection



Live Narrations



Improved Annotations

Pause-and-talk Narrator

Dense Action Segments

Extension Data Collection

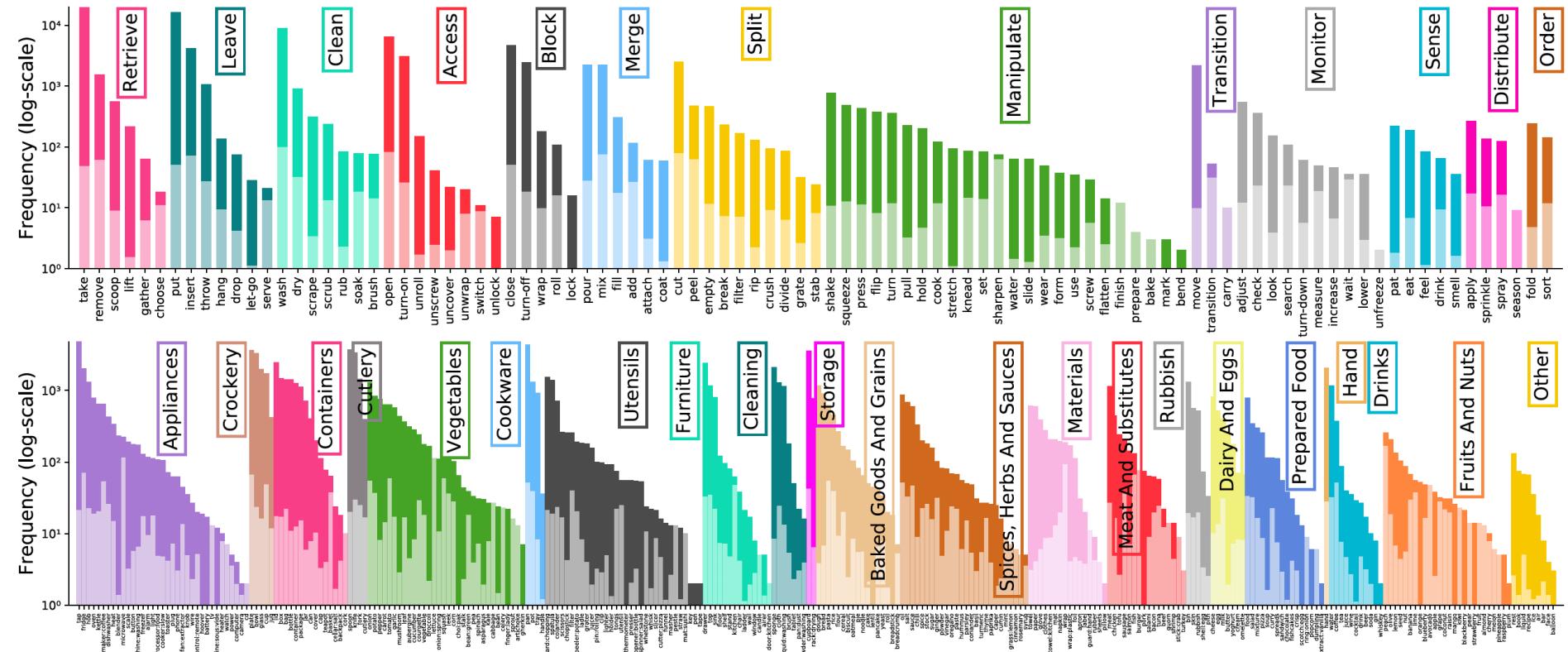


EPIC-KITCHENS-55

37 Participants



Annotations Statistics





Open Challenges

Five currently open challenges:

- Action Recognition
- Action Detection
- Action Anticipation
- Unsupervised Domain Adaptation for Recognition
- Multi-Instance Retrieval



Action Recognition Challenge

Action Recognition Challenge



Given a trimmed action segment:
 $(t_{\text{start}}, t_{\text{stop}})$
classify the action within.

$$\hat{y}_{\text{verb}} = \text{open}$$

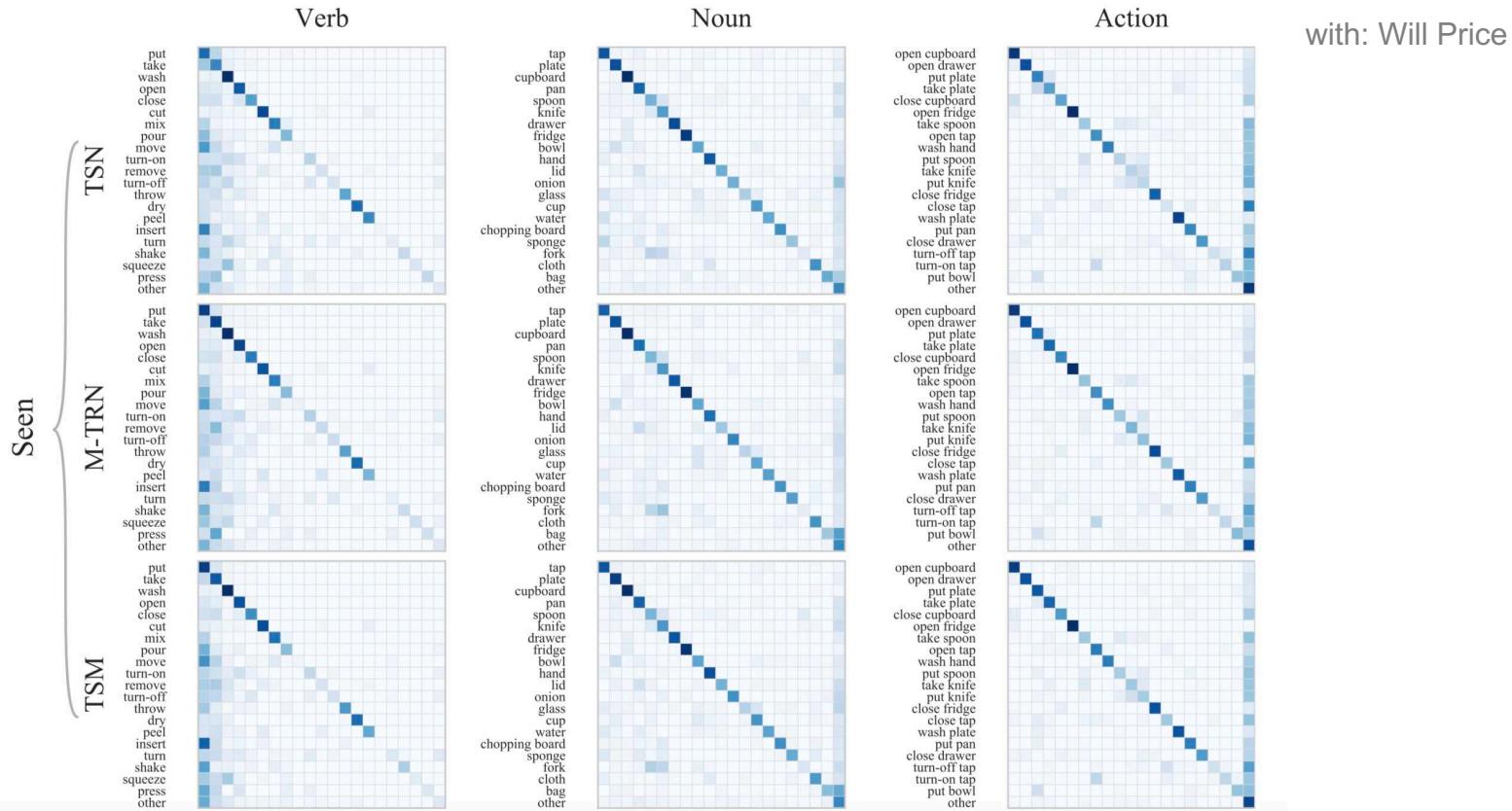
$$\hat{y}_{\text{noun}} = \text{oven}$$

$$\hat{y}_{\text{action}} = (\text{open}, \text{oven})$$

Action Recognition Challenge

Seen Kitchens (S1)																
#	User	Entries	Date of Last Entry	Team Name	Top-1 Accuracy (%)			Top-5 Accuracy (%)			Precision (%)			Recall (%)		
					Verb ▲	Noun ▲	Action ▲	Verb ▲	Noun ▲	Action ▲	Verb ▲	Noun ▲	Action ▲	Verb ▲	Noun ▲	Action ▲
1	wasun	14	05/28/20	UTS-Baidu	70.41 (1)	52.85 (1)	42.57 (1)	90.78 (4)	76.62 (2)	63.55 (2)	60.44 (4)	47.11 (1)	24.94 (3)	45.82 (4)	50.02 (1)	26.93 (2)
2	action_banks	18	05/29/20	NUS_CVML	66.56 (6)	49.60 (4)	41.59 (2)	90.10 (5)	77.03 (1)	64.11 (1)	59.43 (7)	45.62 (3)	25.37 (1)	41.65 (8)	46.25 (4)	26.98 (1)
3	Sudhakaran	50	05/29/20	FBK_HuPBA	68.68 (3)	49.35 (5)	40.00 (3)	90.97 (3)	72.45 (5)	60.23 (4)	60.63 (3)	45.45 (4)	21.82 (6)	47.19 (2)	45.84 (5)	24.34 (4)
4	tnet	34	05/27/20	SAIC_Cambridge	69.43 (2)	49.71 (3)	40.00 (3)	91.23 (2)	73.18 (3)	60.53 (3)	60.01 (5)	45.74 (2)	24.95 (2)	47.40 (1)	46.78 (3)	25.27 (3)
5	aptx4869lm	12	01/30/20	GT-WISC-MPI	68.51 (4)	49.96 (2)	38.75 (4)	89.33 (8)	72.30 (6)	58.99 (5)	51.04 (16)	44.00 (6)	23.70 (5)	43.70 (7)	47.32 (2)	23.92 (5)
6	weiyaowang	14	05/28/20		66.67 (5)	48.48 (6)	37.12 (5)	88.90 (9)	71.36 (7)	56.21 (8)	51.86 (14)	41.26 (7)	20.97 (7)	44.33 (6)	44.92 (6)	21.48 (8)
7	TBN_Ensemble	1	07/20/19	Bristol-Oxford	66.10 (7)	47.88 (7)	36.66 (6)	91.28 (1)	72.80 (4)	58.62 (6)	60.73 (2)	44.89 (5)	24.01 (4)	46.81 (3)	43.88 (7)	22.92 (6)
8	cvg_uni_bonn	21	05/27/20	CVG Lab Uni Bonn	62.86 (8)	43.44 (10)	34.53 (7)	89.64 (6)	69.24 (8)	56.73 (7)	52.82 (13)	38.81 (11)	19.21 (10)	44.72 (5)	39.50 (10)	21.80 (7)
9	antoninofurnari	1	07/19/19		56.93 (16)	43.05 (11)	33.06 (8)	85.68 (20)	67.12 (11)	55.32 (9)	50.42 (17)	39.84 (9)	18.91 (11)	37.82 (14)	38.11 (11)	19.12 (11)
10	Wenda	12	04/25/20	Wenda Go!	61.10 (12)	43.73 (8)	31.54 (9)	89.45 (7)	68.45 (10)	52.62 (10)	55.79 (10)	41.24 (8)	20.67 (8)	40.25 (10)	40.49 (9)	19.33 (10)
11	EPIC TSM FUSION	1	03/30/20		62.37	41.88	29.90	88.55	66.43	49.81	59.51	39.50	18.38	34.44	36.04	15.80

Evaluating Action Recognition Models



W Price, D Damen (2019). An Evaluation of Action Recognition Models on EPIC-Kitchens. Arxiv

Evaluating Action Recognition Models

with: Will Price

Model	GFLOP/s		Params (M)	
	RGB	Flow	RGB	Flow
TSN	33.12	35.33	24.48	24.51
TRN	33.12	35.32	25.33	25.35
M-TRN	33.12	35.33	27.18	27.21
TSM	33.12	35.33	24.48	24.51

Models Released
March 2021

Table 3: Model parameter and FLOP/s count using a ResNet-50 backbone with 8 segments for a single video.

W Price, D Damen (2019). An Evaluation of Action Recognition Models on EPIC-Kitchens. Arxiv



More?

<http://epic-kitchens.github.io>

EPIC-KITCHENS-100 2021 CHALLENGES

Challenge and Leaderboard Details with links to CodaLab Leaderboards

For Challenge Results and winners on EPIC-KITCHENS-55, go to: [Challenge 2020 Details](#).

Note that these are NEW leaderboards, and results are not directly comparable to last year's results.

EPIC-Kitchens 2021 Challenges - Dates

Aug 23rd, 2020	EPIC-Kitchens Challenges 2021 Launched alongside EPIC@ECCV Workshop
May 28, 2021	Server Submission Deadline at 23:59:59 GMT
Jun 4, 2021	Deadline for Submission of Technical Reports
TBC	Results announcement dates will be confirmed later

Challenges Guidelines

The five challenges below and their test sets and evaluation servers are available via CodaLab. The leaderboards will decide the winners for each individual challenge. For each challenge, the CodaLab server page details submission format and evaluation metrics.

To enter any of the five competitions, you need to register an account for that challenge using a valid institute (university/company) email address. A single registration per research team is allowed. We perform a manual check for each submission, and expect to accept registrations within 2 working days.

For all challenges the maximum submissions per day is limited to 1, and the overall maximum number of submissions per team is limited to 50 overall, submitted once a day. This includes any failed submissions due to formats - please do not contact us to ask for increasing this limit.

To submit your results, follow the JSON submission format, upload your results and give time for the evaluation to complete (in the order of several minutes). Note our new rules on declaring the supervision level, given our proposed scale, for each submission. After the evaluation is complete, the results automatically appear on the public leaderboards but you are allowed to withdraw these at any point in time.

To participate in the challenge, you need to have your results on the public leaderboard, along with an informative team name (that represents your institute or the collection of institutes participating in the work), as well as brief information on your method. You are also required to submit a report (details TBC).

Make the most of the starter packs available with the challenges, and should you have any questions, please use our info email wob-epic-kitchens@bristol.ac.uk

EPIC KITCHENS

- ABOUT
- STATS
- DOWNLOADS
- CHALLENGES
- TEAM

NEWS

- 1st of July 2020: EPIC-KITCHENS-100 is now Released! [Watch release webinar recording](#)
- Watch the dataset's [trailer](#) and [video demonstration](#) on YouTube

What is EPIC-KITCHENS-100?

The *extended* largest dataset in first-person (egocentric) vision, multi-faceted, audio-visual, non-scripted recordings in native environments - i.e. the wearers' homes, capturing all daily activities in the kitchen over multiple days. Annotations are collected using a novel 'Pause-and-Talk' narration interface.

Characteristics

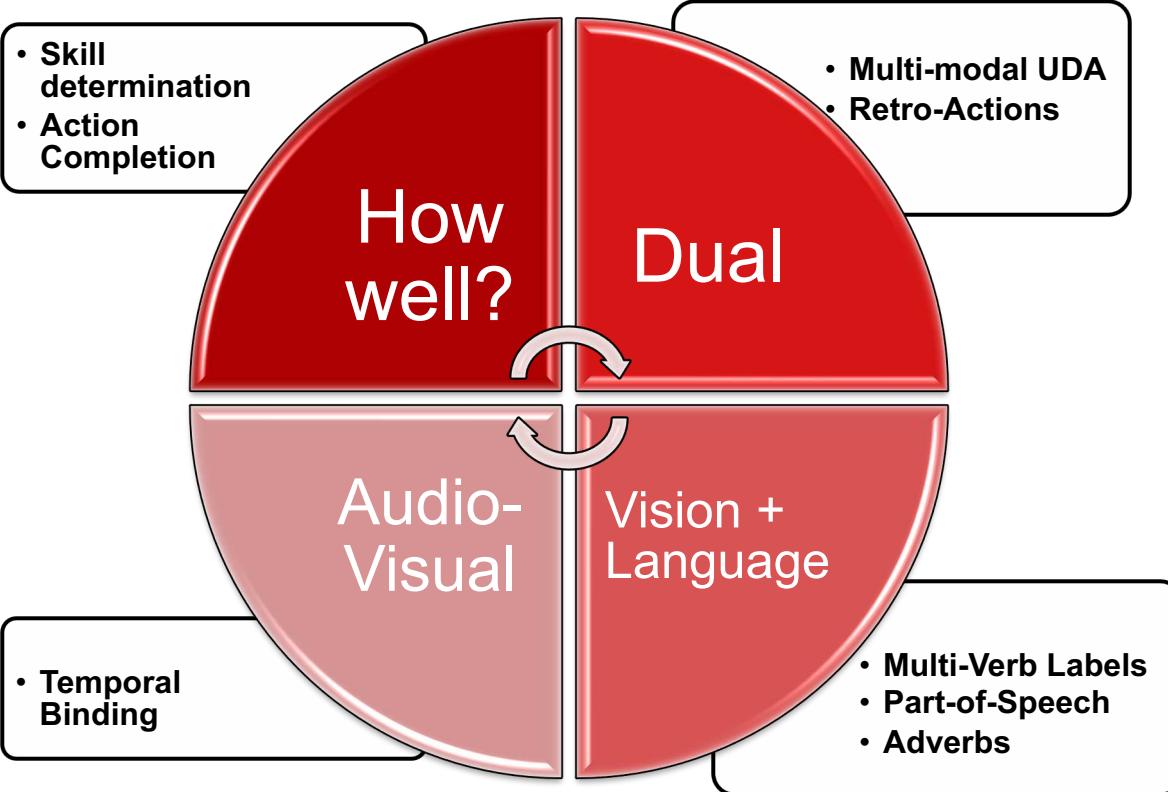
- 45 kitchens - 4 cities
- Head-mounted camera
- 100 hours of recording - Full HD
- 20M frames
- Multi-language narrations
- 90K action segments
- 20K unique narrations
- 97 verb classes, 300 noun classes
- 6 challenges

Previous versions...

- The previous version of the dataset (55 hours) was released in April 2018
- Refer to [EPIC-KITCHENS-55](#) for details
- 2020 Challenges: [Results](#), [Tech Report](#)
- 2019 Challenges: [Results](#), [Tech Report](#)
- EPIC-KITCHENS-55 leaderboards remain open until the end of 2020



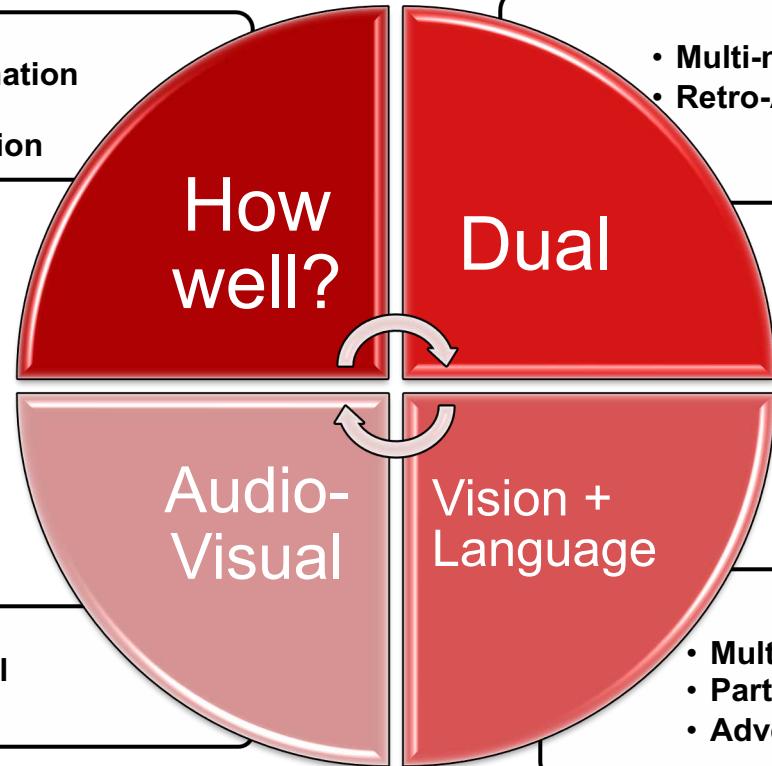
Fine(r)-grained?



