A Fine(r)-Grained Egocentric Perspective onto Object Interactions

Fine(r)-grained?

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…




University of BRISTOL · UNIVERSITY OF TORONTO · UNIVERSITÀ degli STUDI di CATANIA

Scaling and Rescaling Egocentric Vision:
The EPIC-KITCHENS Dataset


Dima Damen


Hazel Doughty


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Evangelos Kazakos


Jian Ma


Davide Moltisanti

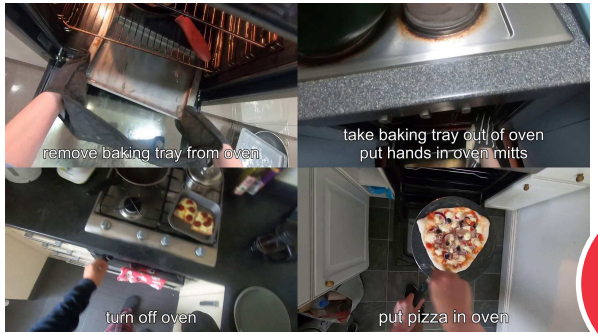

Jonathan Munro


Toby Perrett


Will Price


Michael Wray

Scaling and Rescaling Egocentric Vision



EPIC-KITCHENS-55

Avg actions per video

91.3

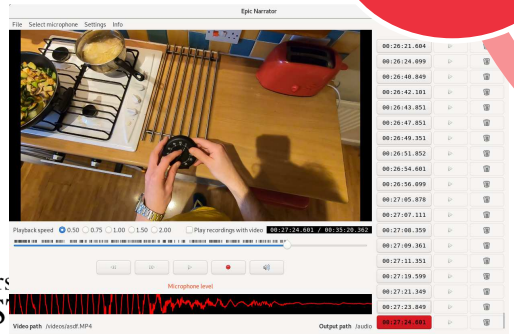
188.6

EPIC-KITCHENS-100

Avg actions per minute

13

20



Data Collection

Live Narrations

Dense Action Segments

Extension Data Collection

Pause-and-talk Narrator

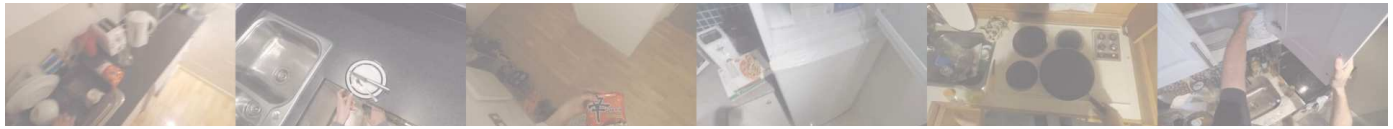
Improved Annotations

EPIC-KITCHENS -100

EPIC-KITCHENS-55

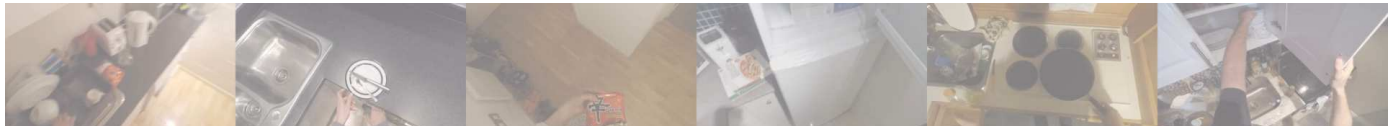
37 Participants

37 Participants



16 returning participants

37 Participants – 8 in the same kitchen



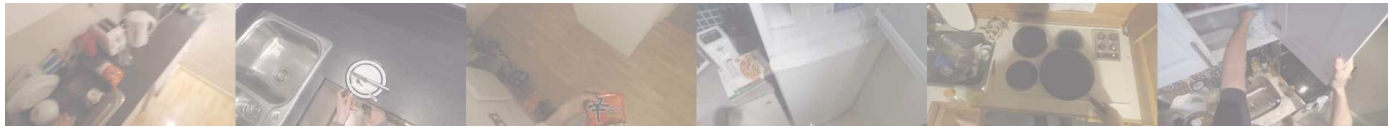
8 in original home

37 Participants – 8 in the same kitchen

EPIC-KITCHENS-55

2 years later

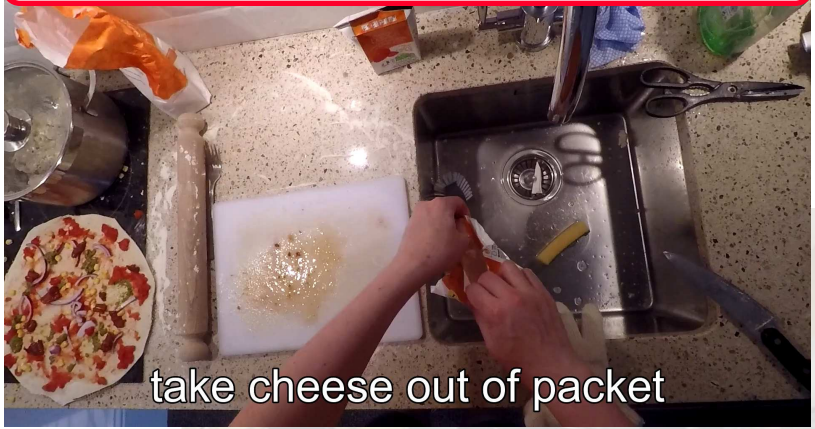
37 Participants – 8 in a different kitchen



8 in a new home

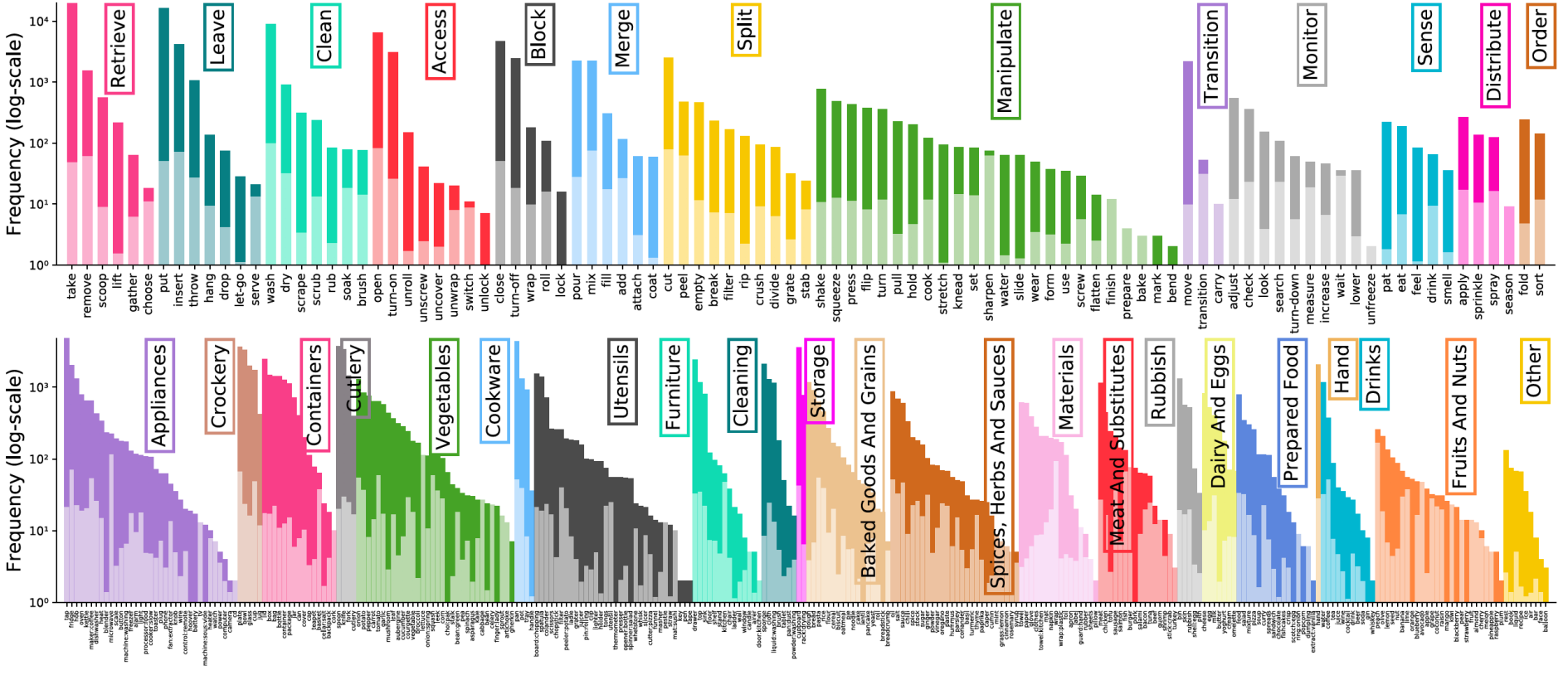
37 Participants – 8 in a different kitchen

EPIC-KITCHENS-55



2 years later

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.