Fine(r)-grained?

CVPR18, CVPR19
BMVC18, ICCVW19

- Skill determination
- Action Completion



CVPR20
ICCVW19

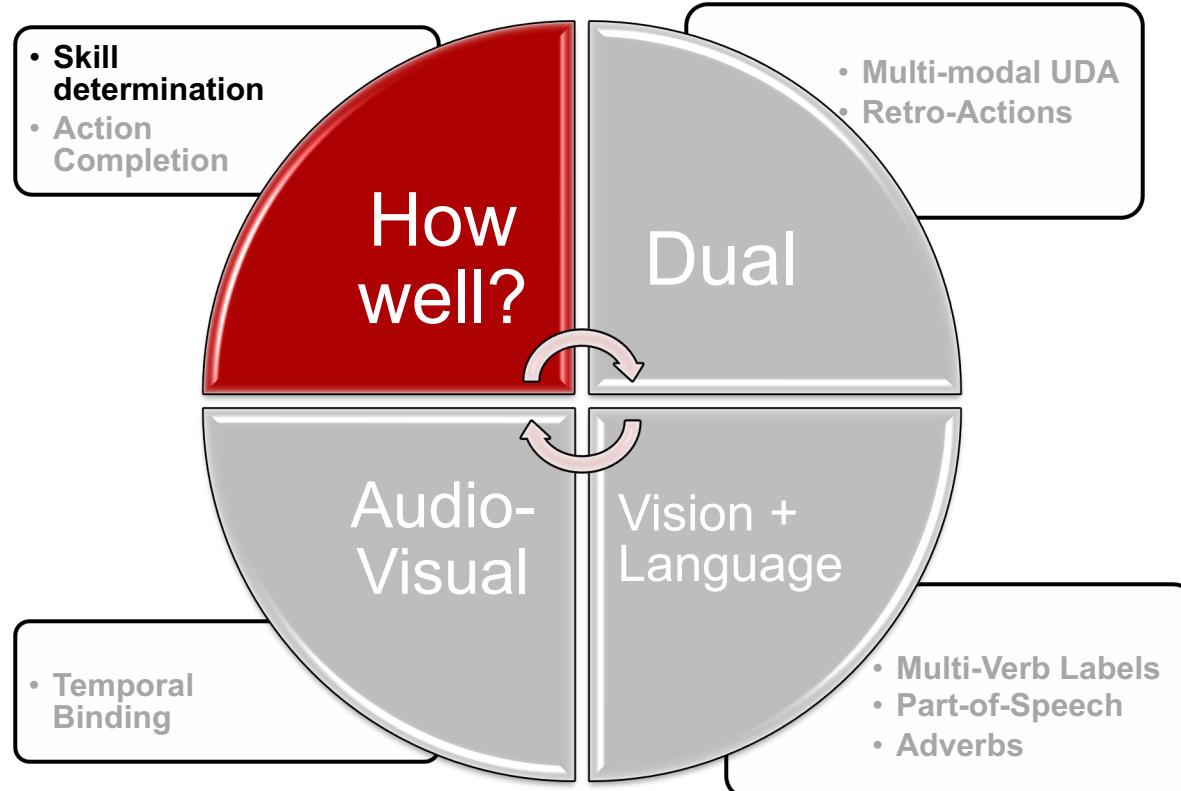
- Multi-modal UDA
- Retro-Actions

ICCV19

- Temporal Binding

BMVC19
ICCV19
CVPR20

Fine(r)-grained?



Skill determination in video

with: Hazel Doughty
Walterio Mayol-Cuevas

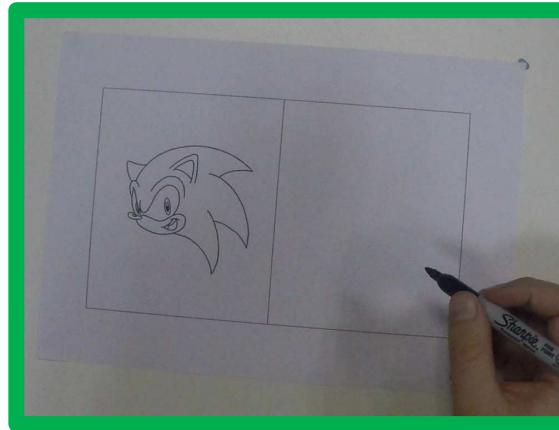
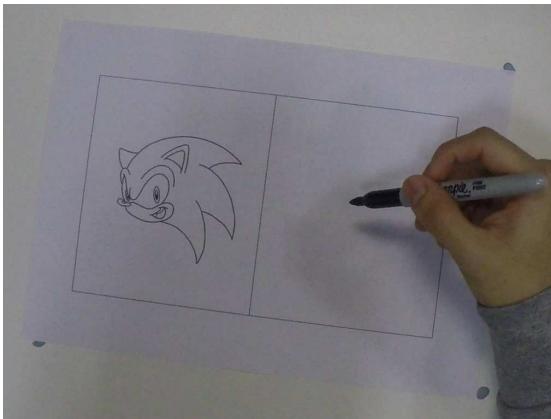


Assess relative skill for a collection of video sequences,
applicable to a variety of tasks.

Skill determination in video

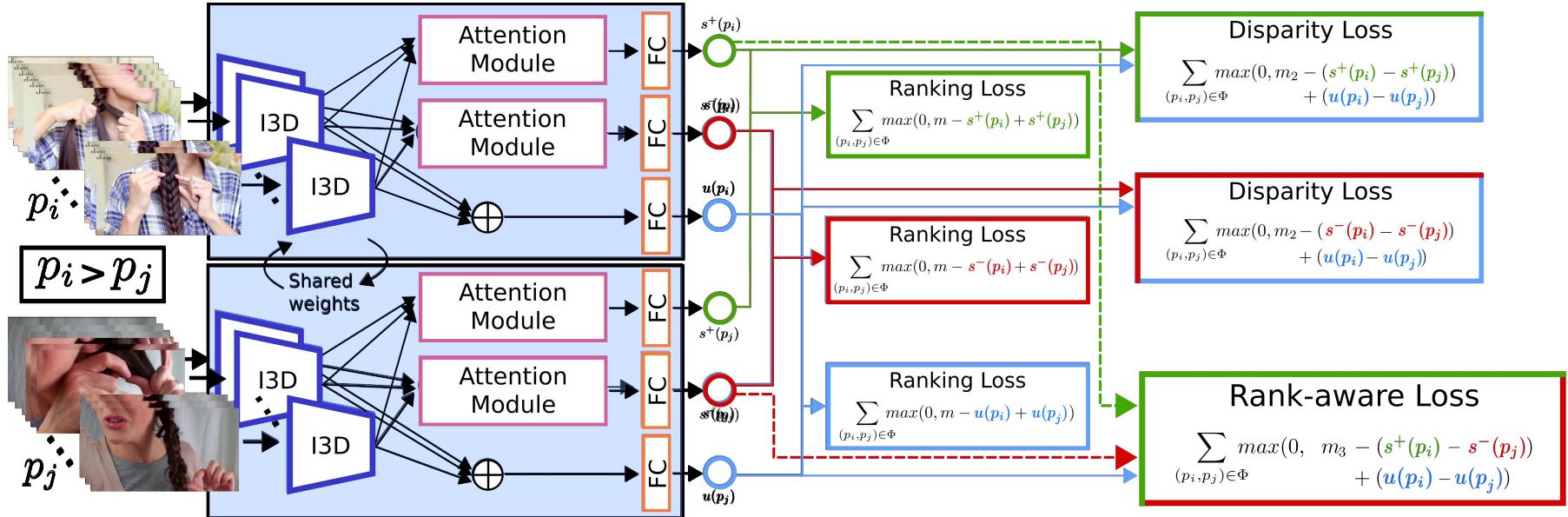
with: Hazel Doughty
Walterio Mayol-Cuevas

Input: Pairwise annotations of videos, indicating higher skill or no skill preference



Skill determination in video

with: Hazel Doughty
Walterio Mayol-Cuevas



Low-skill Attention Module

Surgery



Apply Eyeliner



Origami



High-skill Attention Module

Dough Rolling



Origami



Drawing



Skill determination in video

with: Hazel Doughty
Walterio Mayol-Cuevas

Computer Vision and Pattern Recognition (CVPR) 2019

The Pros and Cons: Rank-aware Temporal Attention for Skill Determination in Long Videos

Hazel Doughty

Walterio Mayol-Cuevas

Dima Damen

University of Bristol

ABSTRACT VIDEO DOWNLOADS BIBTEX RELATED

Abstract

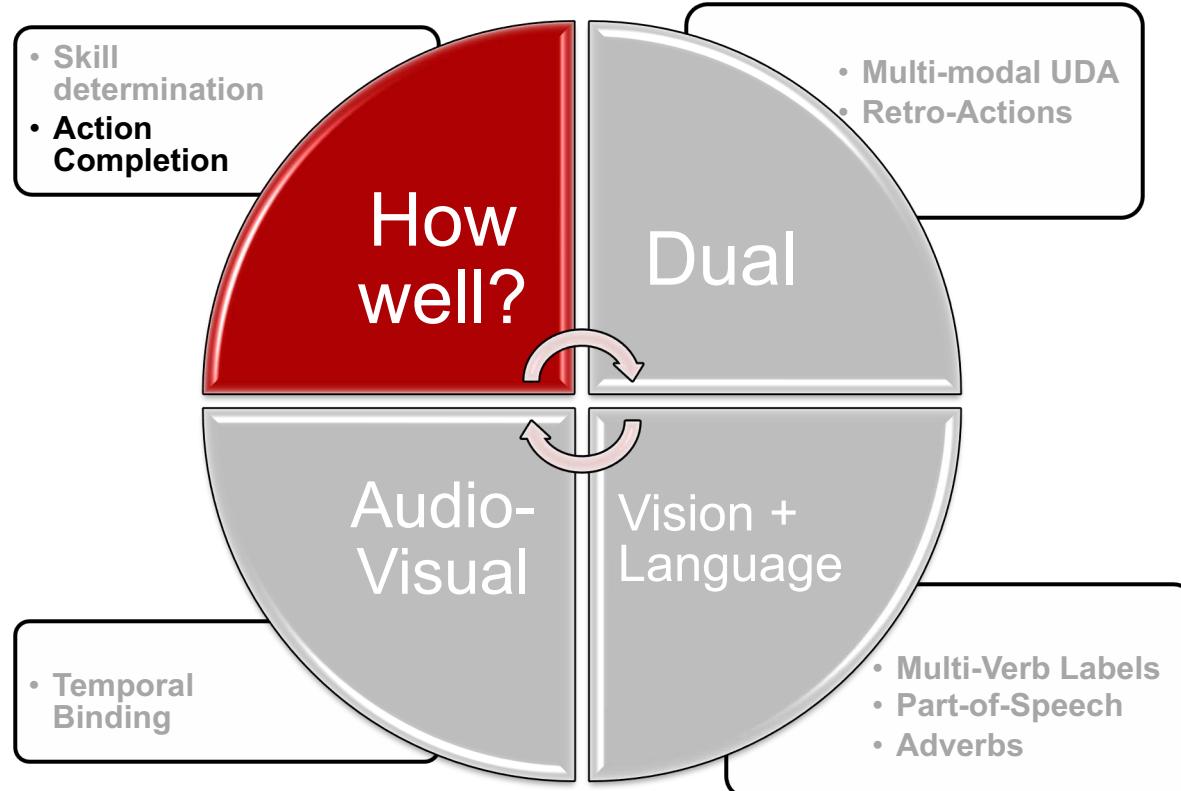
We present a new model to determine relative skill from long videos, through learnable temporal attention modules. Skill determination is formulated as a ranking problem, making it suitable for common and generic tasks. However, for long videos, parts of the video are irrelevant for assessing skill, and there may be variability in the skill exhibited throughout a video. We therefore propose a method which assesses the relative overall level of skill in a long video by attending to its skill-relevant parts.

Our approach trains temporal attention modules, learned with only video-level supervision, using a novel rank-aware loss function. In addition to attending to task-relevant video parts, our proposed loss jointly trains two attention modules to separately attend to video parts which are indicative of higher (pros) and lower (cons) skill. We evaluate our approach on the EPIC-Skills dataset and additionally annotate a larger dataset from YouTube videos for skill determination with five previously unexplored tasks. Our method outperforms previous approaches and classic softmax attention on both datasets by over 4% pairwise accuracy, and as much as 12% on individual tasks. We also demonstrate our model's ability to attend to

Downloads

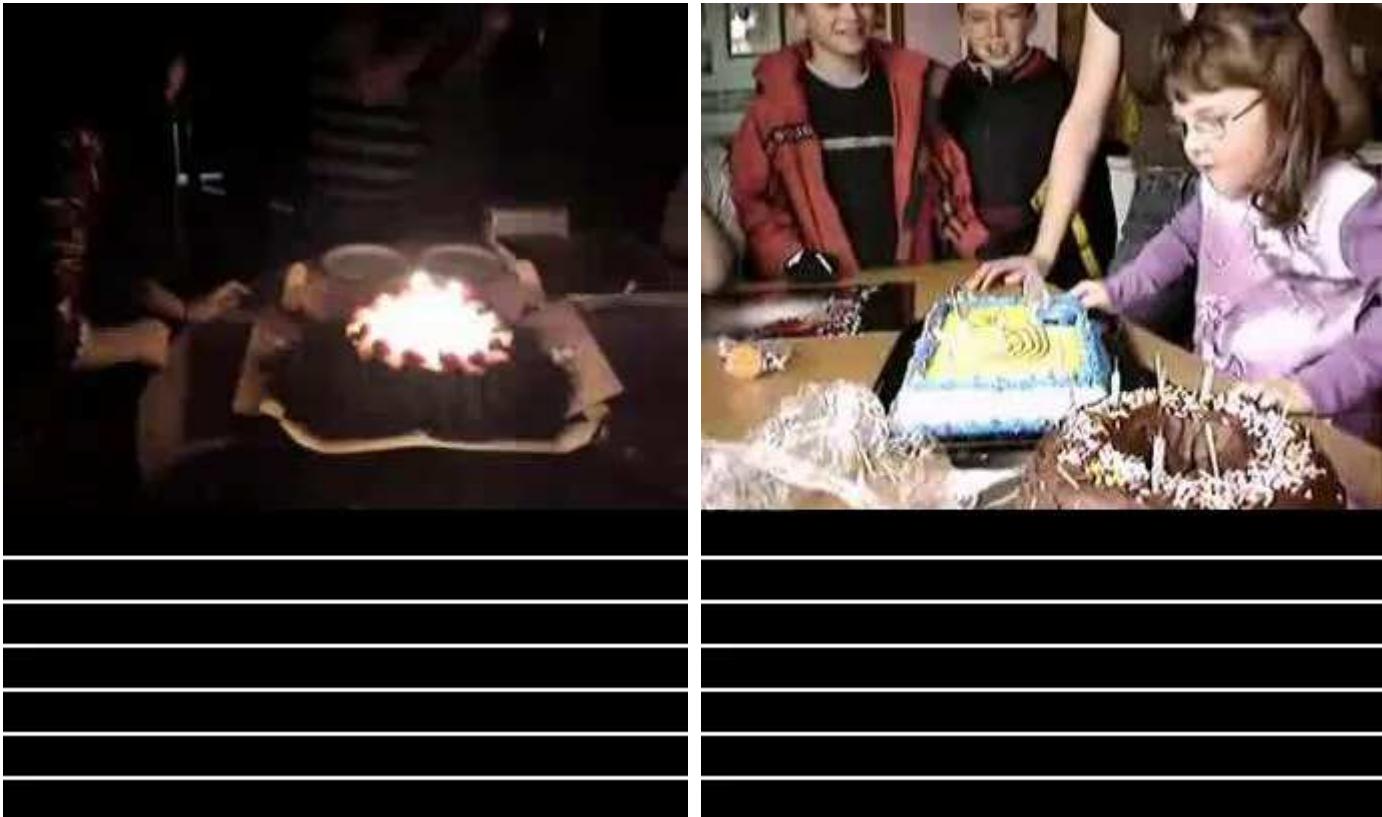
- Paper [[PDF](#)] [[ArXiv](#)]
- Supplementary [[Video](#)]
- Code and data [[GitHub - Available Now](#)]

Fine(r)-grained?



Action Completion Detection

with: Farnoosh Heidarivincheh
Majid Mirmehdi



Action Completion Detection

with: Farnoosh Heidarivincheh
Majid Mirmehdi



Pre-V ←
 V_R^T ←
C-C ←
R-R ←
R-C ←
C-R ←
GT ←

Action Completion Detection

with: Farnoosh Heidarivincheh
Majid Mirmehdi

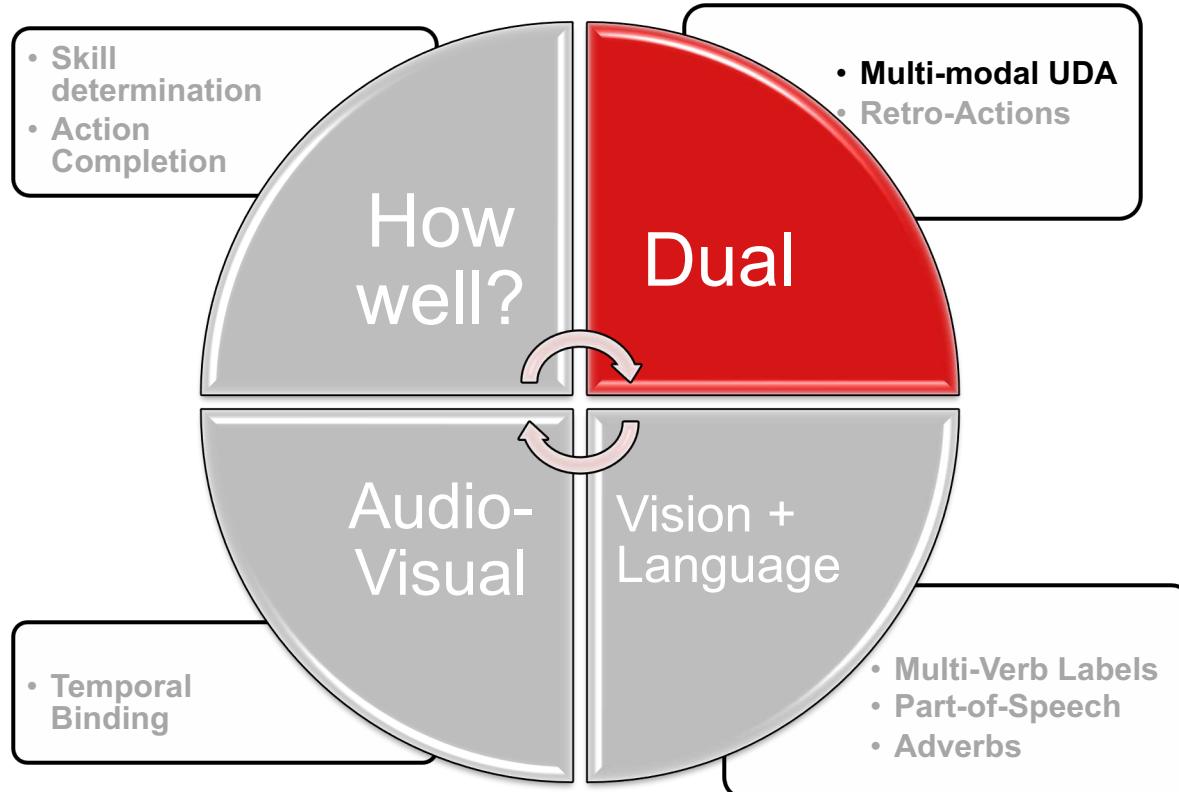
Frame-level labels: annotations are expensive, subjective and noisy.



We detect completion using only **weak labels** during training.

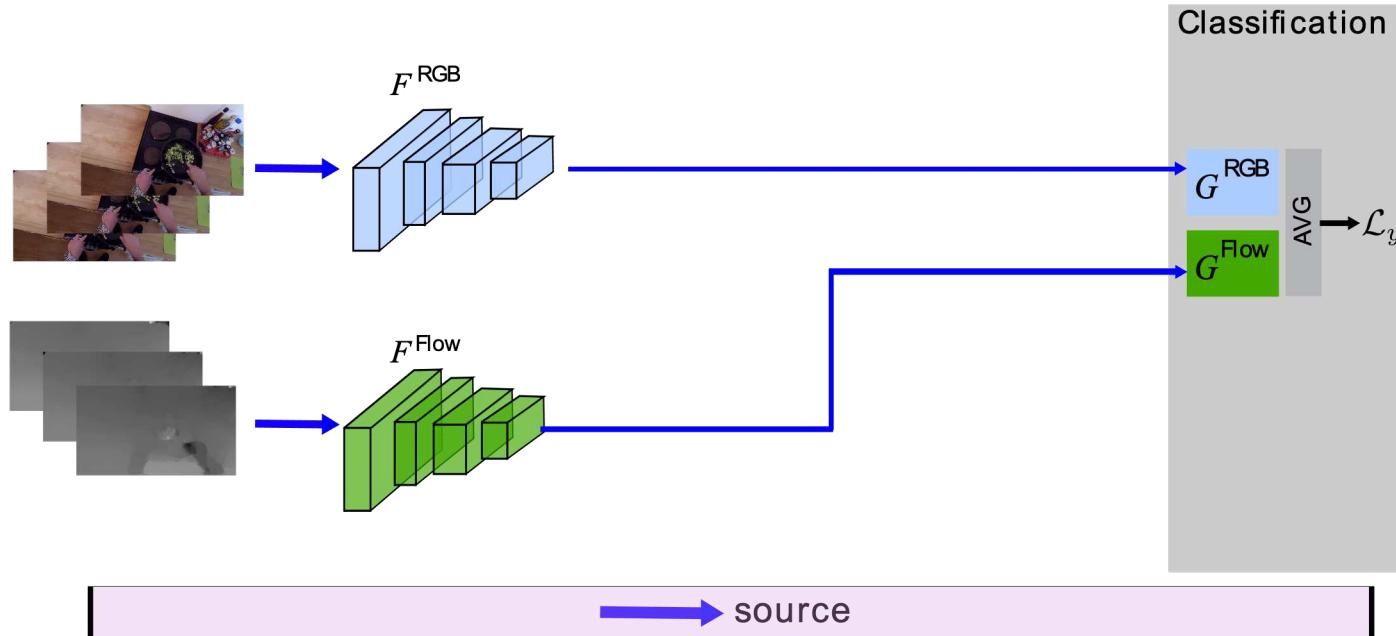


Fine(r)-grained?



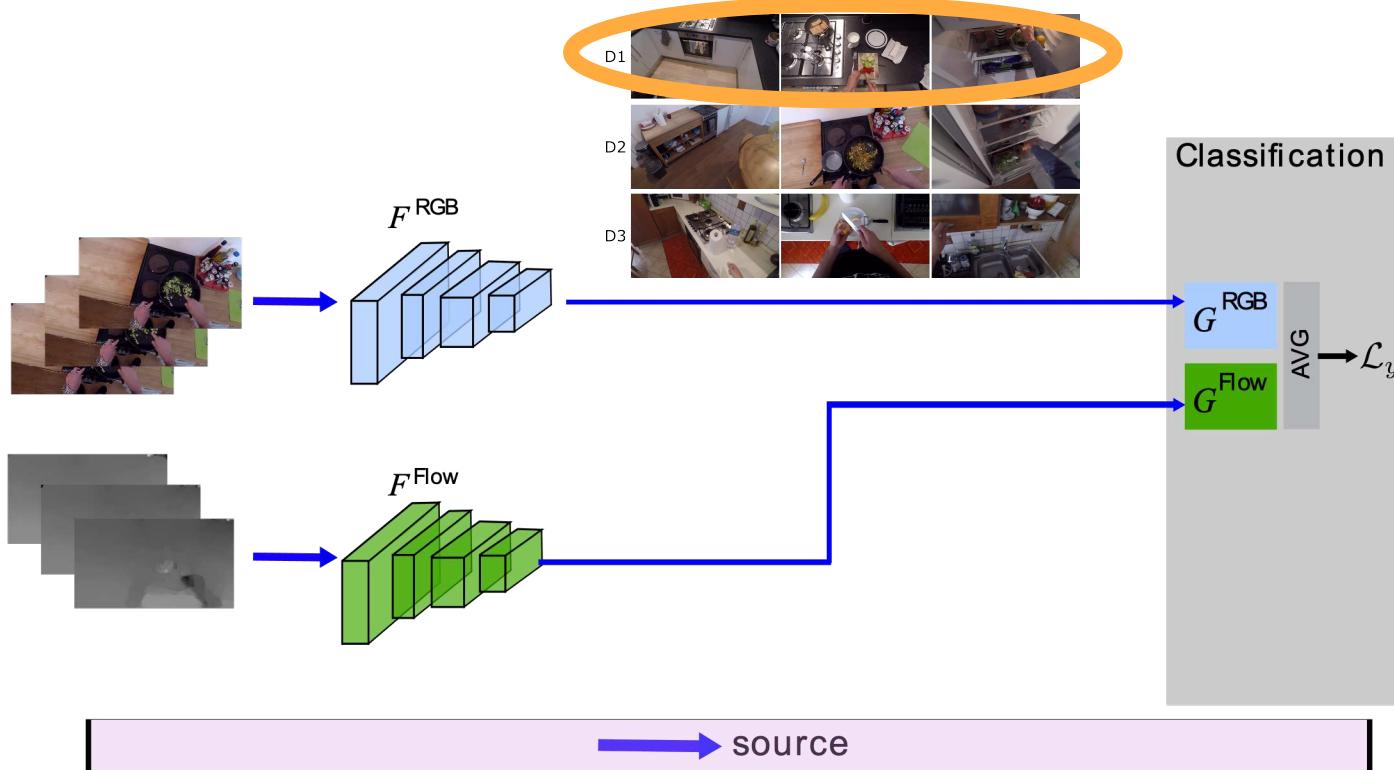
Multi-modal UDA

with: Jonathan Munro



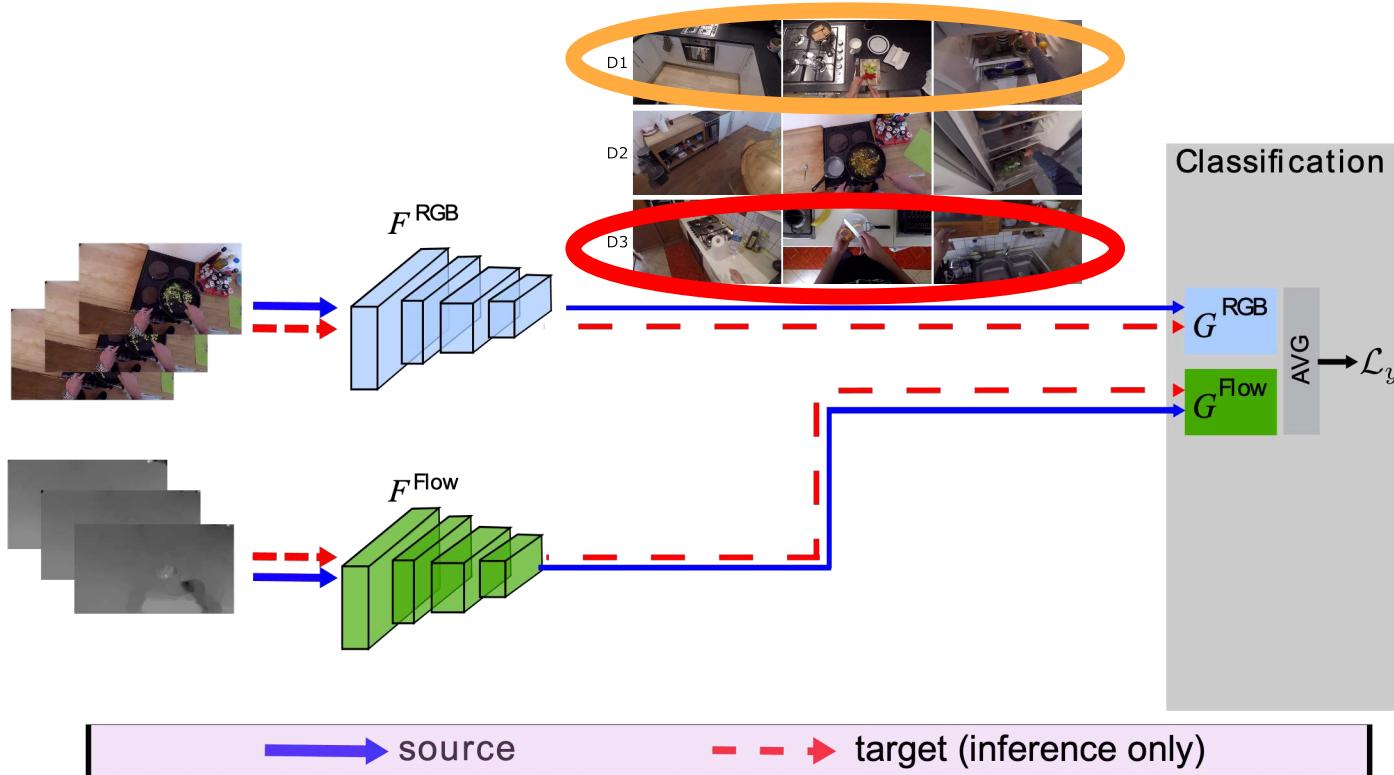
Multi-modal UDA

with: Jonathan Munro



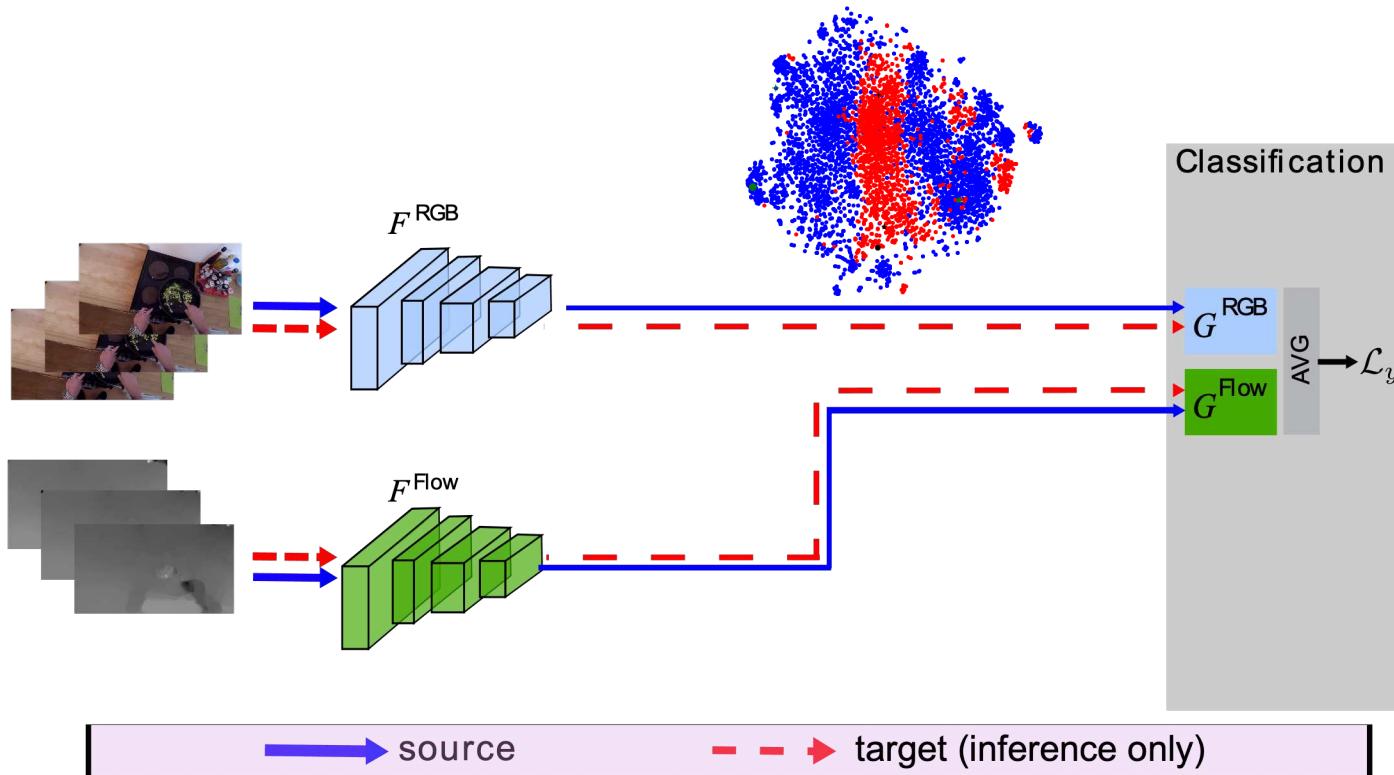
Multi-modal UDA

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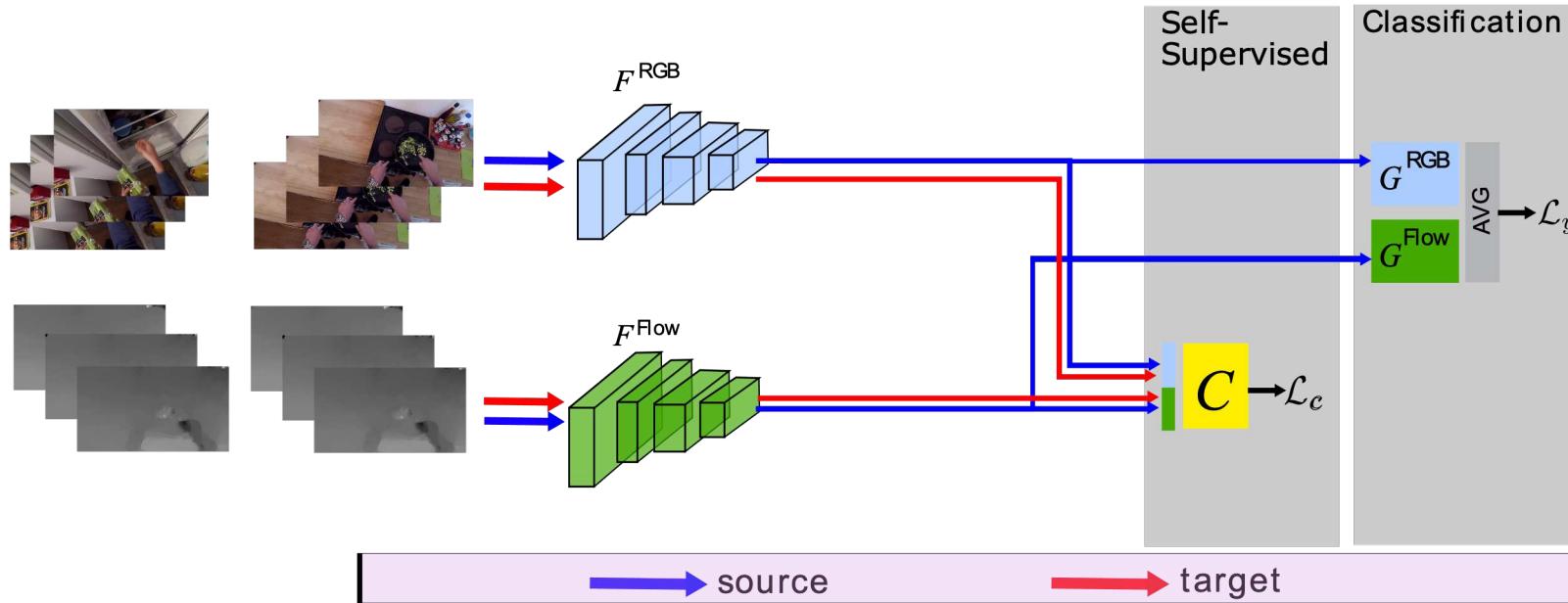
Multi-modal UDA