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

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

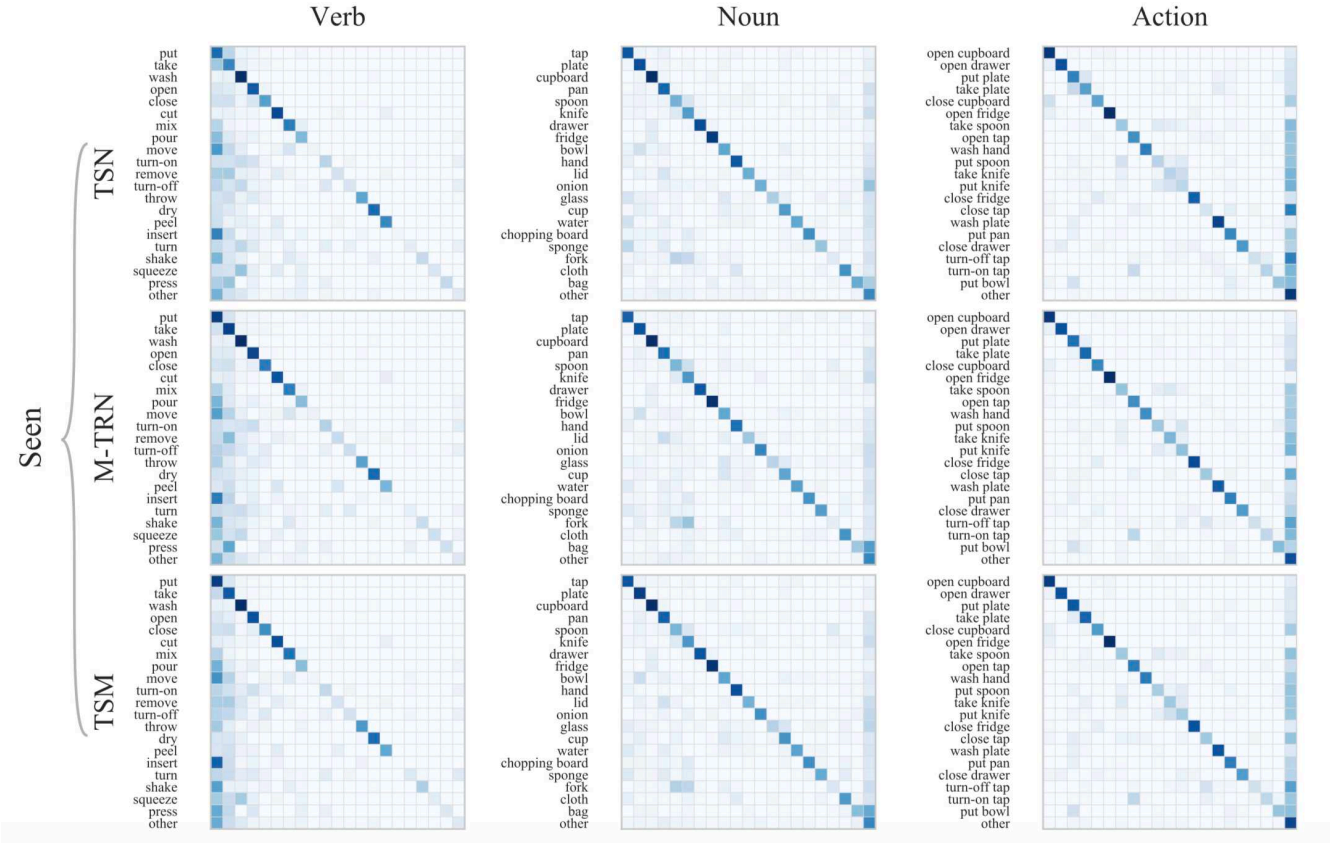
$$\hat{y}_{\text{action}} = (\text{open}, \text{oven})$$

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

with: Will Price



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

Evaluating Action Recognition Models

with: Will Price

	GFLOP/s		Params (M)	
Model	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

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 alongisde 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 uob-epic-kitchens@bristol.ac.uk

University of BRISTOL

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.