with: Jonathan Munro



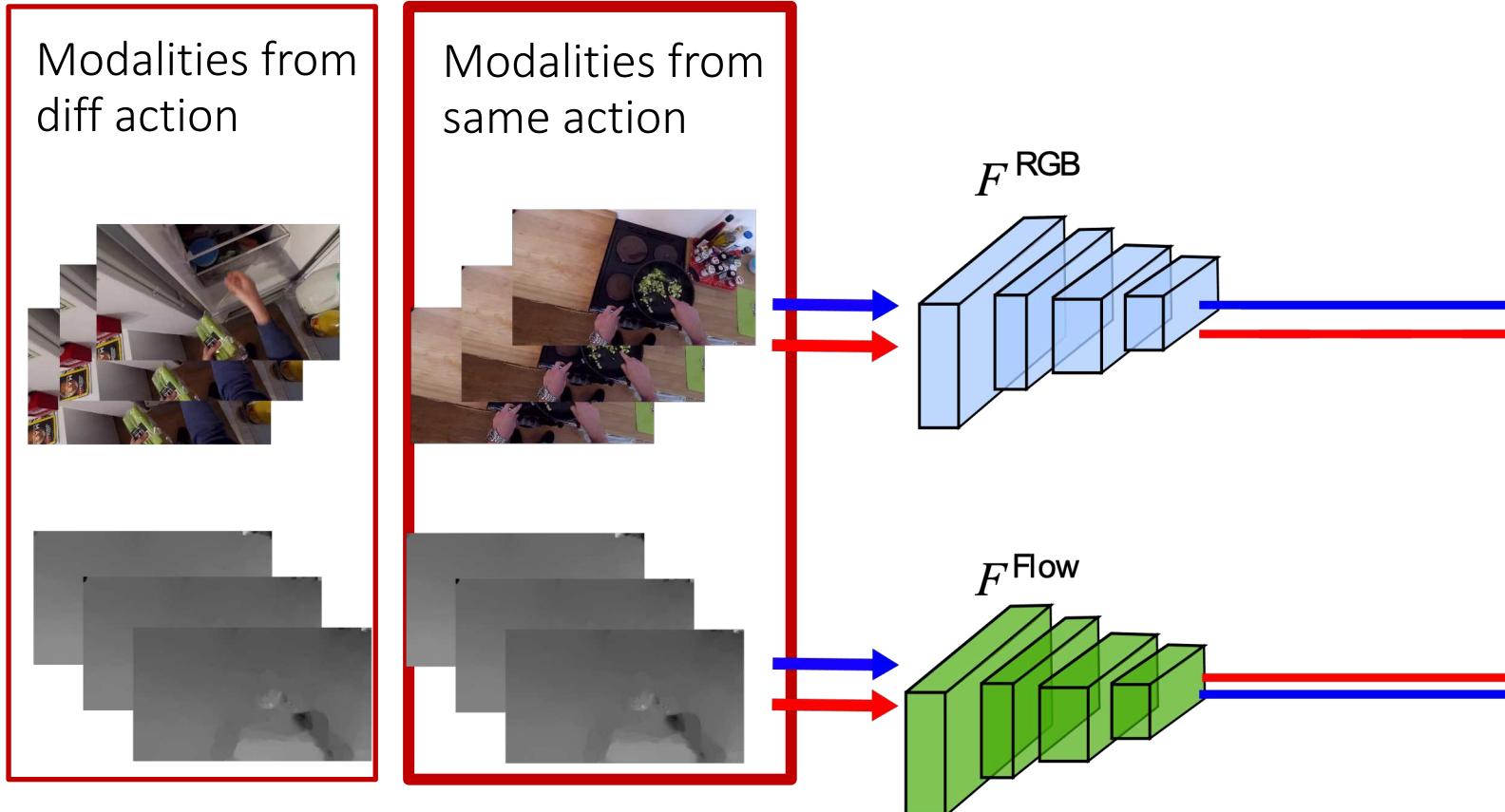
Multi-modal UDA

with: Jonathan Munro



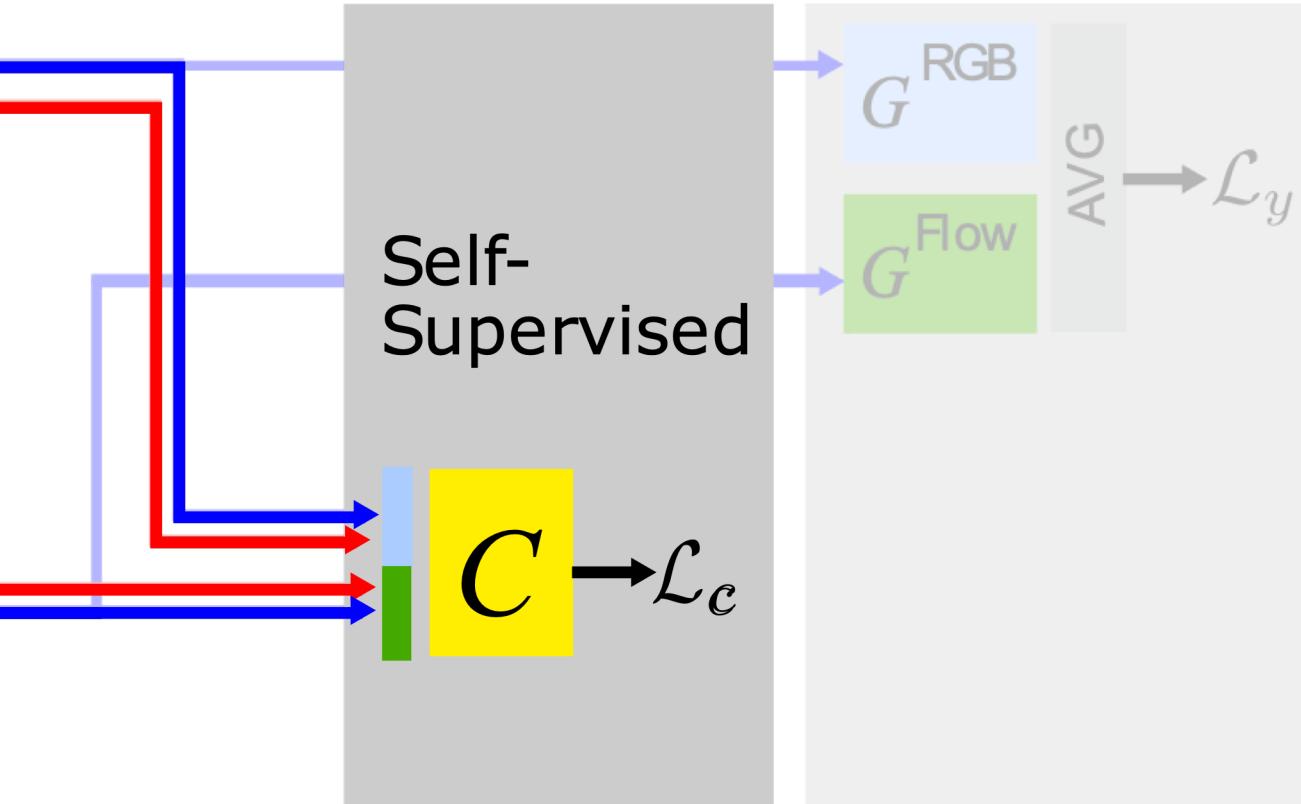
Multi-modal UDA

with: Jonathan Munro



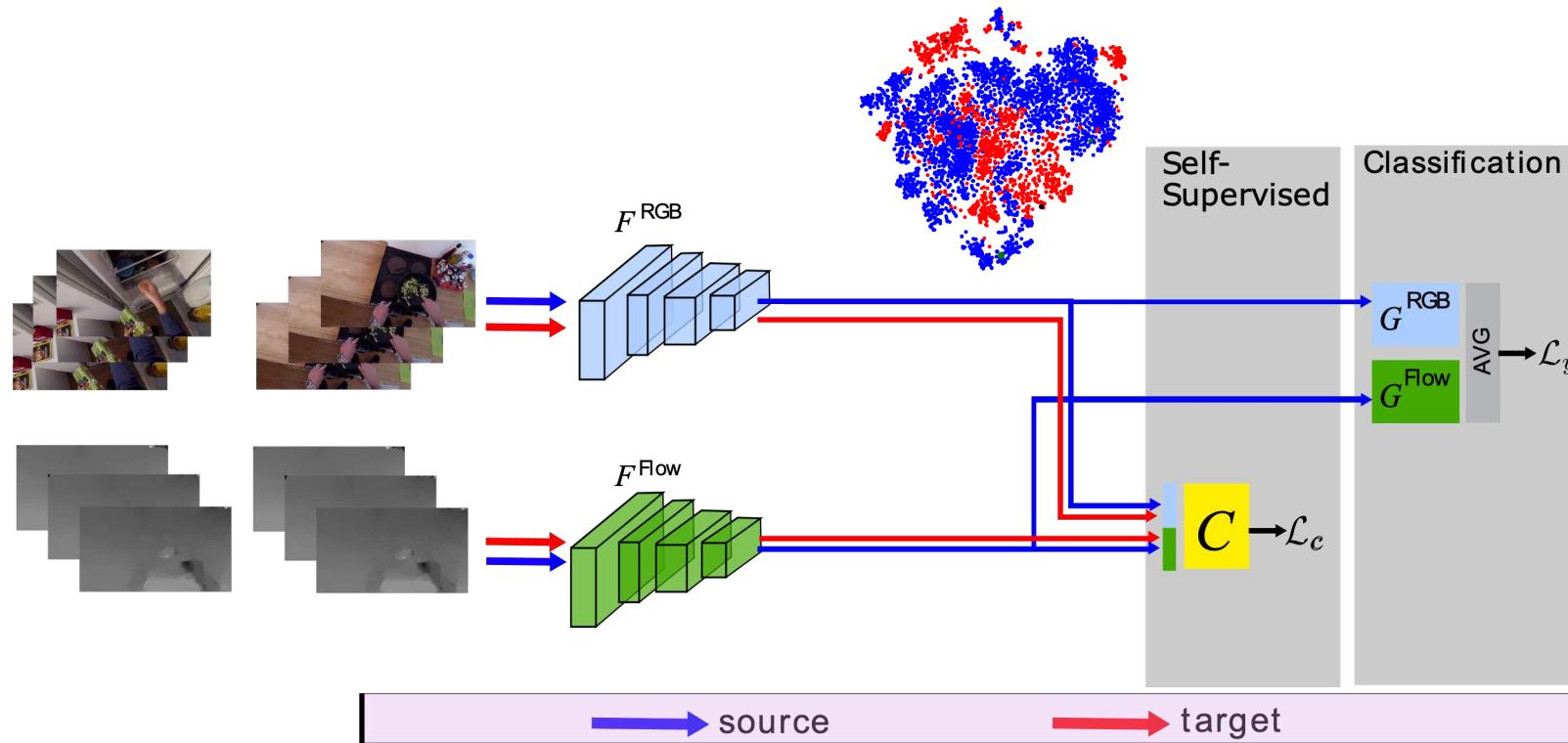
Multi-modal UDA

with: Jonathan Munro



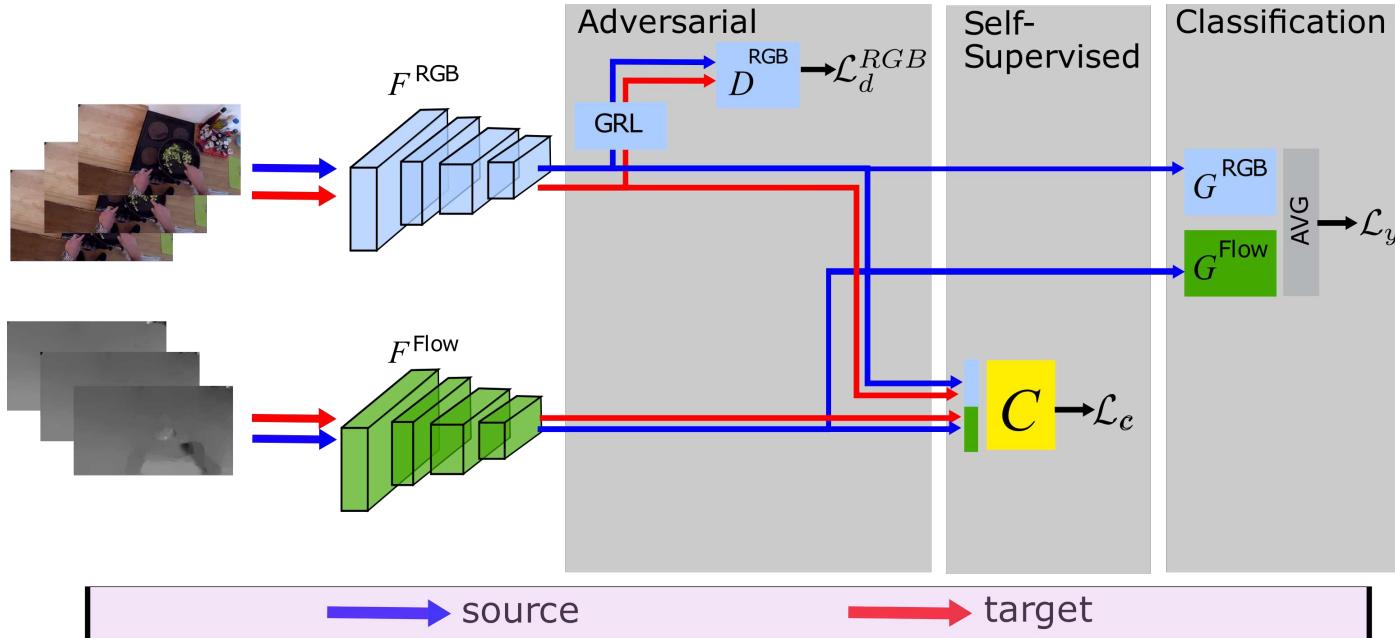
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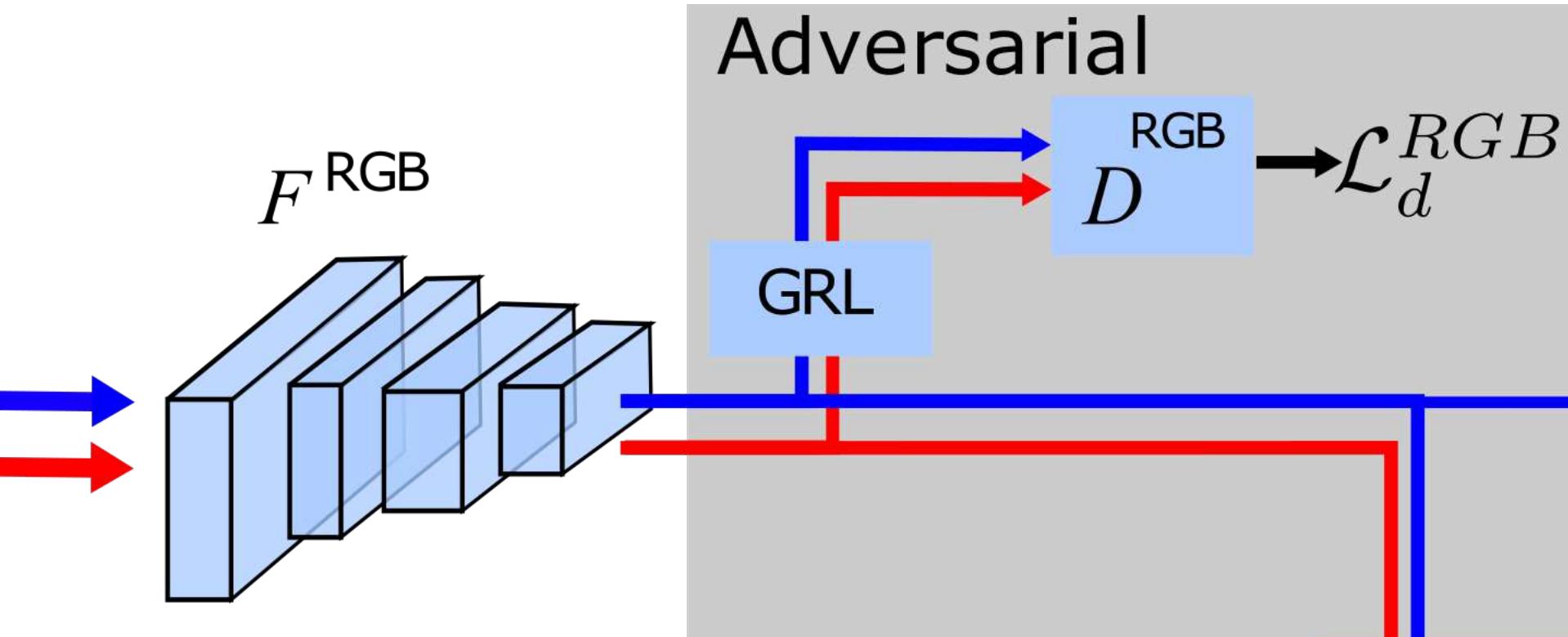
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Multi-modal UDA

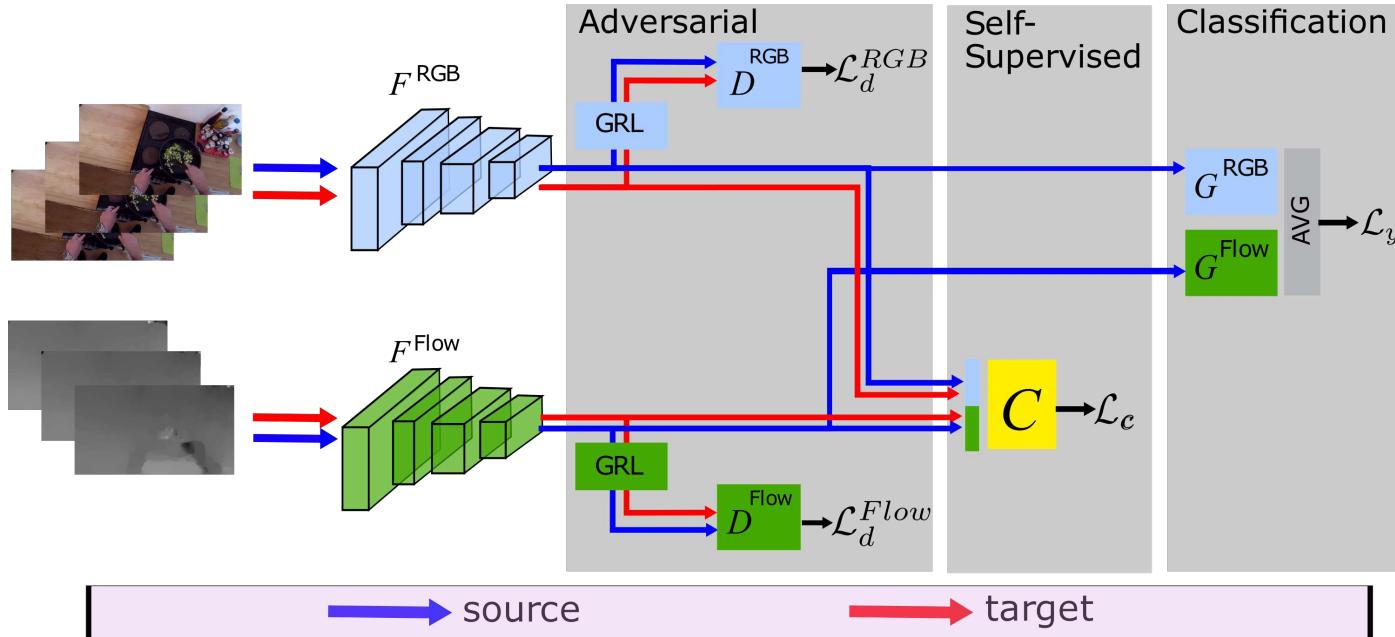
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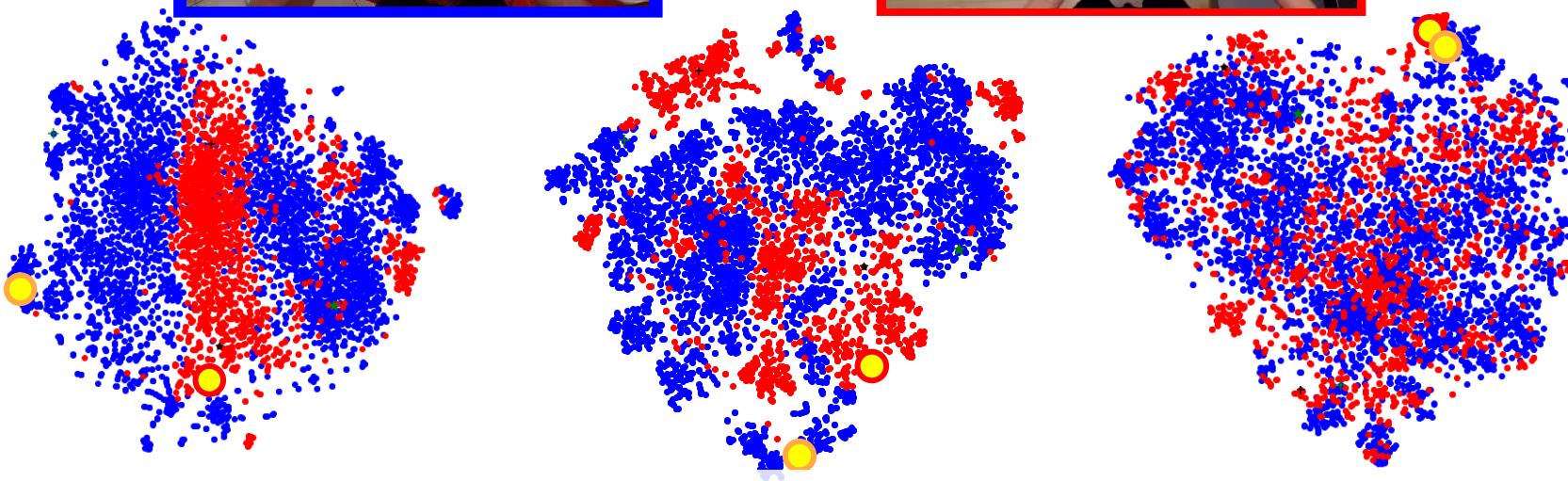
Multi-modal UDA

with: Jonathan Munro



Multi-modal UDA

with: Jonathan Munro



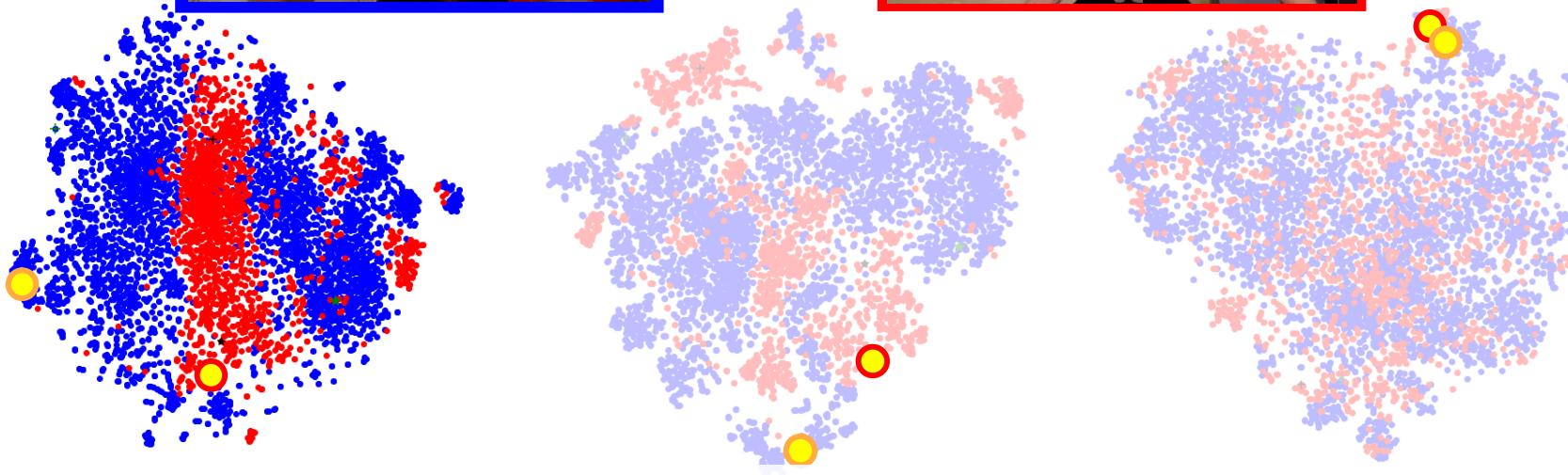
Source-Only

Self-Supervision

MM-SADA

Multi-modal UDA

with: Jonathan Munro



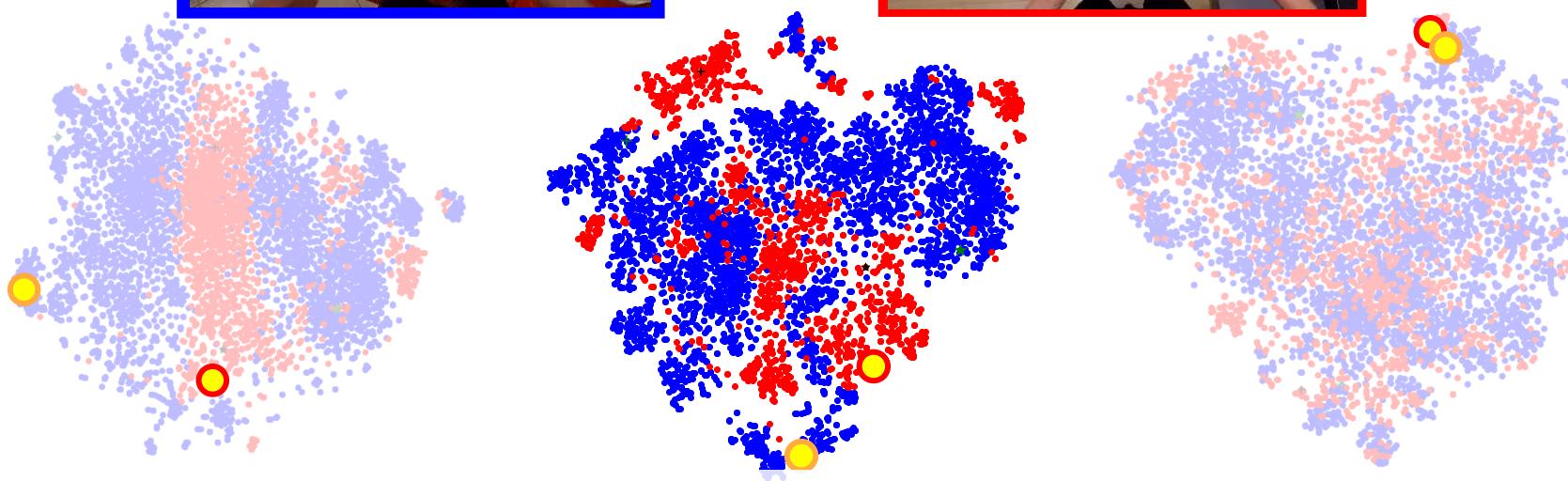
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Self-Supervision

MM-SADA

Multi-modal UDA

with: Jonathan Munro



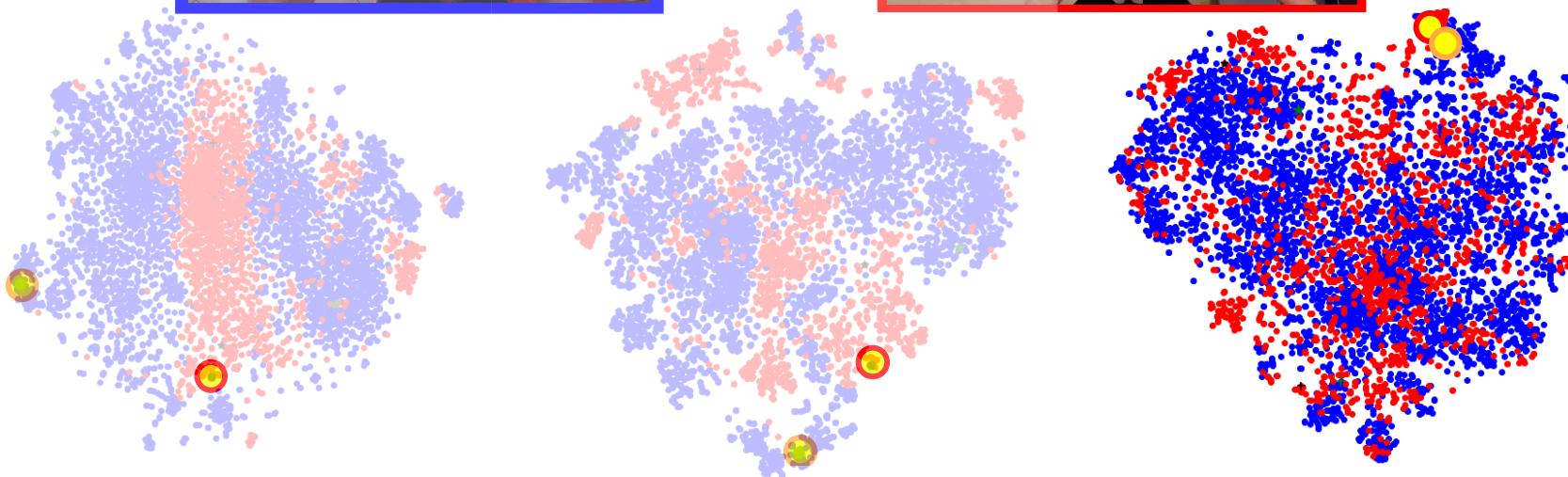
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Self-Supervision

MM-SADA

Multi-modal UDA

with: Jonathan Munro

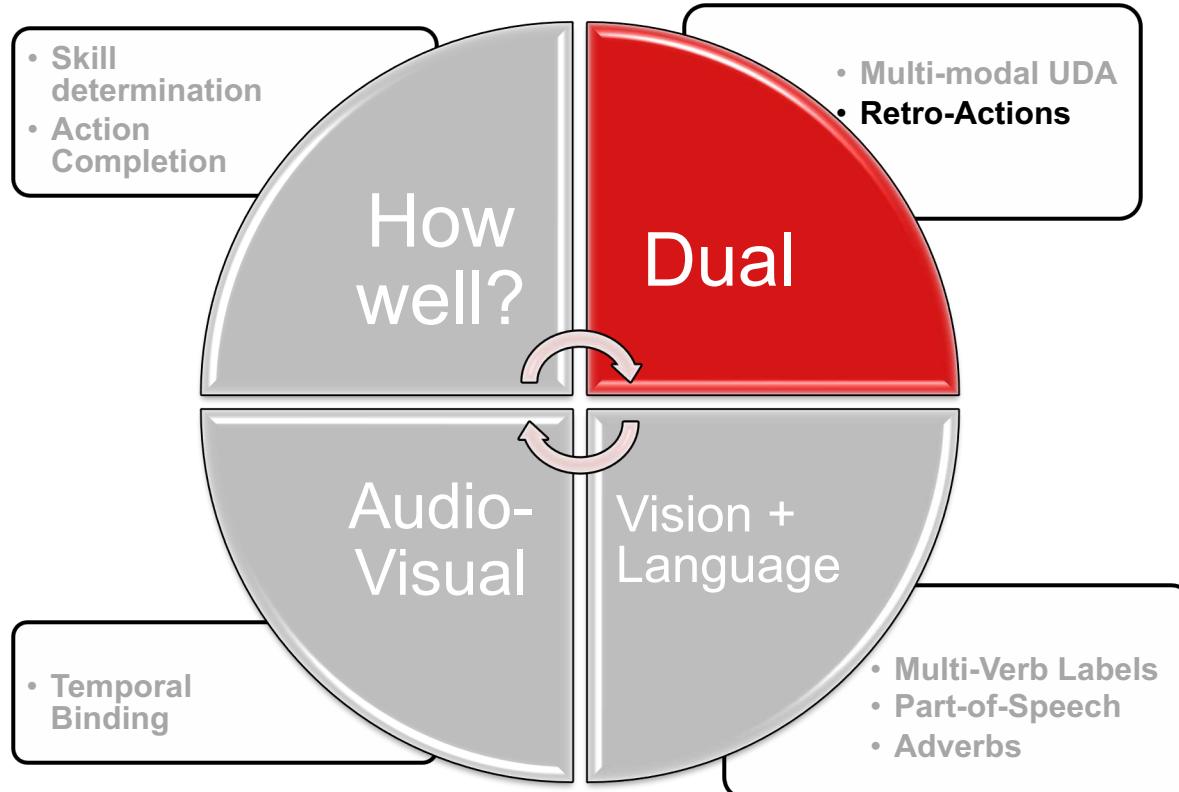


Source-Only

Self-Supervision

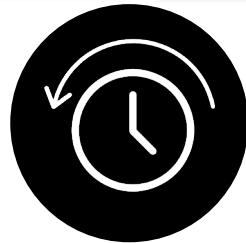
MM-SADA

Fine(r)-grained?



Retro-Actions

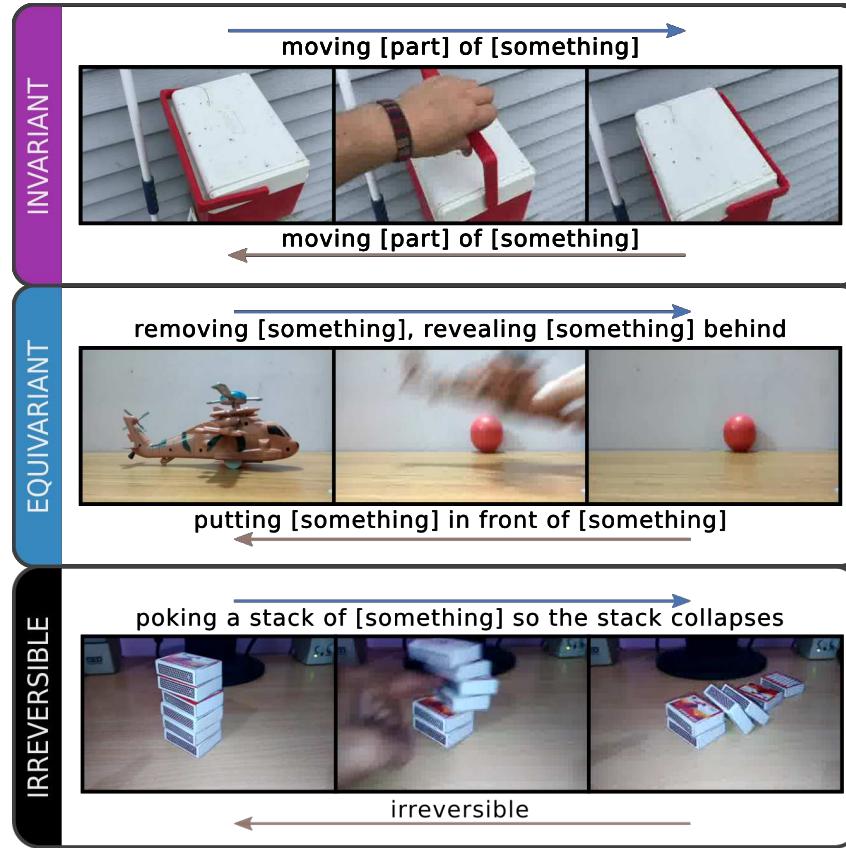
with: Will Price



W Price, D Damen (2019). Retro-Actions: Learning 'Close' by Time-Reversing 'Open' Videos. ICCV MDALC Workshop

Retro-Actions

with: Will Price



Retro-Actions

with: Will Price

TR

Approaching something with your camera
Moving away from something with your camera
Burying something in something
Digging something out of something
Covering something with something
Uncovering something

Moving something and something closer to each other
Moving something and something away from each other
Moving something away from something
Moving something closer to something
Moving something away from the camera
Moving something towards the camera
Moving something up
Moving something down

Opening something
Closing something

Pushing something from left to right
Pulling something from right to left
Pushing something from right to left
Pulling something from left to right
Putting something behind something

Pulling something from behind of something
Putting something into something
Pulling something out of something

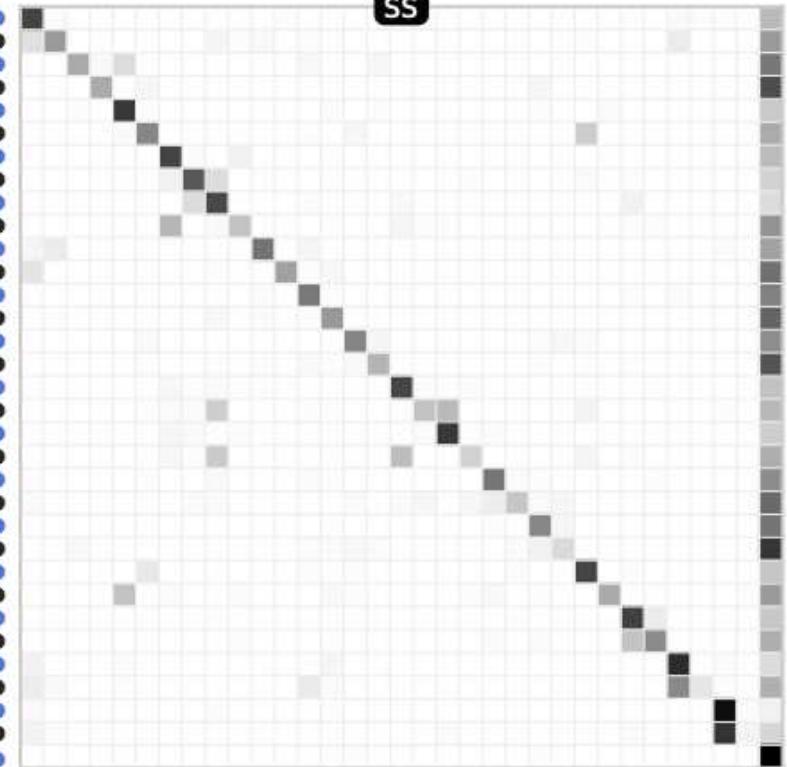
Removing something, revealing something behind
Putting something in front of something

Taking one of many similar things on the table
Putting something similar to other things that are already on the table

Turning the camera downwards while filming something
Turning the camera upwards while filming something
Turning the camera left while filming something
Turning the camera right while filming something