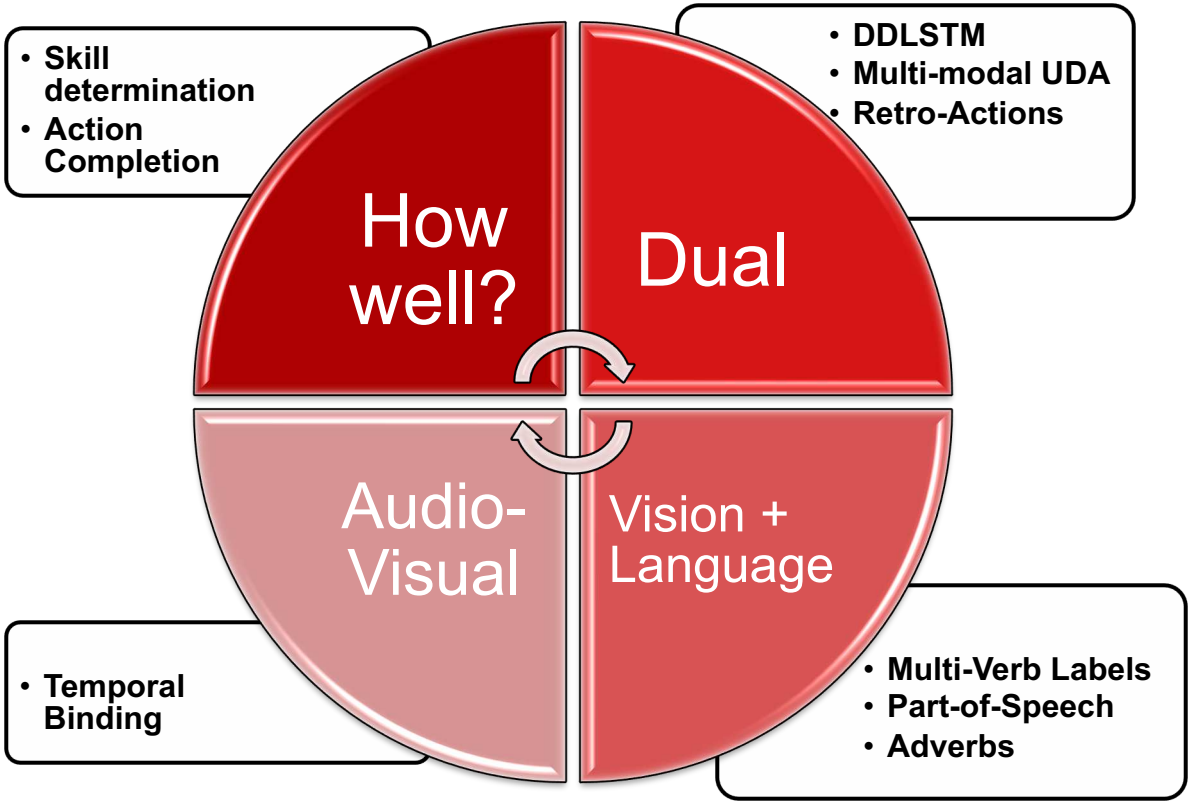
Characteristics

- 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

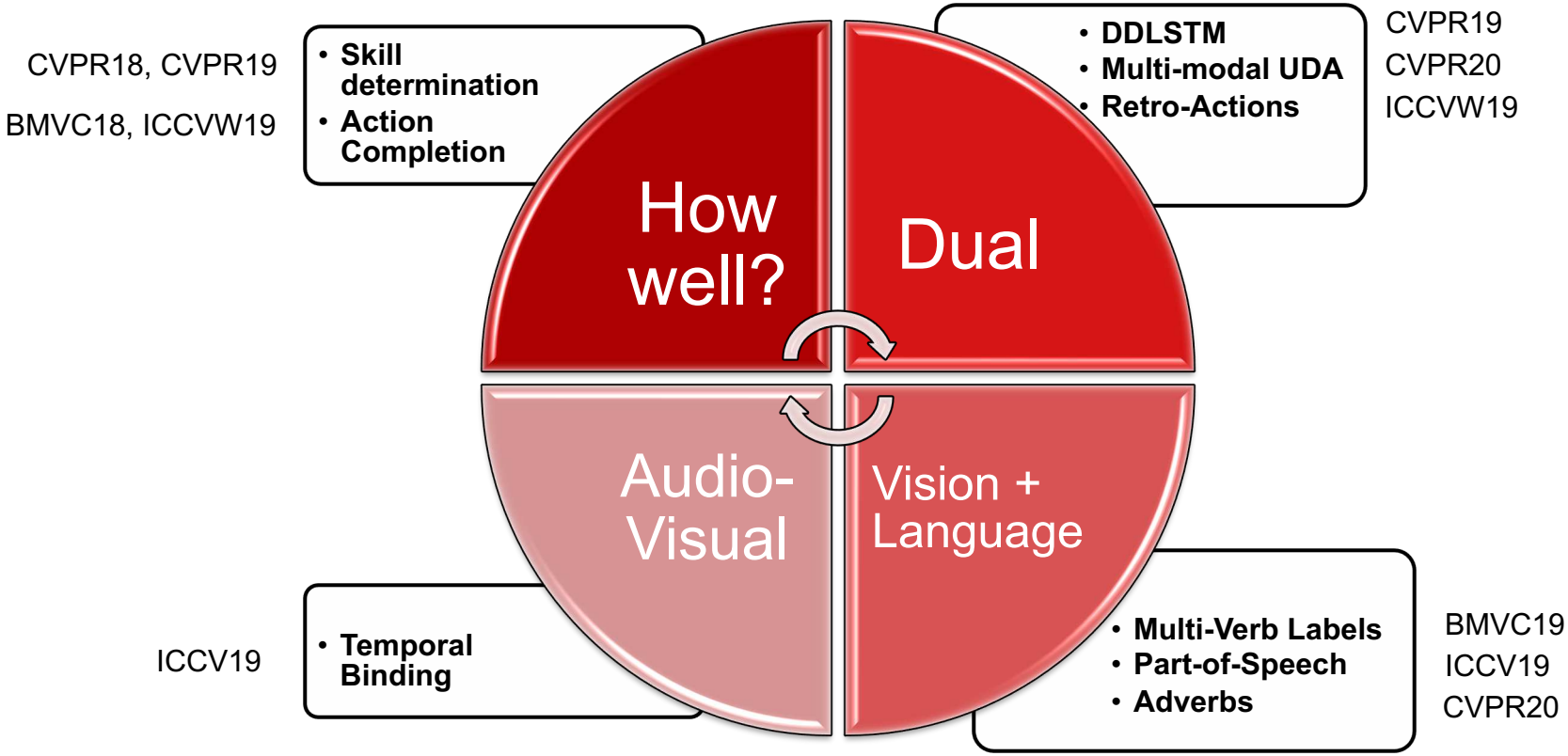
Previous versions...

- 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

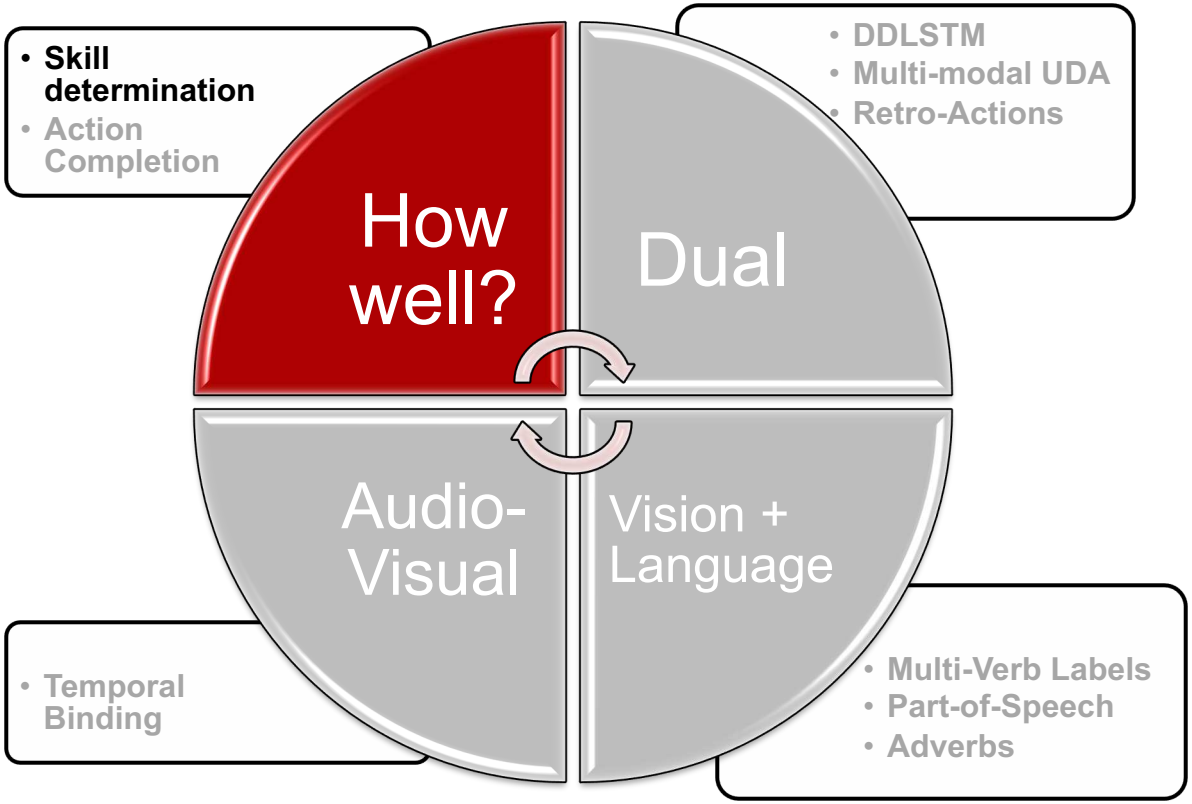
Fine(r)-grained?



Fine(r)-grained?



Fine(r)-grained?



Skill determination in video

with: Hazel Doughty
Walterio Mayol-Cuevas

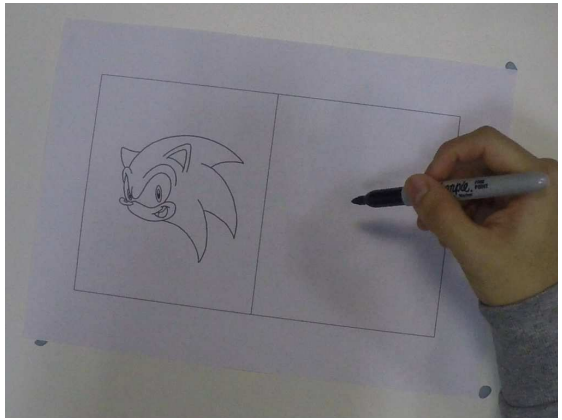
Assess relative skill for a collection of video sequences, applicable to a variety of tasks.

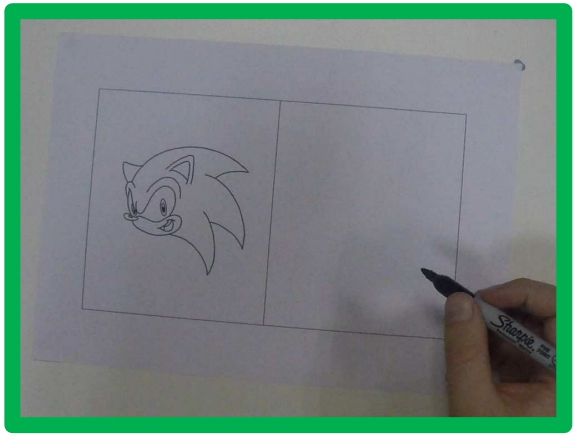
H Doughty, D Damen, W Mayol-Cuevas (2018). Who's Better? Who's Best? Pairwise Deep Ranking for Skill Determination. CVPR

Skill determination in video

with: Hazel Doughty
Walterio Mayol-Cuevas

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





H Doughty, W Mayol-Cuevas, D Damen (2019). The Pros and Cons: Rank-aware Temporal Attention for Skill Determination in Long Videos. *Computer Vision and Pattern Recognition (CVPR)*