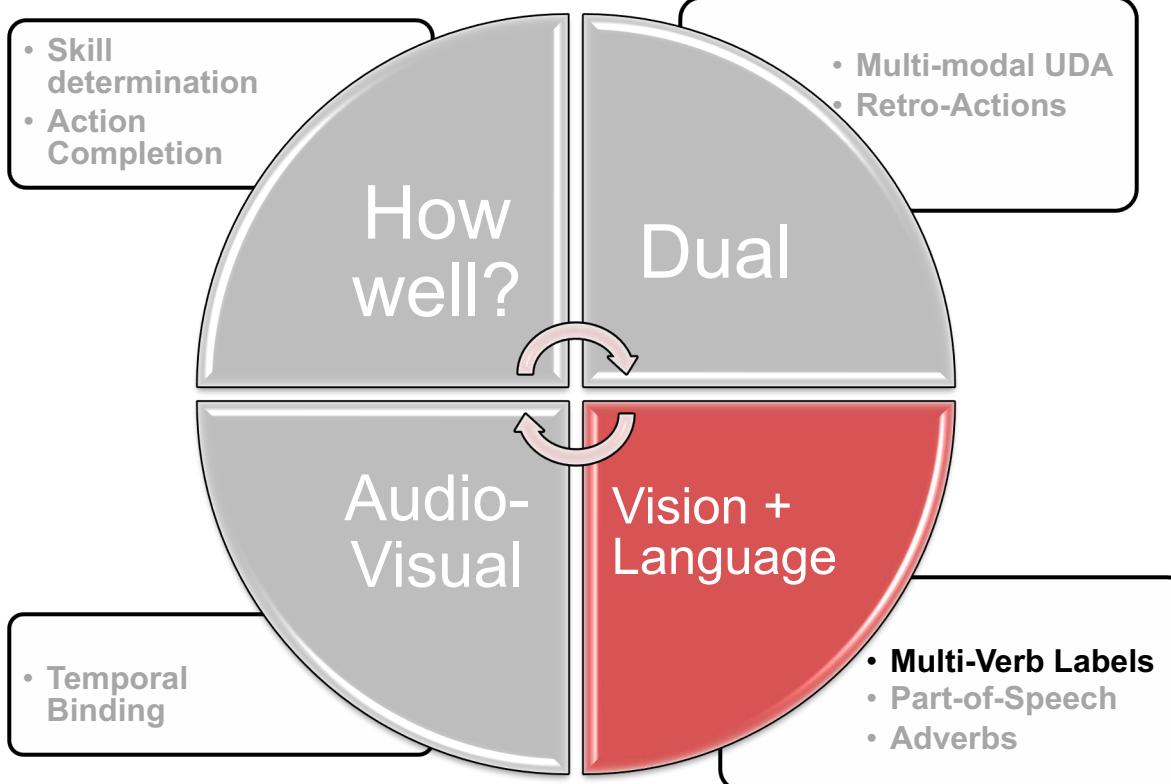
Other

SS



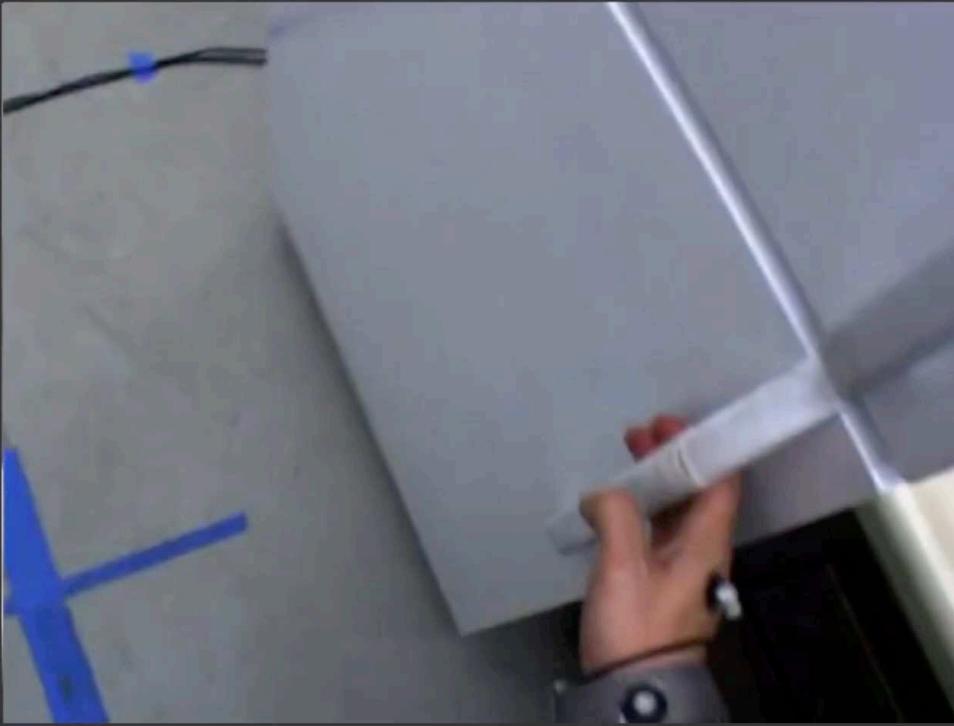
- Many-shot
- Zero-shot

Fine(r)-grained?



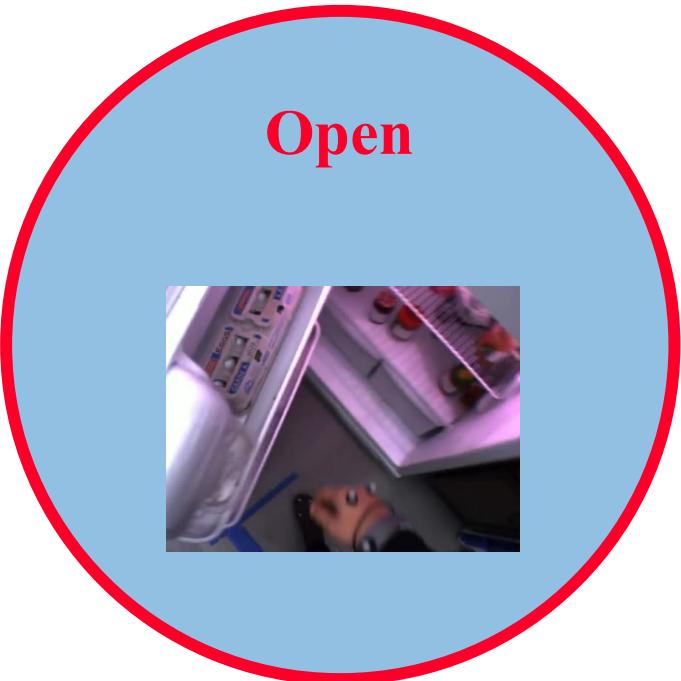
The Verbs Dilemma

with: Michael Wray



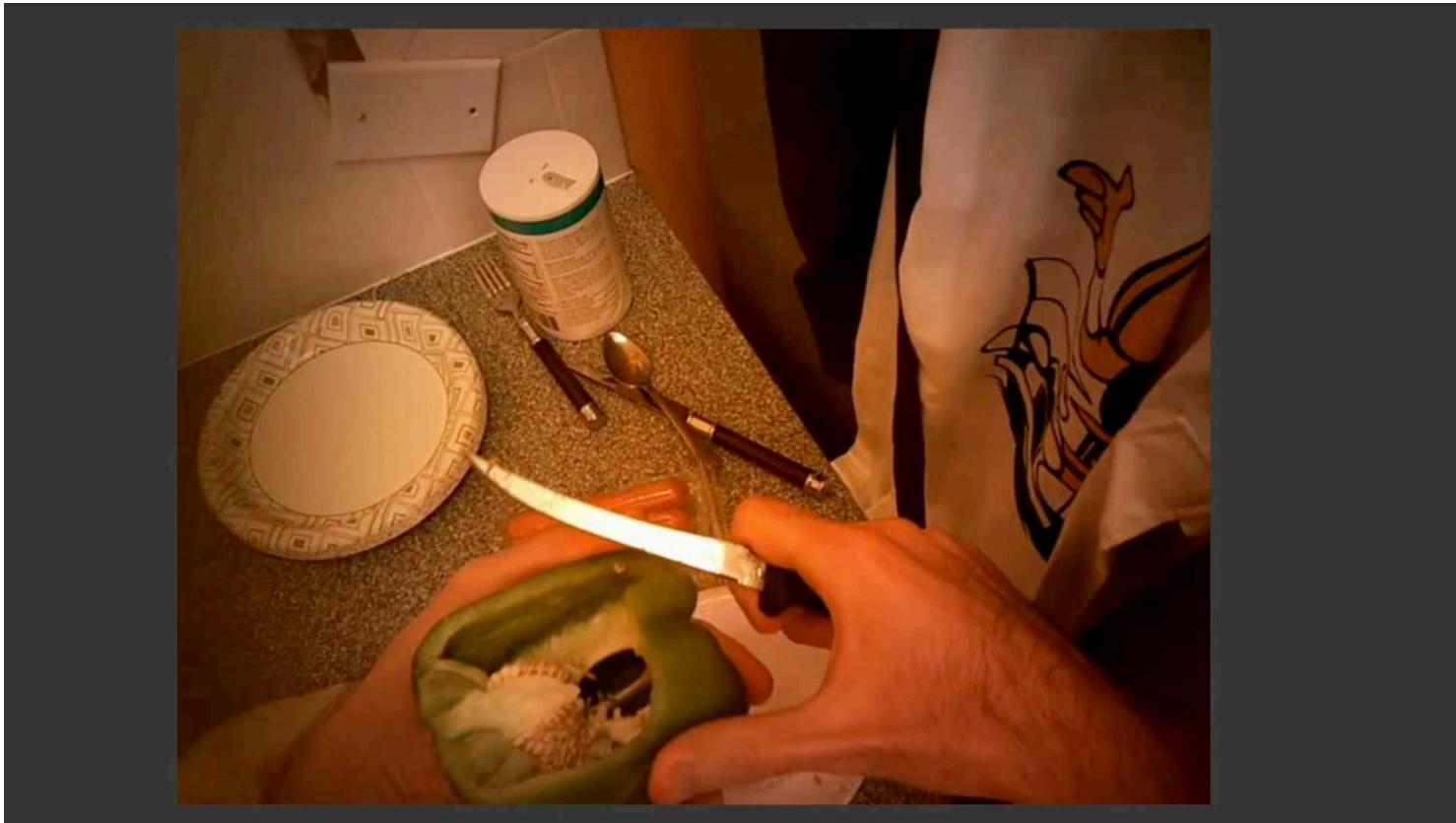
The Verbs Dilemma

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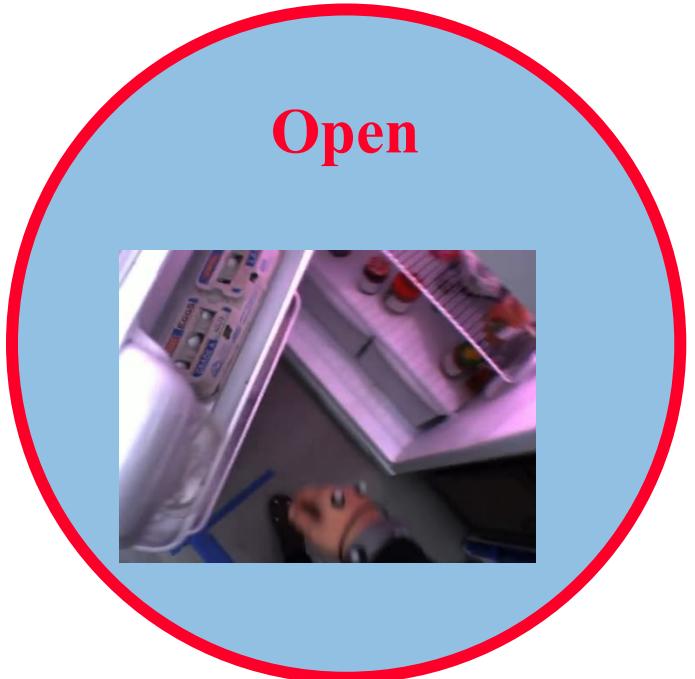
The Verbs Dilemma

with: Michael Wray



The Verbs Dilemma

with: Michael Wray



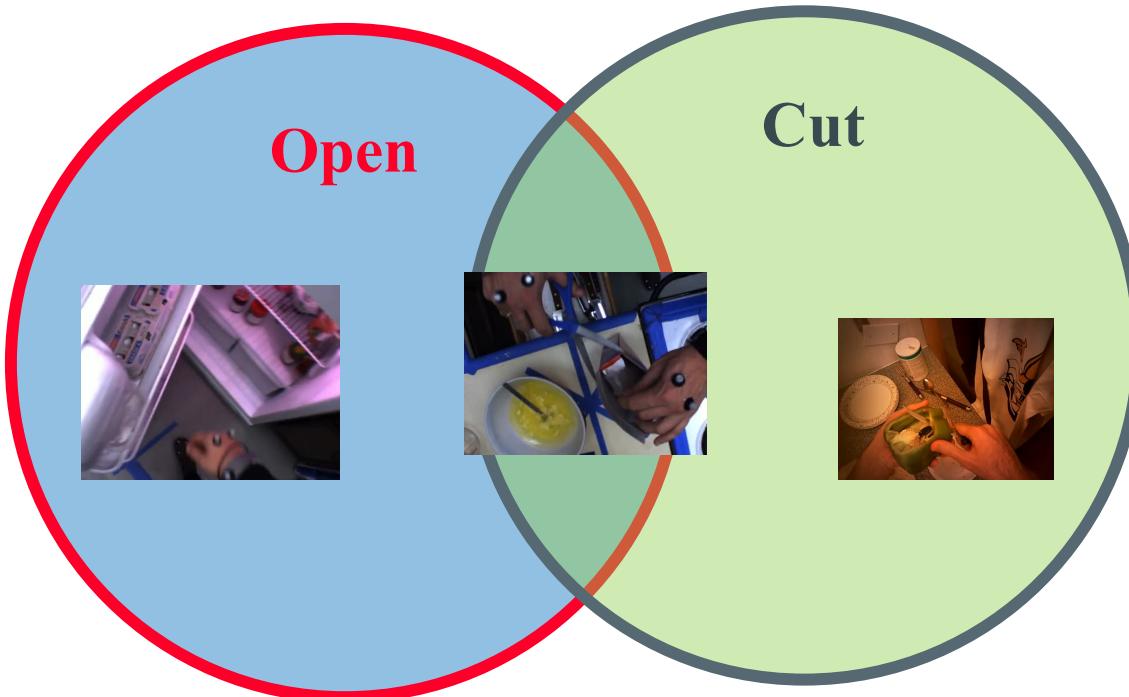
The Verbs Dilemma

with: Michael Wray



The Verbs Dilemma

with: Michael Wray



The Verbs Dilemma

with: Michael Wray

- Action representations using a single verb is highly-ambiguous
 - Solution1: pre-selected non-overlapping verbs (SL)
 - run, walk, open, close
 - Solution2: Using nouns to disambiguate actions (V-N)
 - open-drawer, open-bottle, open-fridge
 - actions constrained to known nouns
 - Solution3: Multi-verb labels (ML, SAML)
 - open, hold, pull

The Verbs Dilemma



with: Michael Wray

Single Verb

Multi Verb

Soft Assigned Multi Verb

A horizontal color calibration strip consisting of seven colored squares arranged from left to right. The colors transition from black on the far left to a bright orange-red on the far right. Below each square is a corresponding label: Pour, Fill, Move, Hold, Grasp, Push, Take, Open, and Close.

The Verbs Dilemma

with: Michael Wray

Top 3 retrieved classes across all datasets.

Turn On/Off



Press



Rotate



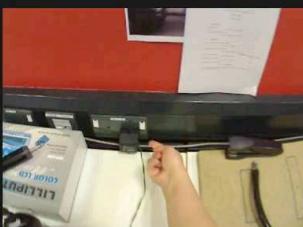
Turn On/Off



Press

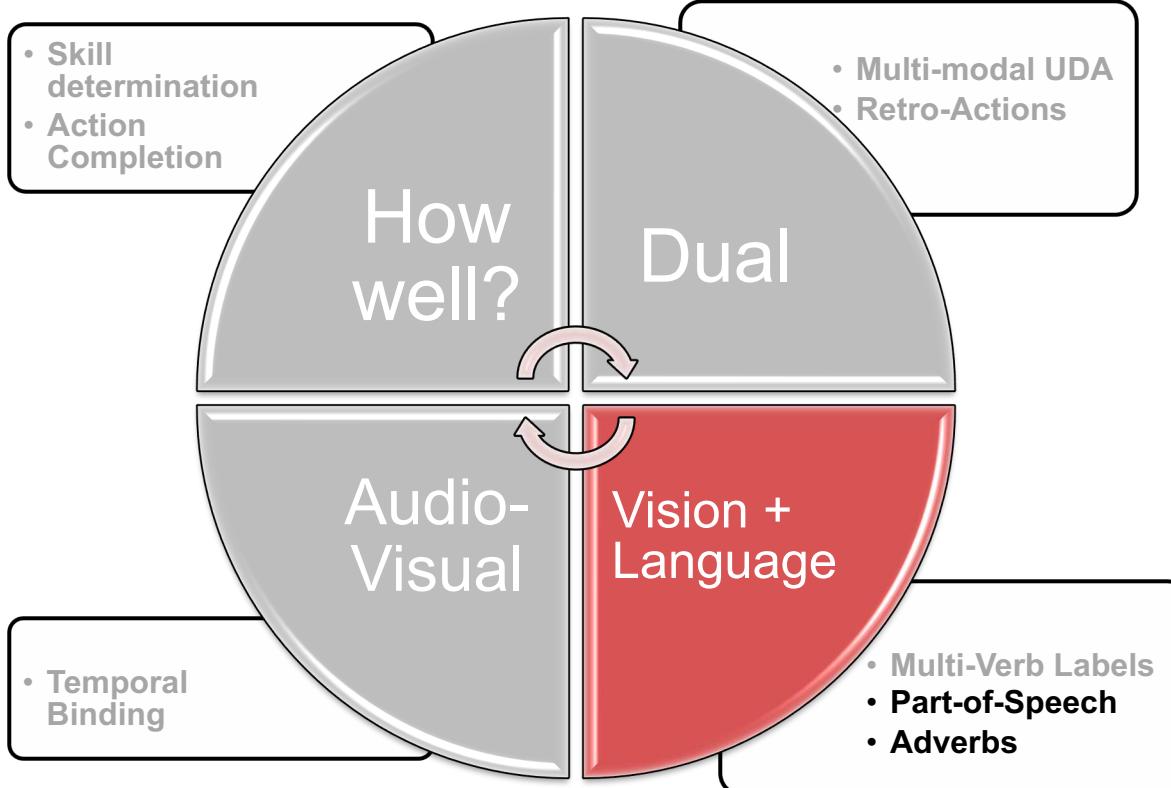


Rotate



Labelling Method can differentiate turn On/Off tap by pressing and by rotating.

Fine(r)-grained?



Fine-Grained Action Retrieval

with: Michael Wray
Gabriela Csurka
Diane Larlus

In this work we focus on
Fine-Grained Action Retrieval

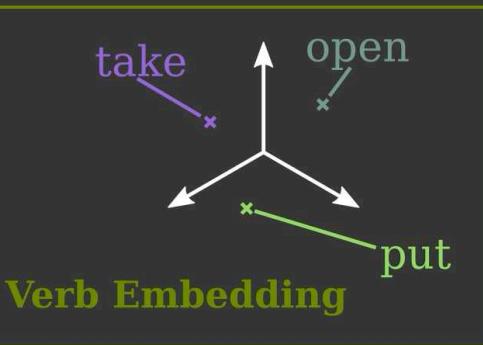
I put meat on a
ball of dough



Fine-Grained Action Retrieval

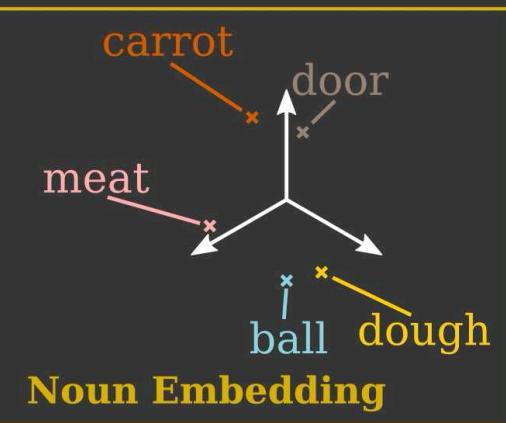
with: Michael Wray
Gabriela Csurka
Diane Larlus

We embed the video and representations



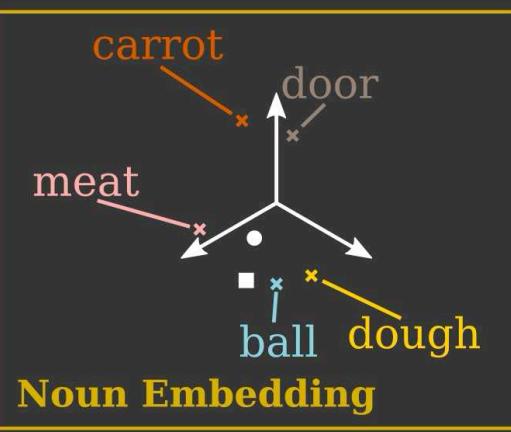
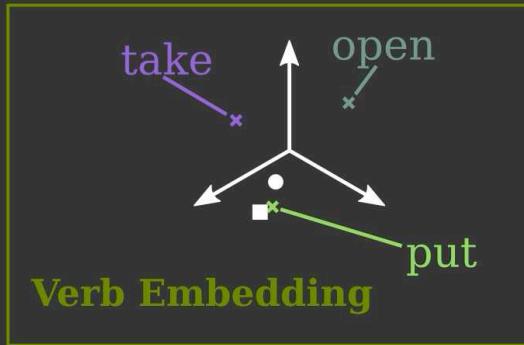
[put]

[meat, ball, dough]

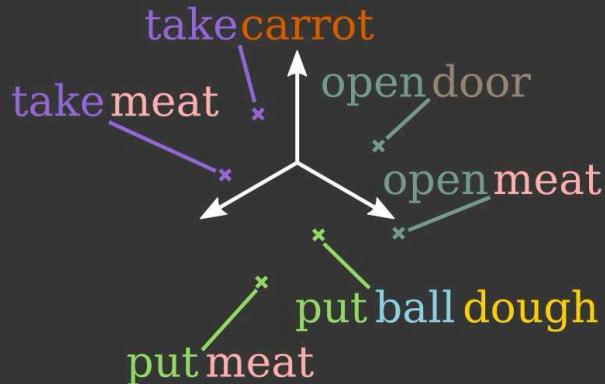


Fine-Grained Action Retrieval

with: Michael Wray
Gabriela Csurka
Diane Larlus

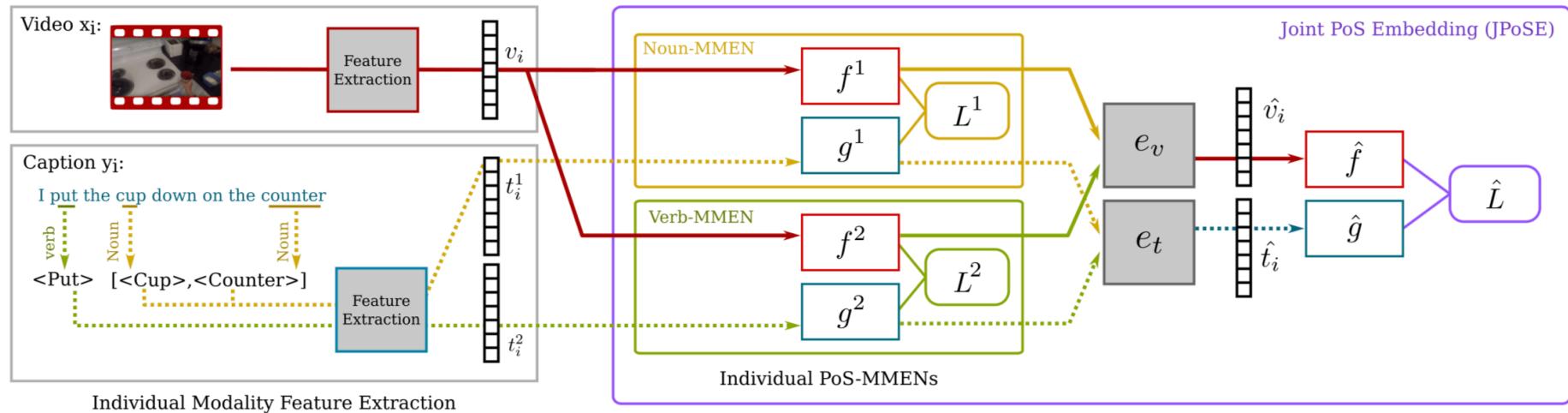


Finally, we combine the outputs and embed these into an action space



Fine-Grained Action Retrieval

with: Michael Wray
Gabriela Csurka
Diane Larlus



Maximum activation examples for a neuron in a noun PoS Embedding (Cutting Board) - Figure 4



Action Modifiers: Learning from Adverbs

with: Hazel Doughty
Ivan Laptev
Walterio Mayol-Cuevas



... if you **turn** the bowl upside down **slowly** they won't come out ...



... mix it well until it is **completely dissolved** ...



... you want to make sure you **fill** it up **partially** ...



... you want to **dice** it **finely**...

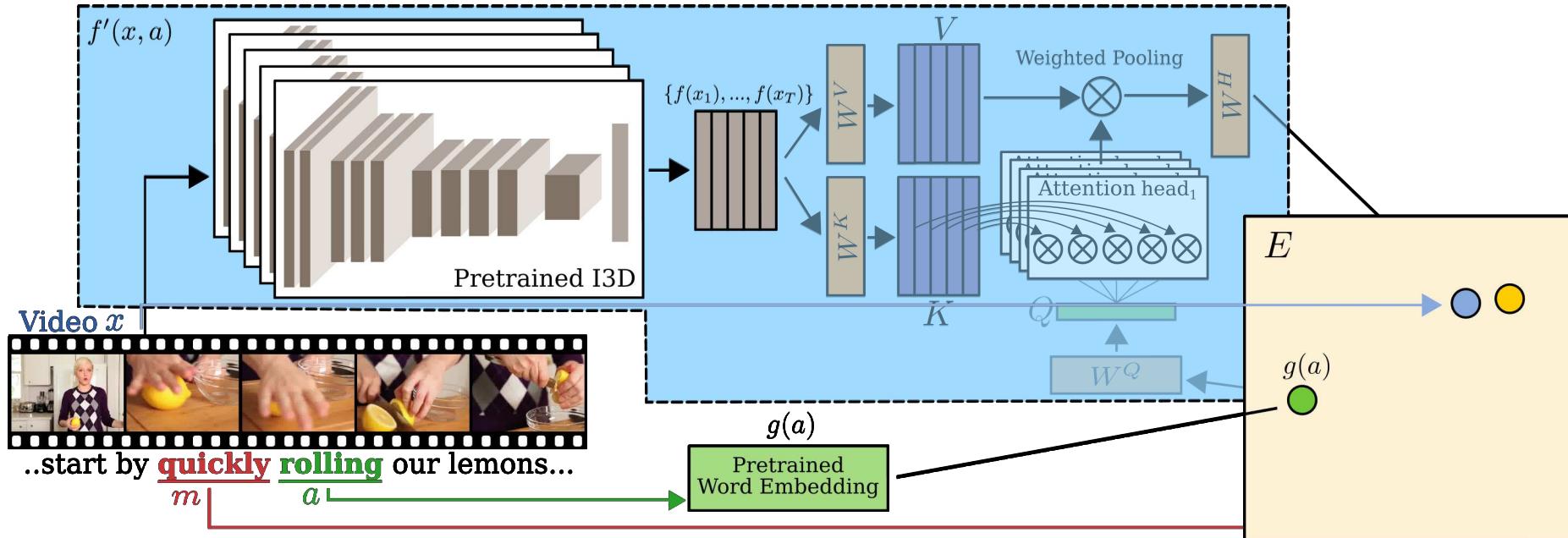
-10 seconds

timestamp

+10 seconds

Action Modifiers: Learning from Adverbs

with: Hazel Doughty
Ivan Laptev
Walterio Mayol-Cuevas



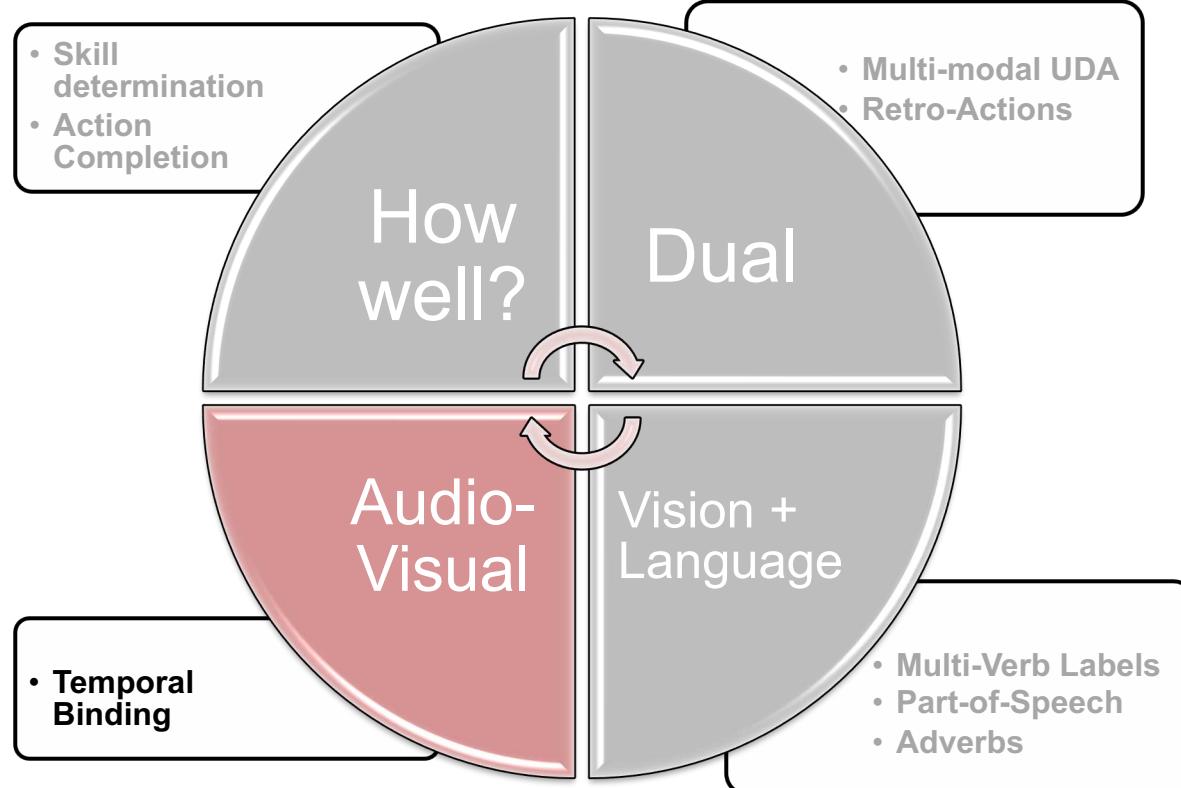
Action Modifiers: Learning from Adverbs

with: Hazel Doughty
Ivan Laptev
Walterio Mayol-Cuevas



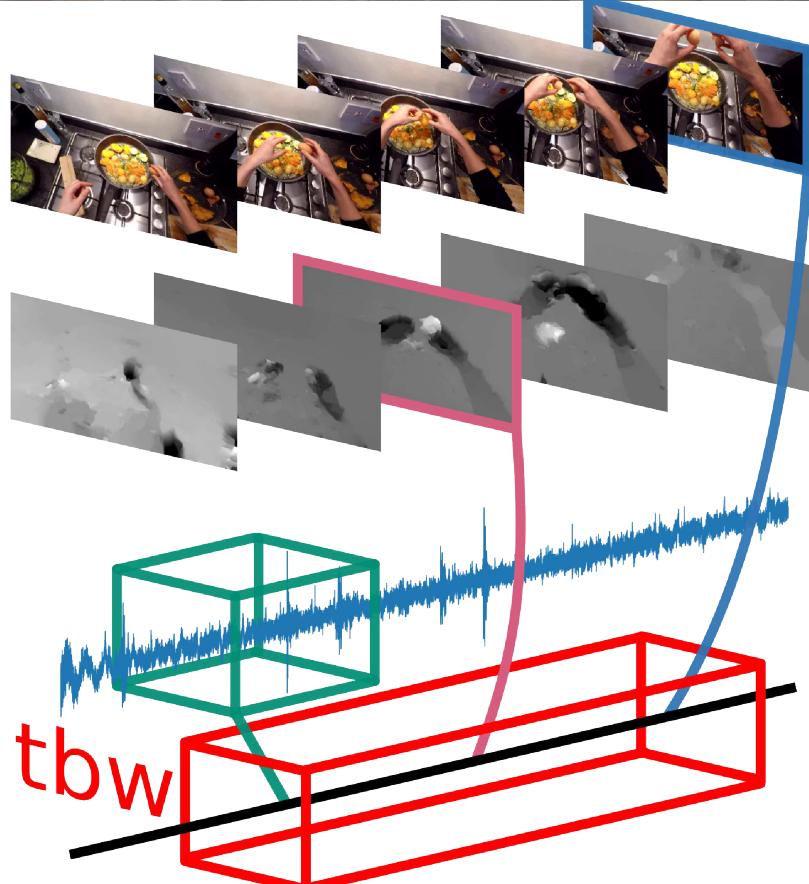
... we're going to **mix** these up real **quick**...

Fine(r)-grained?



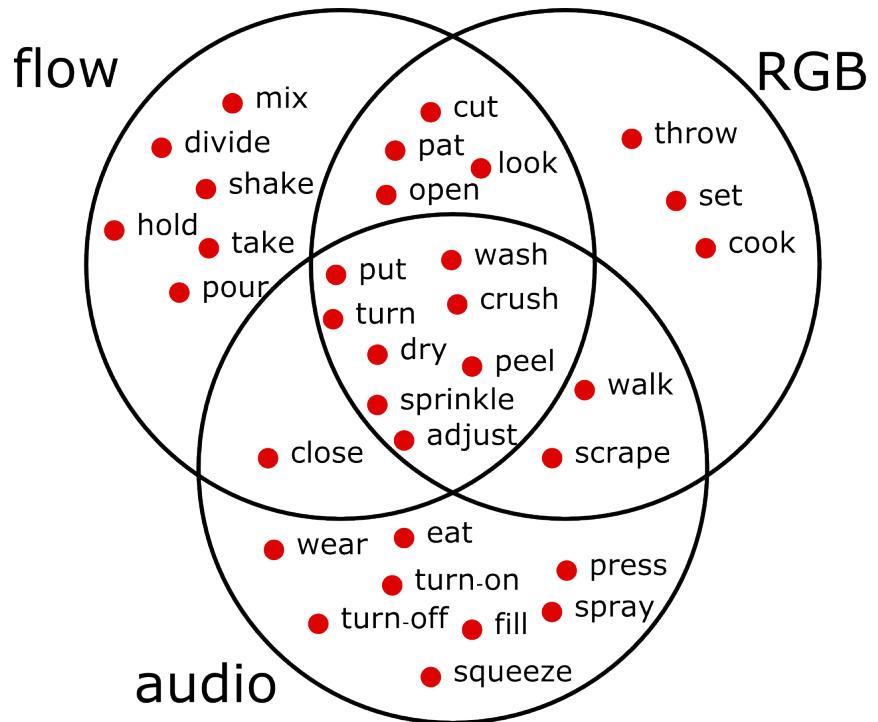
Audio-Visual Temporal Binding

with: Vangelis Kazakos
Arsha Nagrani
Andrew Zisserman



Audio-Visual Temporal Binding

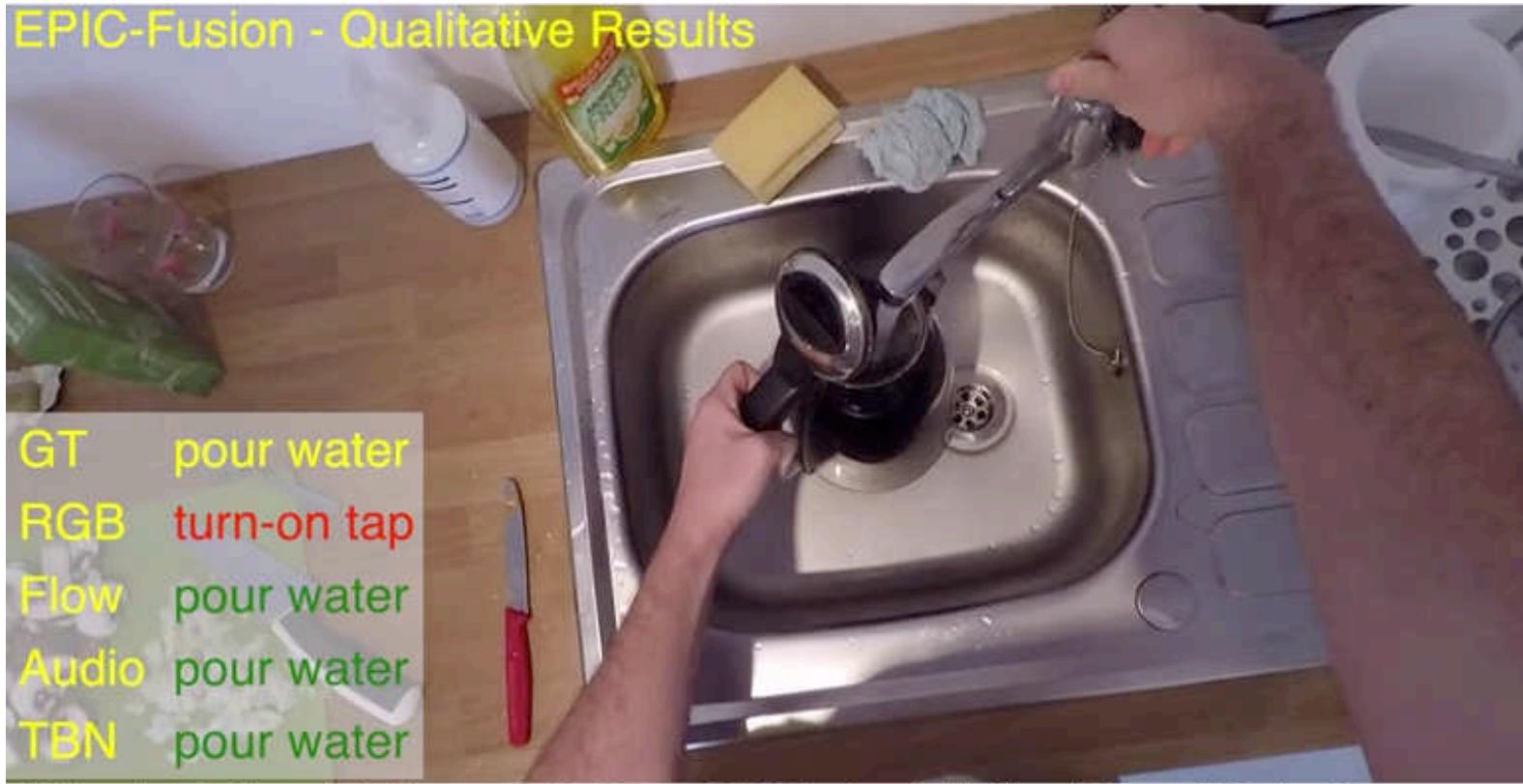
with: Vangelis Kazakos
Arsha Nagrani
Andrew Zisserman



Audio-Visual Temporal Binding

with: Vangelis Kazakos
Arsha Nagrani
Andrew Zisserman

EPIC-Fusion - Qualitative Results



E. Kazakos, A. Nagrani, A. Zisserman, D. Damen, EPIC-Fusion: Audio-Visual Temporal Binding for Egocentric Action Recognition, ICCV 2019