Skill determination in video

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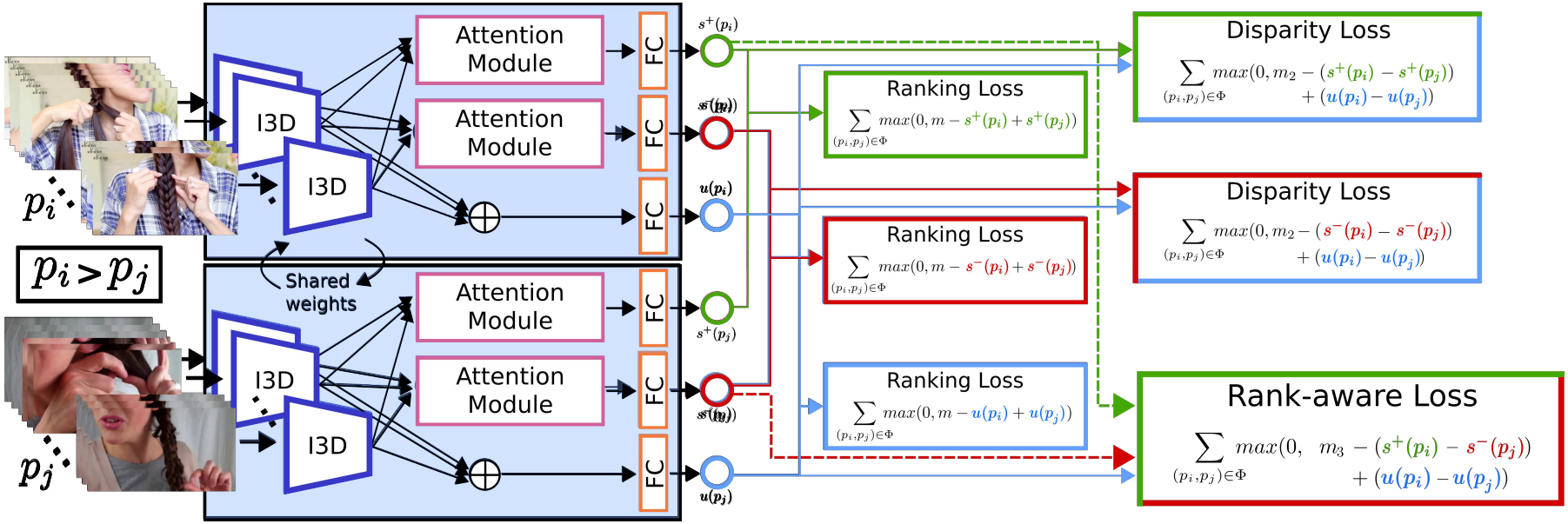

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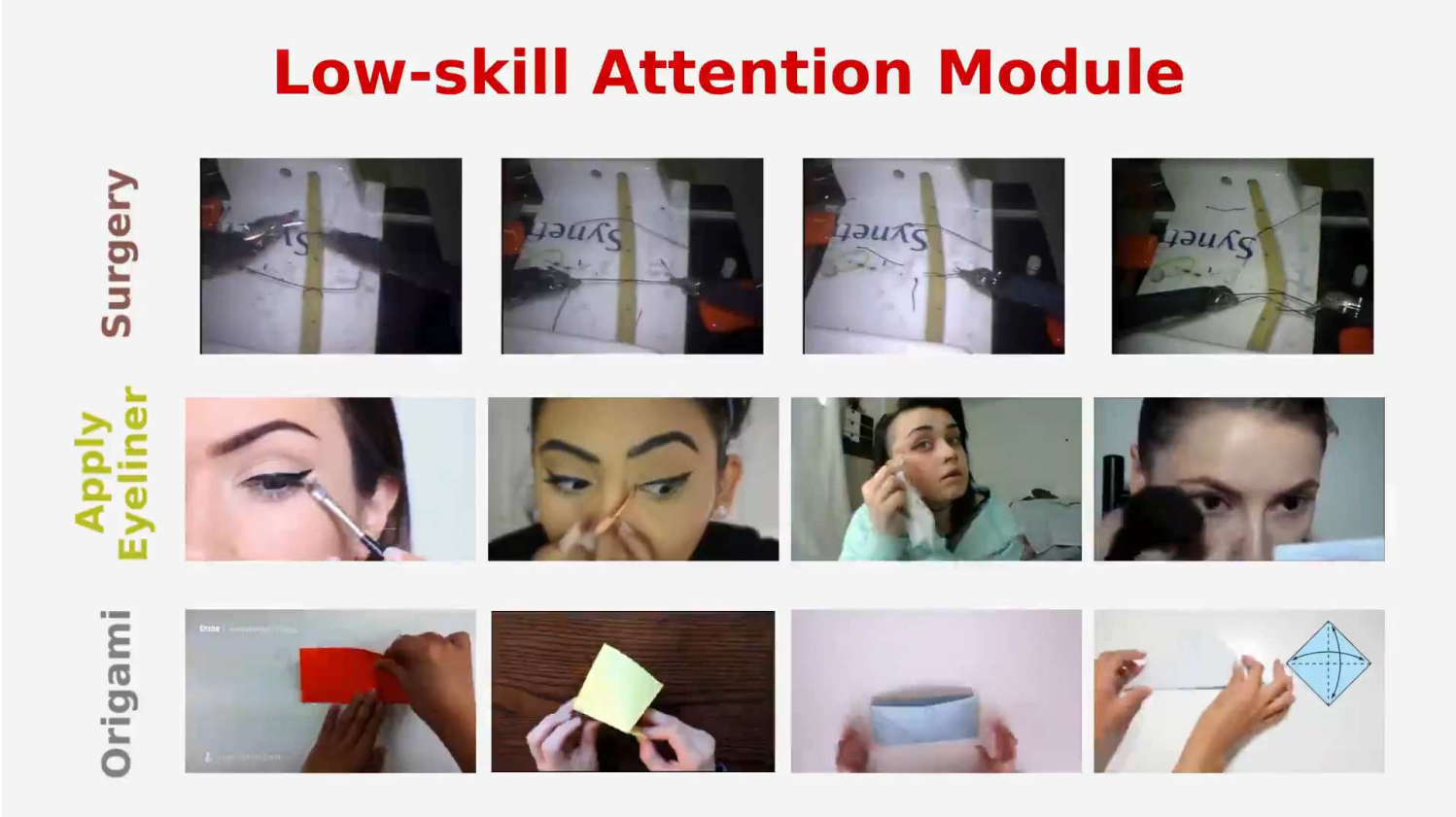

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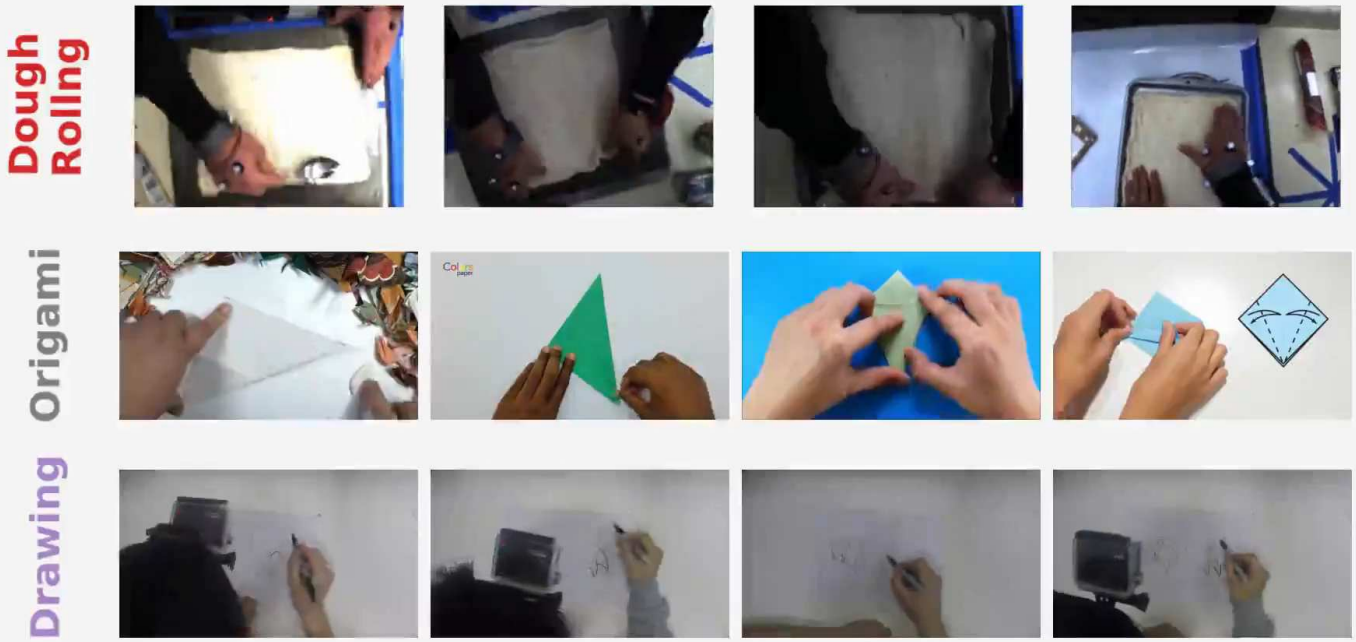
Skill determination in video

with: Hazel Doughty
Walterio Mayol-Cuevas

High-skill Attention Module



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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.

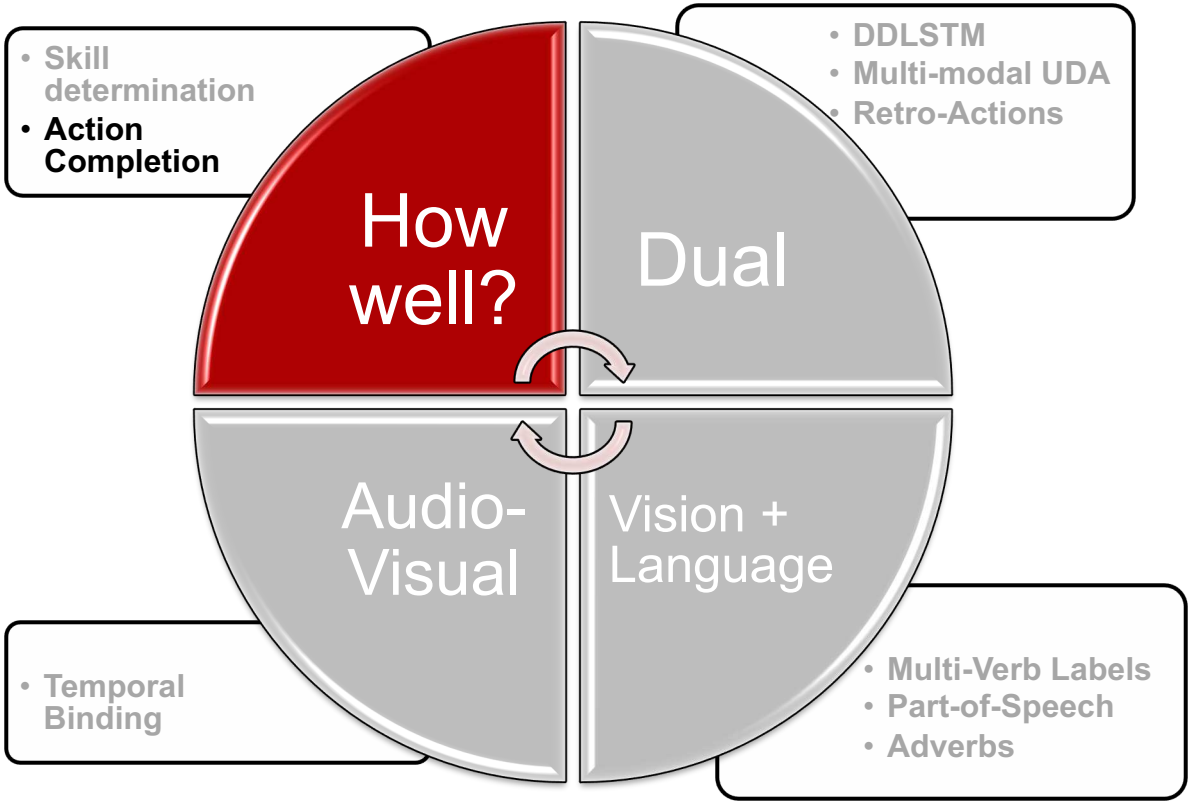
Our approach trains temporal attention modules, learned with only video-level supervision, using a novel rank-aware loss function. In addition to attending to task-relevant video parts, our proposed loss jointly trains two attention modules to separately attend to video parts which are indicative of 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]

H Doughty, W Mayol-Cuevas, D Damen (2019). The Pros and Cons: Rank-aware Temporal Attention for Skill Determination in Long Videos. *Computer Vision and Pattern Recognition (CVPR)*

Fine(r)-grained?



Action Completion Detection

with: Farnoosh Heidarivincheh
Majid Mirmehdi

F Heidarivincheh, M Mirmehdi, D Damen (2018). Action Completion: A Temporal Model for Moment Detection. BMVC

Action Completion Detection

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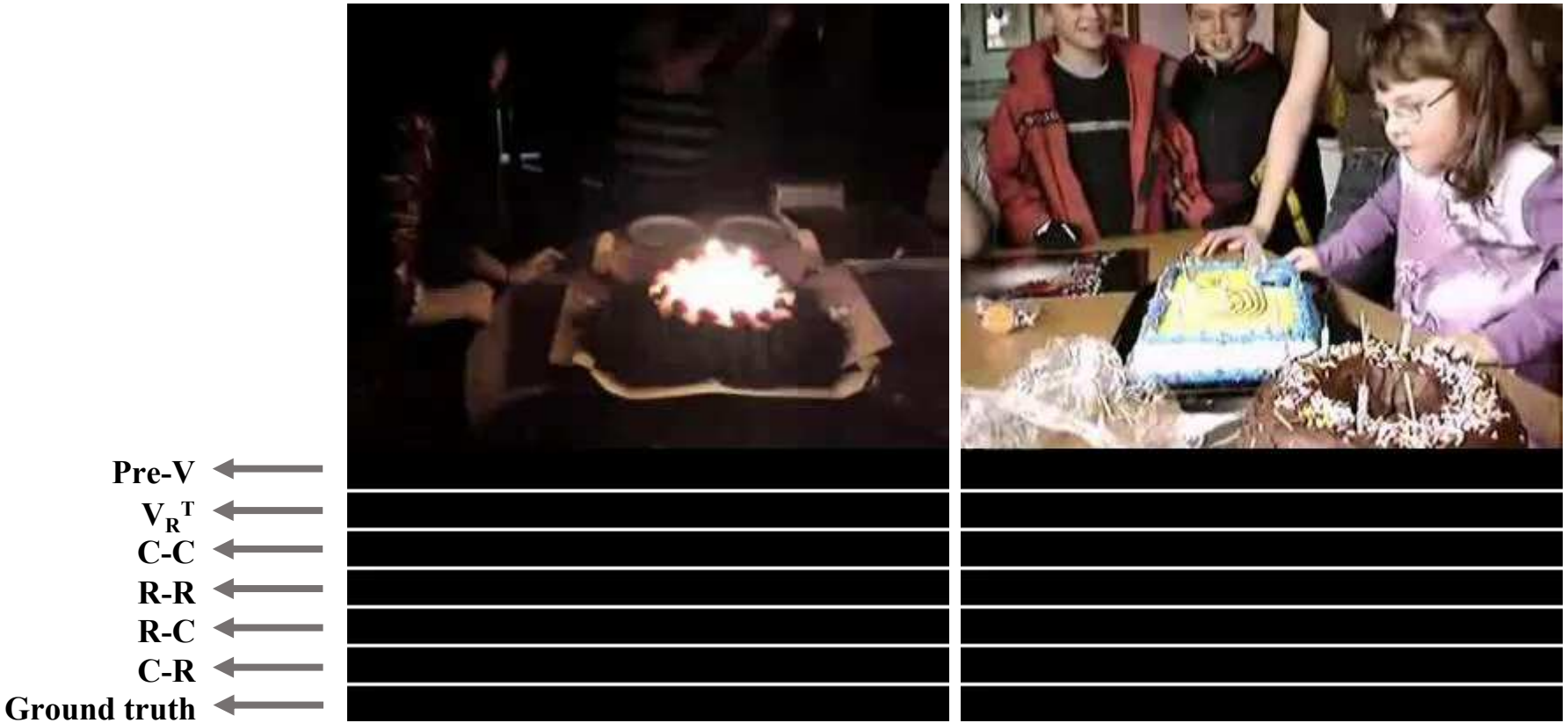
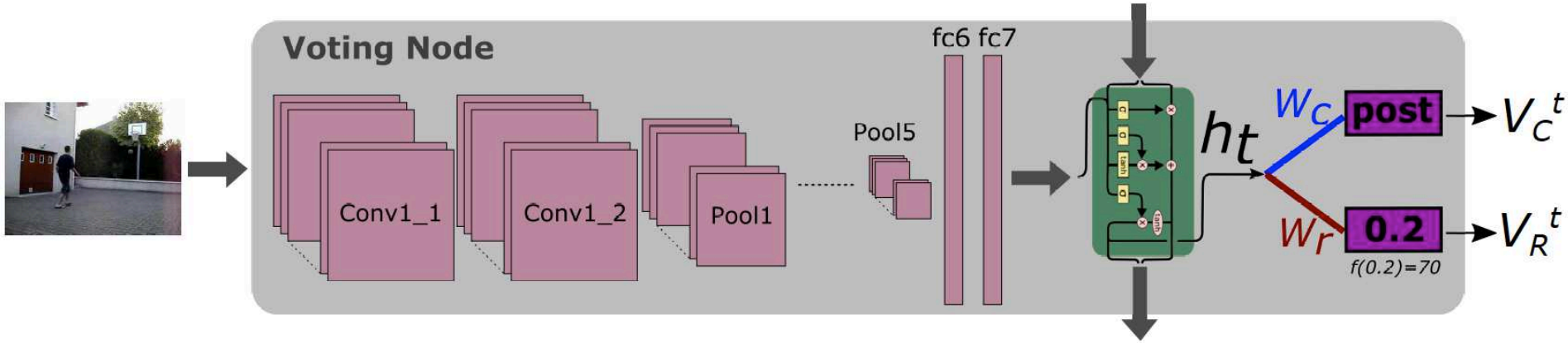