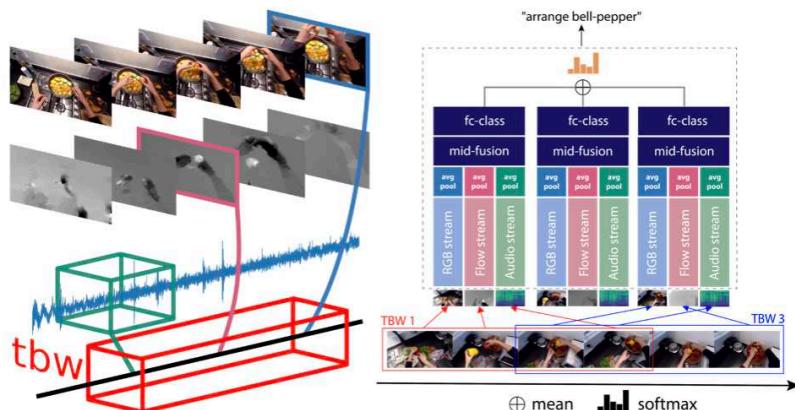
Audio-Visual Temporal Binding

with: Vangelis Kazakos
Arsha Nagrani
Andrew Zisserman

EPIC-Fusion: Audio-Visual Temporal Binding for Egocentric Action Recognition

Evangelos Kazakos¹, Arsha Nagrani², Andrew Zisserman² and Dima Damen¹

¹University of Bristol, VIL, ²University of Oxford, VGG



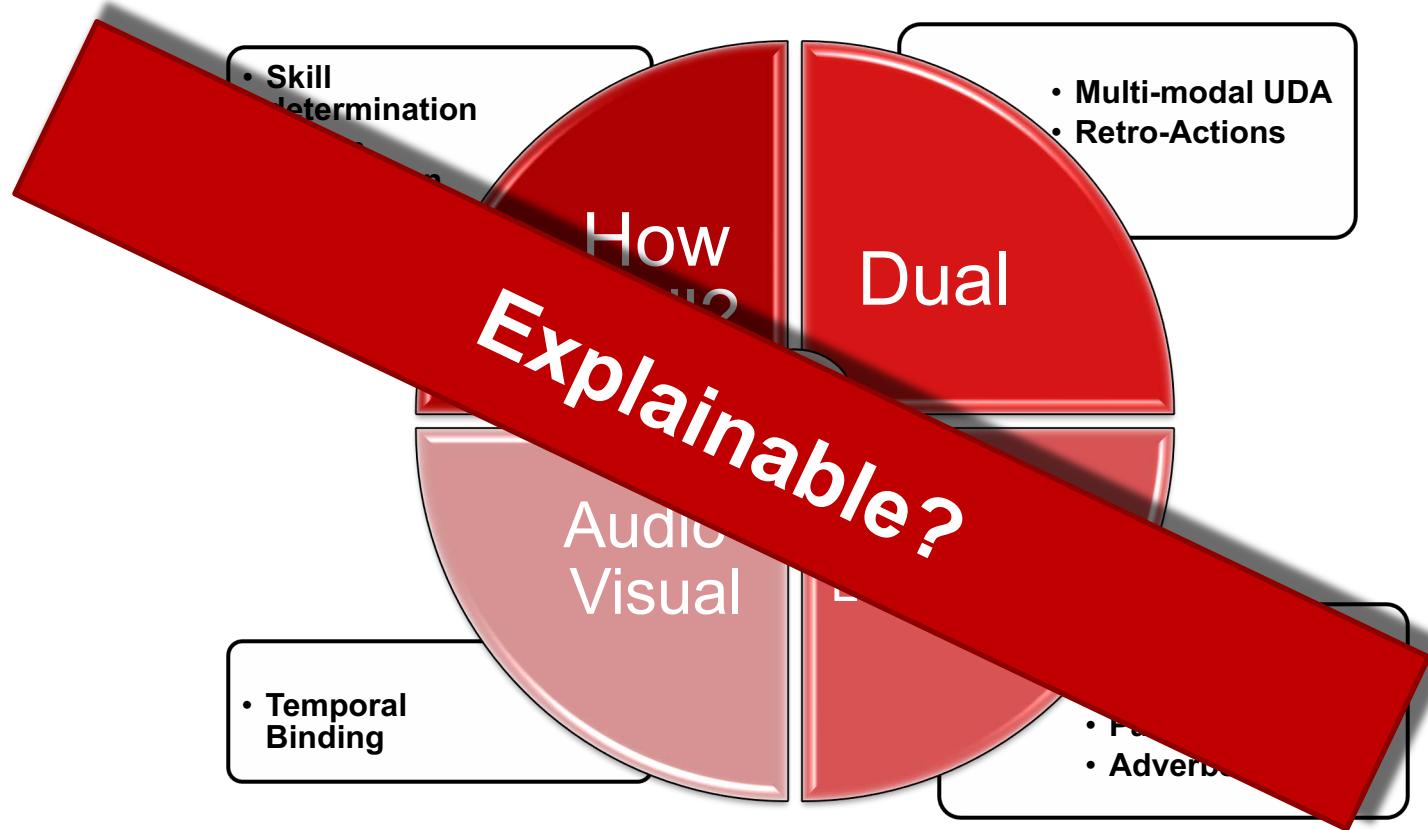
Abstract

We focus on multi-modal fusion for egocentric action recognition, and propose a novel architecture for multi-modal temporal-binding, i.e. the combination of modalities within a range of temporal offsets. We train the

Downloads

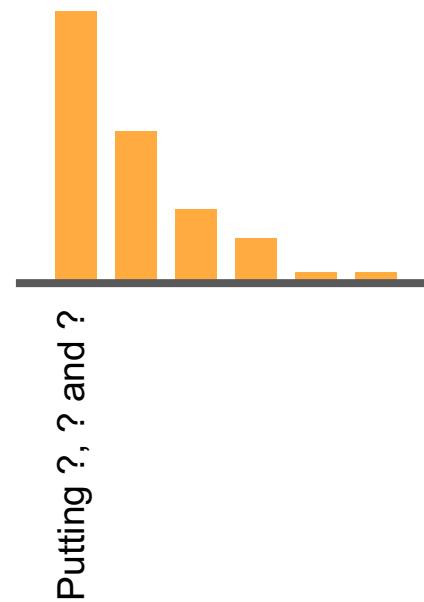
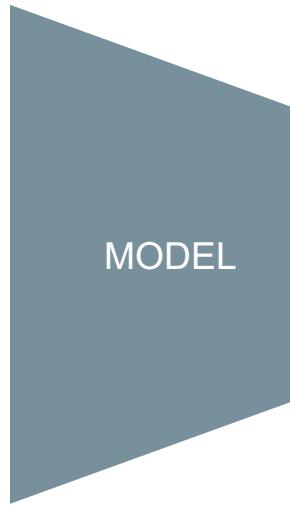
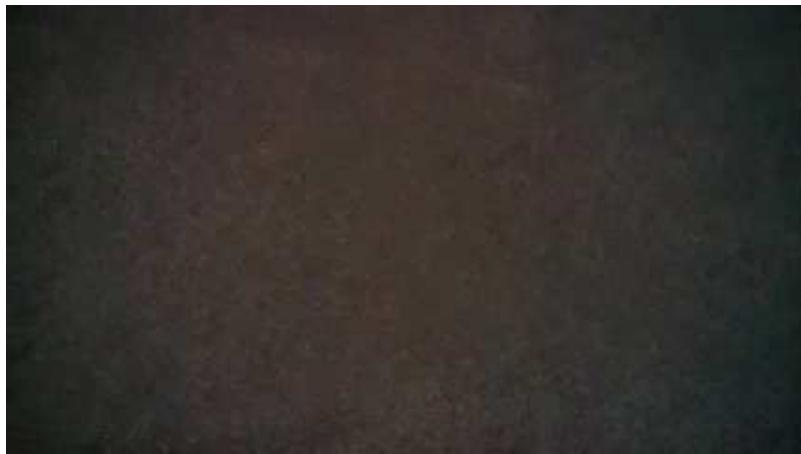
- Paper [\[ArXiv\]](#)
- Code and models [\[GitHub\]](#)

Fine(r)-grained?



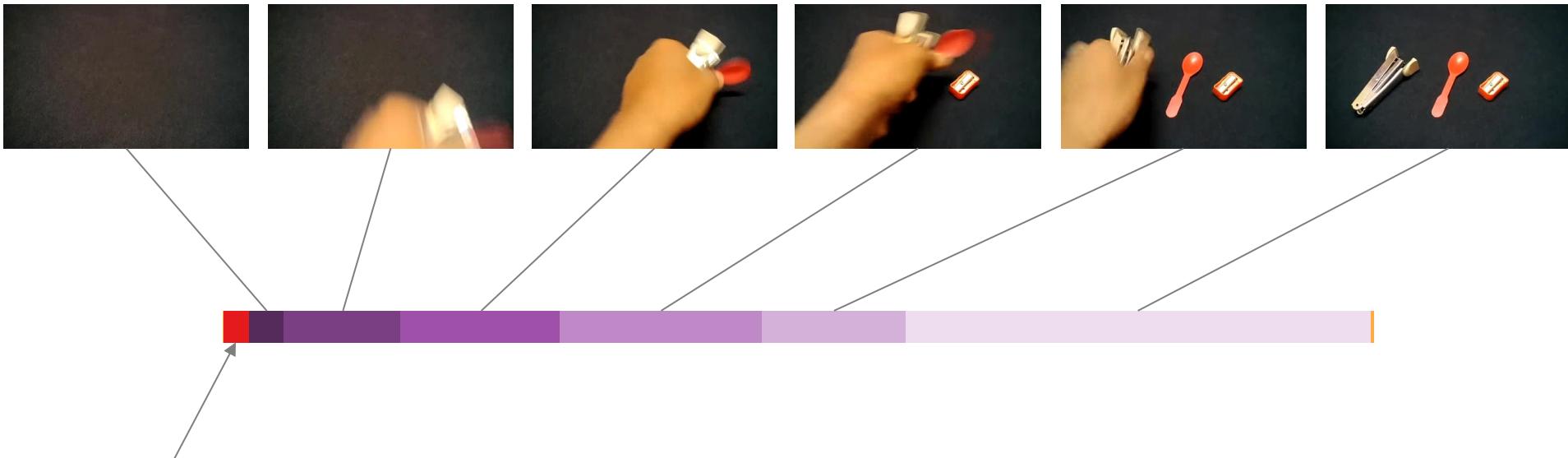
Frame Attributions in Video Models

with: Will Price



Frame Attributions in Video Models

with: Will Price



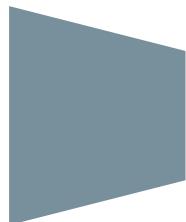
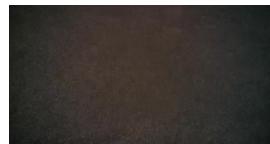
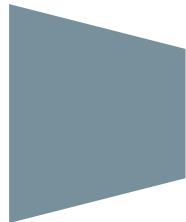
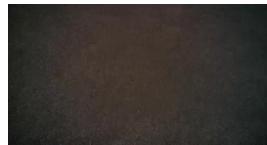
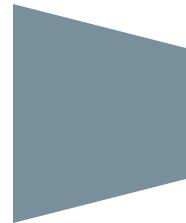
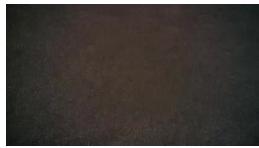
Expected output
(Prior probability for
classification model)

Frame Attributions in Video Models

with: Will Price

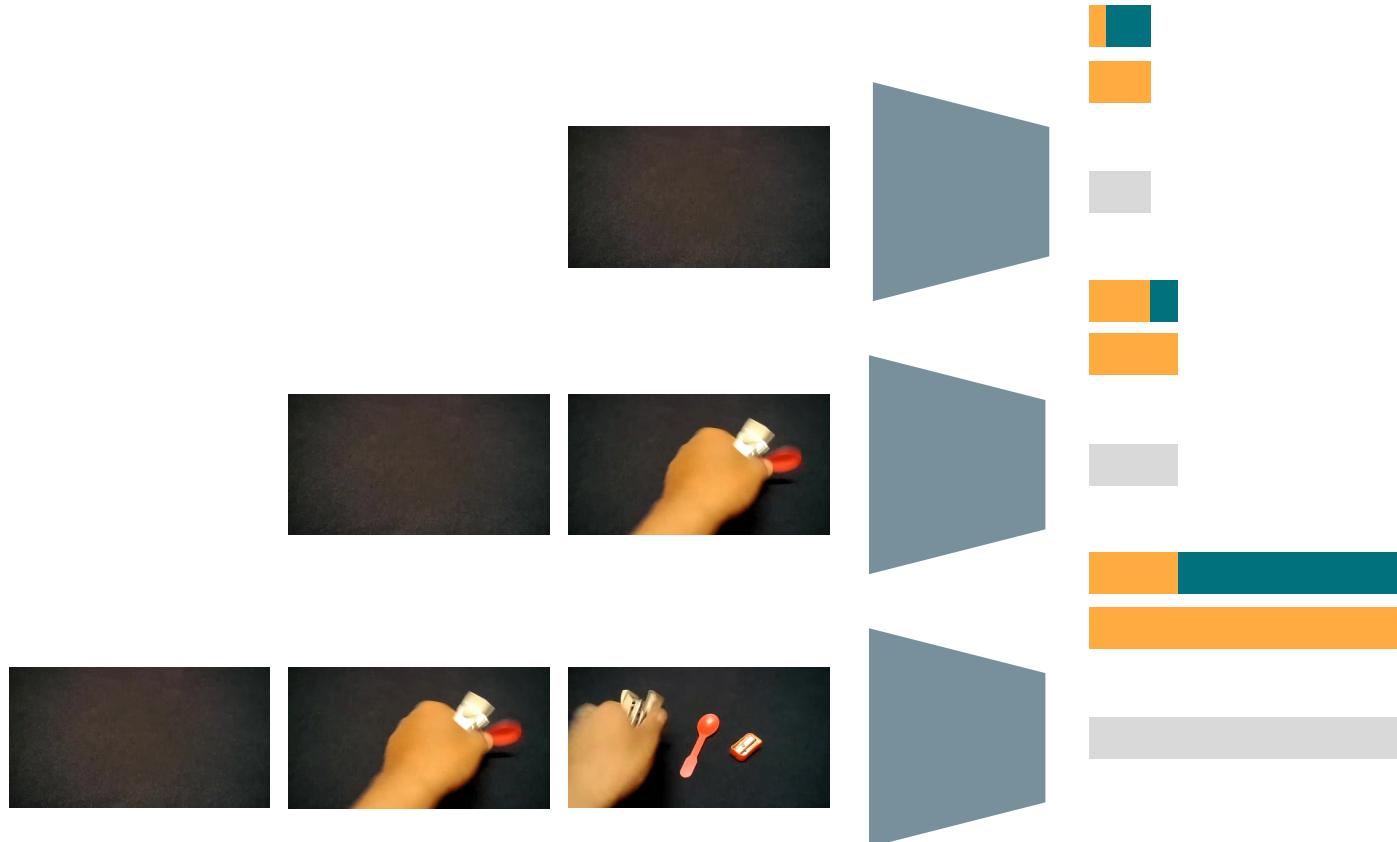


■ (expected output)



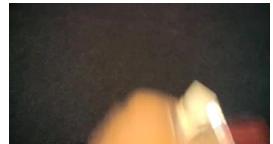
Frame Attributions in Video Models

with: Will Price



Frame Attributions in Video Models

with: Will Price



Frame Attributions in Video Models

with: Will Price

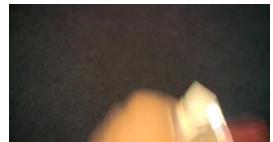


Frame Attributions in Video Models

with: Will Price



$$\Delta_3(\{1,2,4,5\}) = -.2$$



Frame Attributions in Video Models

with: Will Price

Closing [...]



ESV

IG

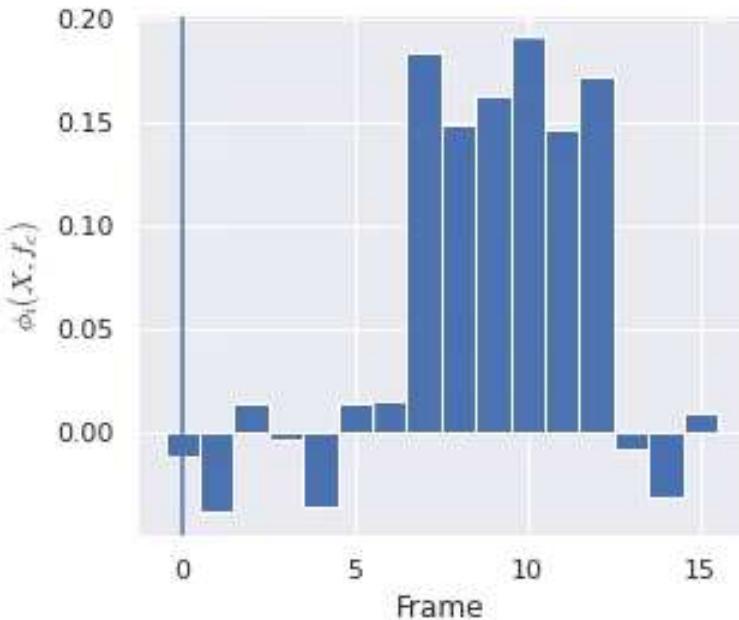
GradCam

Pushing [...] so it spins



Frame Attributions in Video Models

with: Will Price

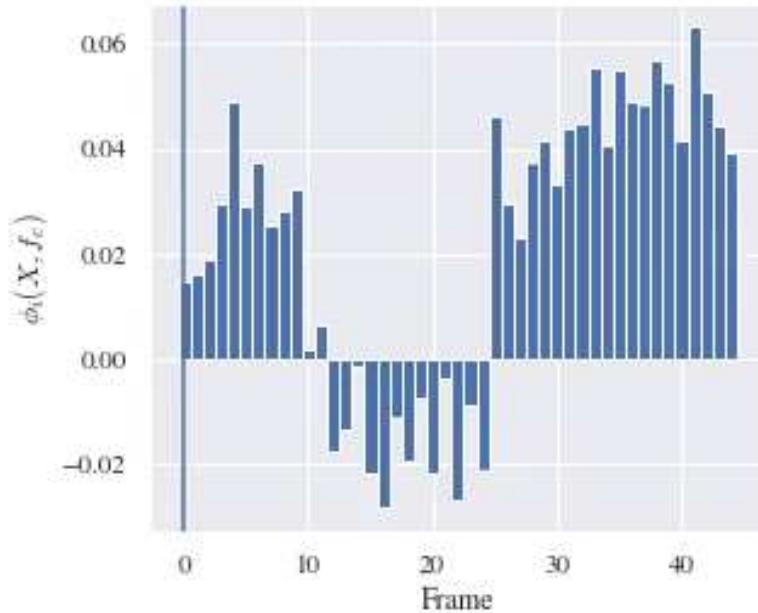


Twisting (wringing) something wet until water comes out



Frame Attributions in Video Models

with: Will Price



Showing that something is empty



Dashboard

The Team



2017



2019



2018



2020

Thank you



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

<http://dimadamen.github.io>



@dimadamen



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

Q&A