F Heidarivincheh, M Mirmehdi, D Damen (2018). Action Completion: A Temporal Model for Moment Detection. BMVC

Action Completion Detection

with: Farnoosh Heidarivincheh
Majid Mirmehdi

- Each frame in the sequence, contributes to the completion moment detection via ‘voting’



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Action Completion Detection

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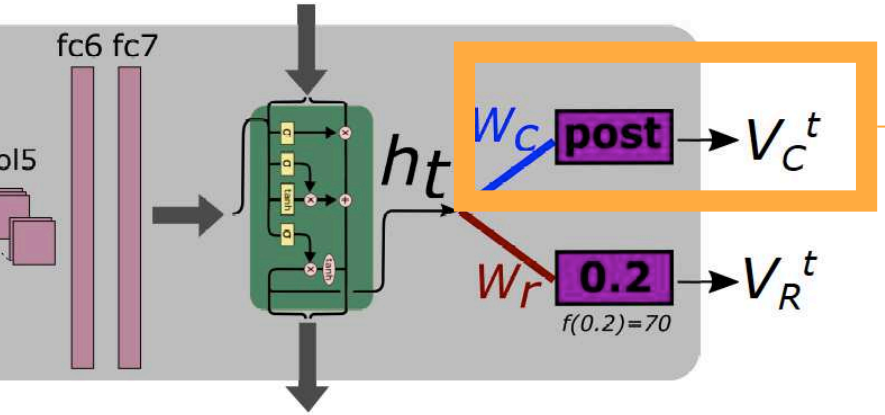
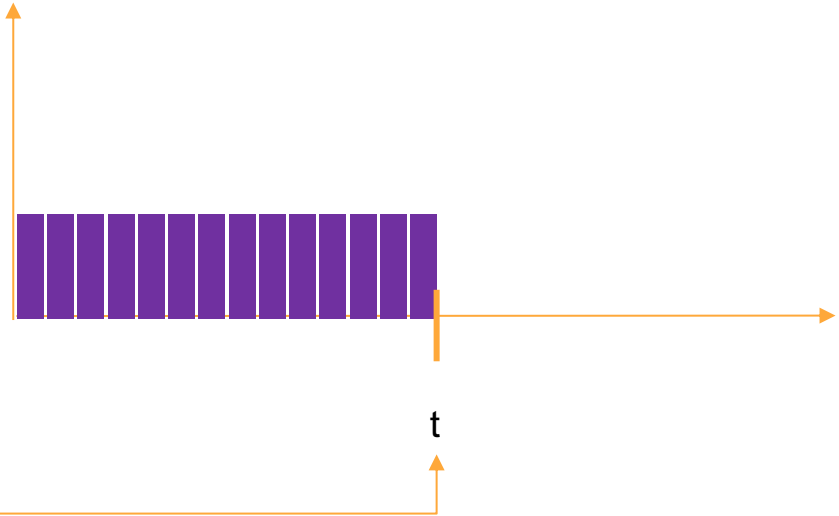
Majid Mirmehdi

1. Classification-Based Voting





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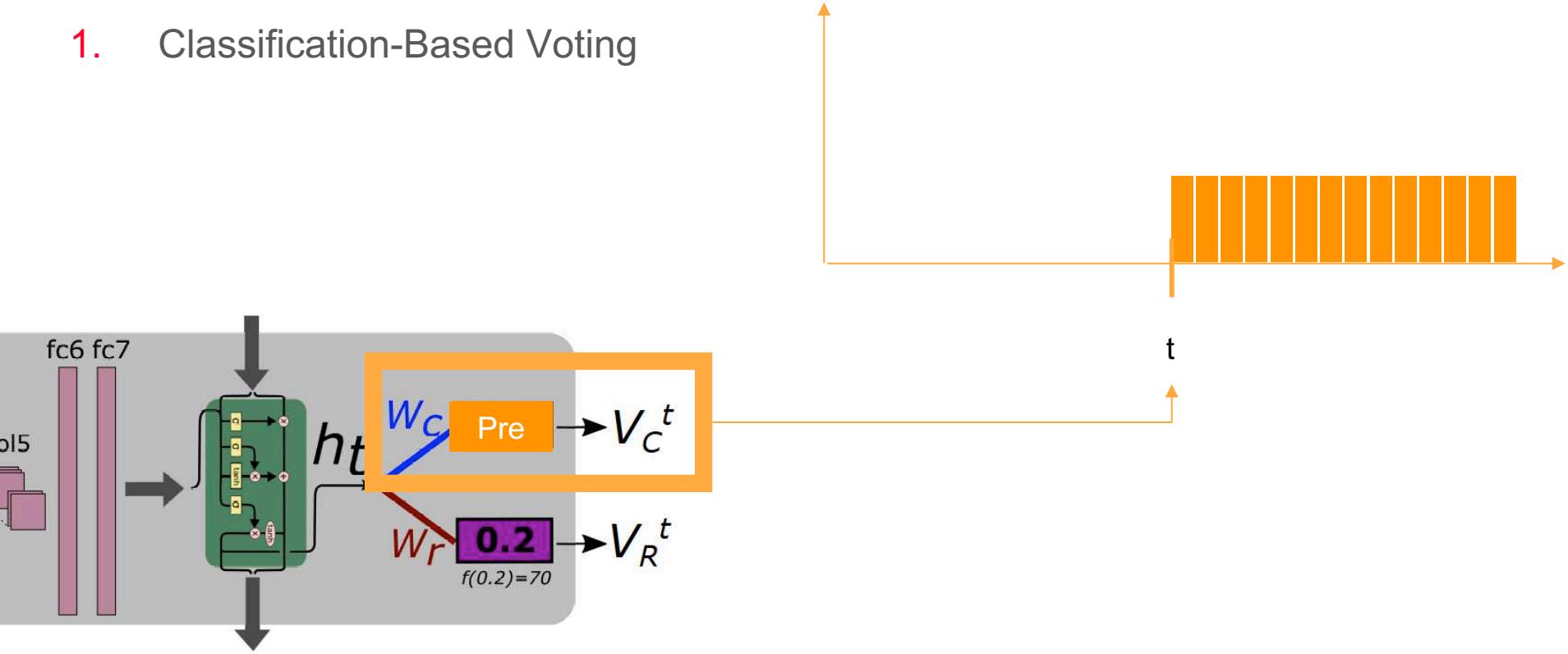
Action Completion Detection

with: Farnoosh Heidarivincheh
Majid Mirmehdi

1. Classification-Based Voting



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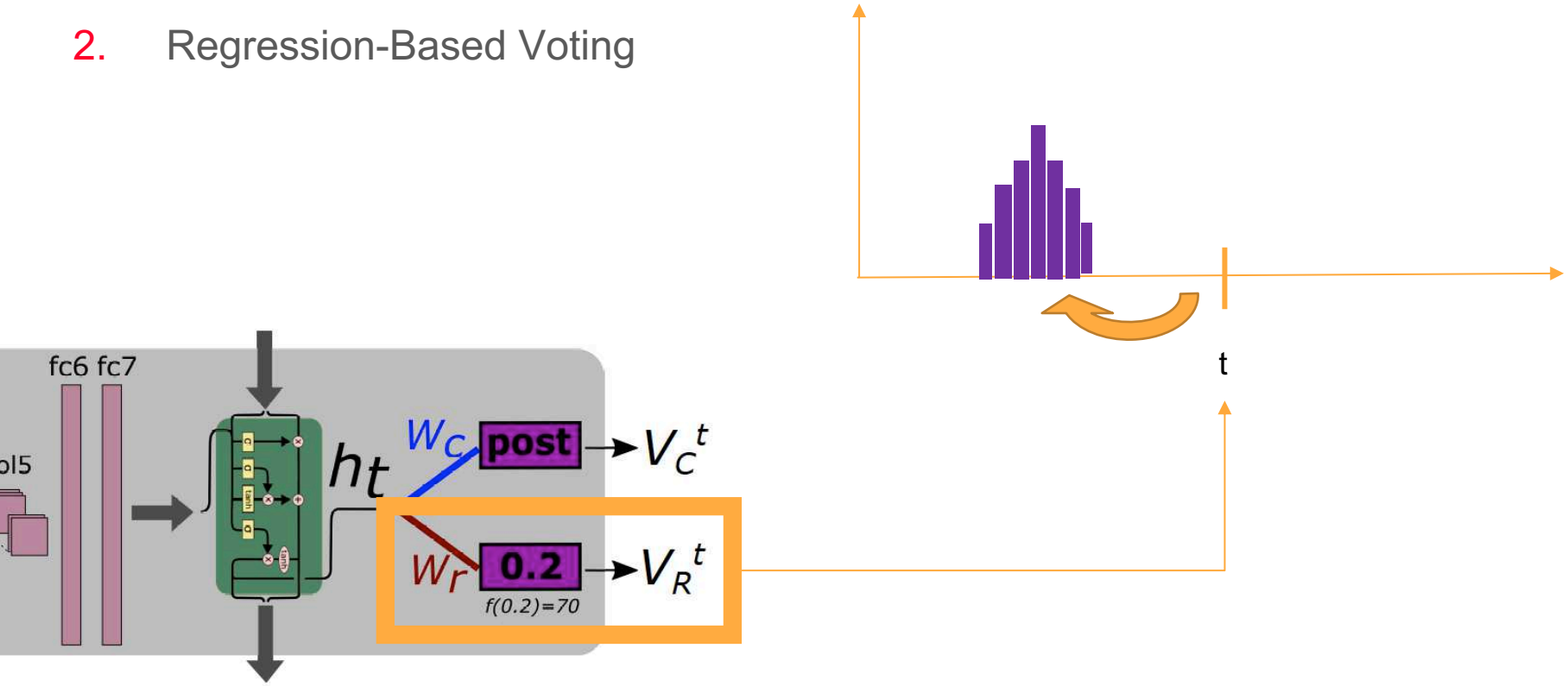
Action Completion Detection

with: Farnoosh Heidarivincheh
Majid Mirmehdi

2. Regression-Based Voting



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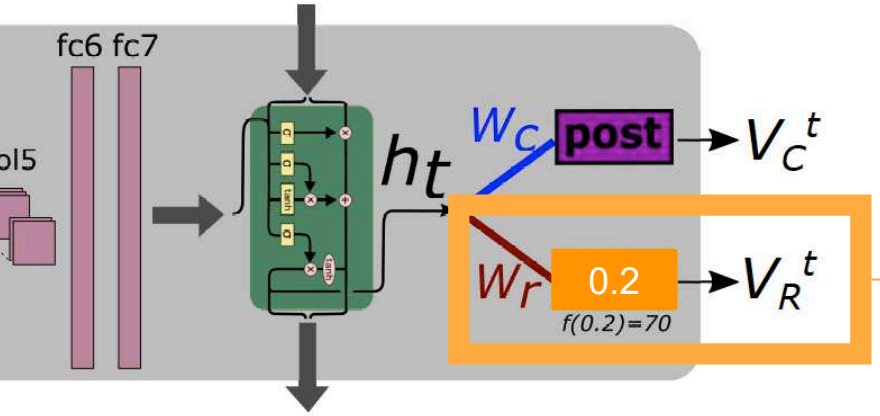
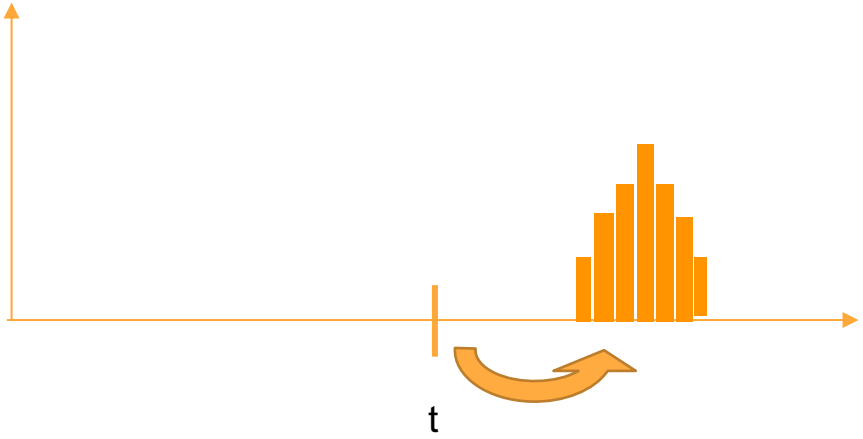
Action Completion Detection

with: Farnoosh Heidarivincheh
Majid Mirmehdi

2. Regression-Based Voting





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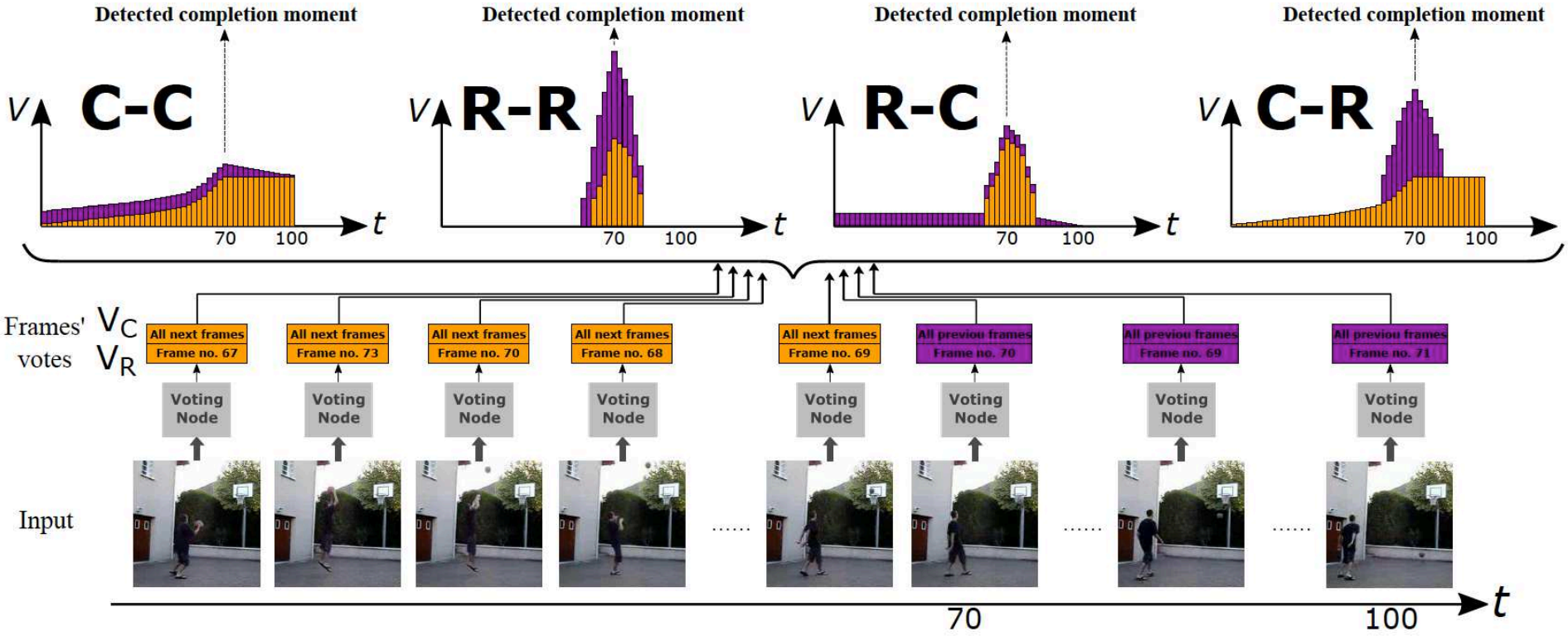
with: Farnoosh Heidarivincheh
Majid Mirmehdi



F Heidarivincheh, M Mirmehdi, D Damen (2018). Action Completion: A Temporal Model for Moment Detection. BMVC

Action Completion Detection

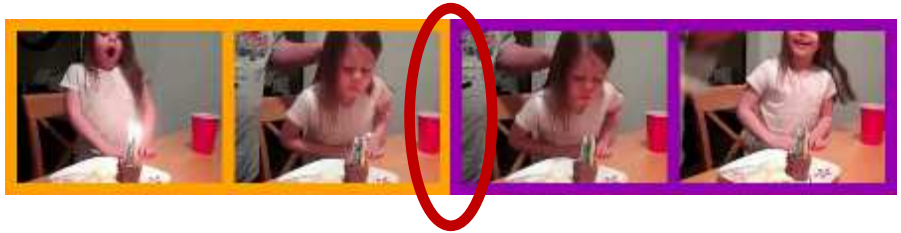
with: Farnoosh Heidarivincheh
Majid Mirmehdi

F Heidarivincheh, M Mirmehdi, D Damen (2018). Action Completion: A Temporal Model for Moment Detection. BMVC

Action Completion Detection

with: Farnoosh Heidarivincheh
Majid Mirmehdi

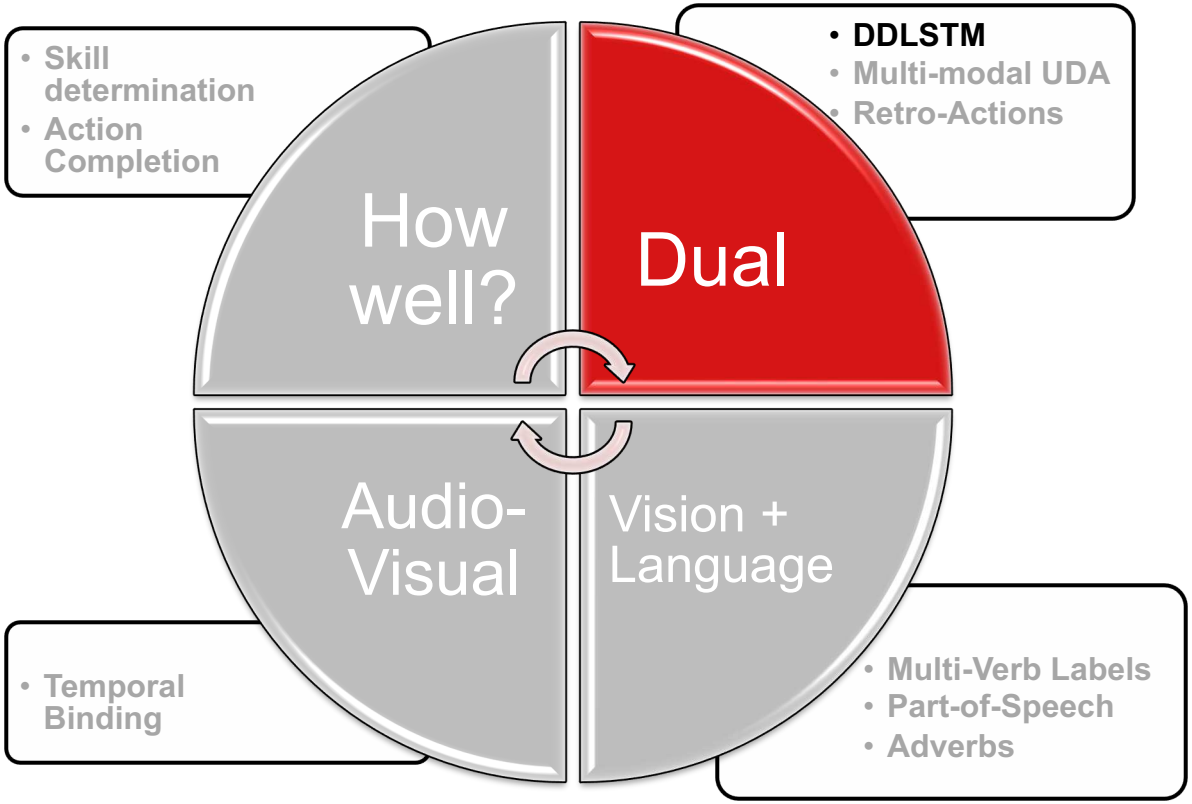
Frame-level labels: annotations are expensive, subjective and noisy.



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

F Heidarivincheh, M Mirmehdi, D Damen (2019). Weakly-Supervised Completion Moment Detection using Temporal Attention. ICCV Workshop on Human Behaviour Understanding

Fine(r)-grained?



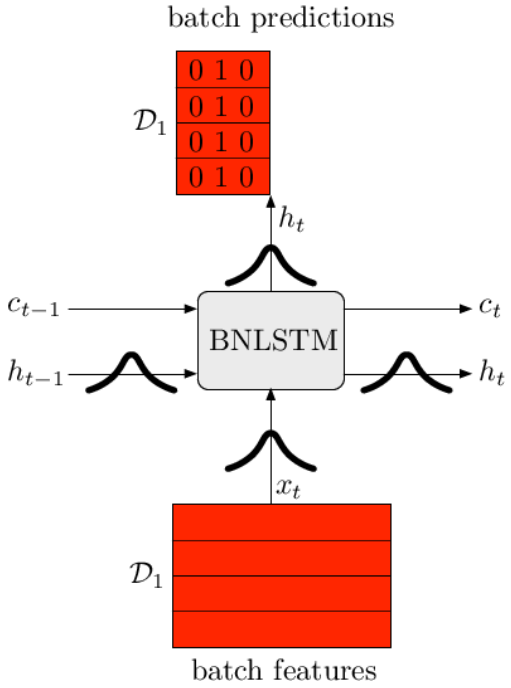
Dual-Domain LSTM for Cross-Dataset Action

with: Toby Perrett

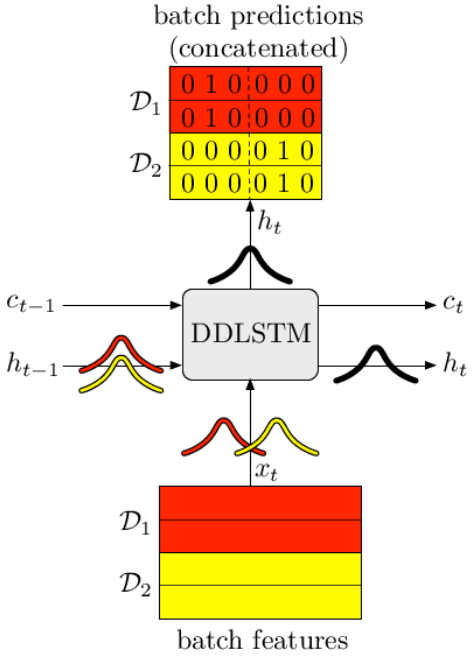
T Perrett, D Damen (2019). DDLSTM: Dual-Domain LSTM for Cross-Dataset Action Recognition. CVPR

Dual-Domain LSTM for Cross-Dataset Action

BNLSTM
1 dataset



DDLSTM
2 datasets



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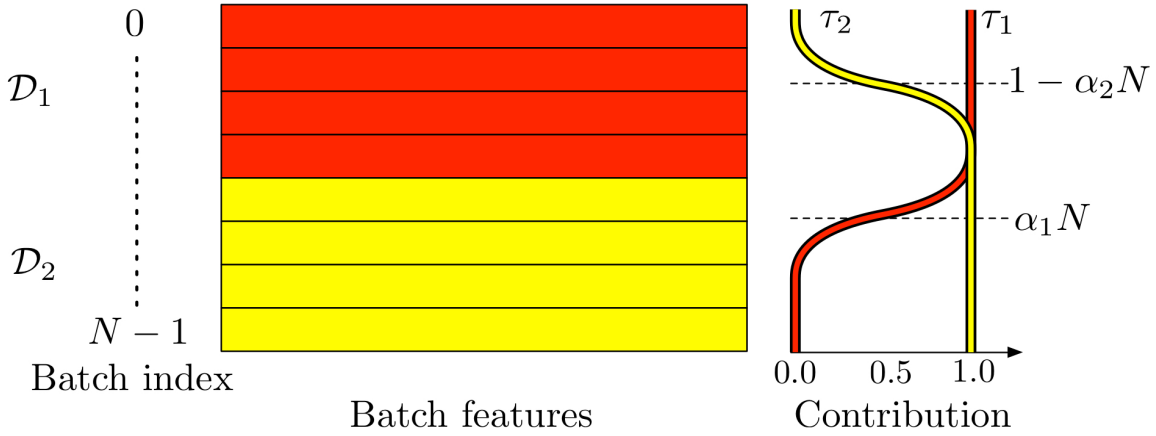
Dual-Domain LSTM for Cross-Dataset Action

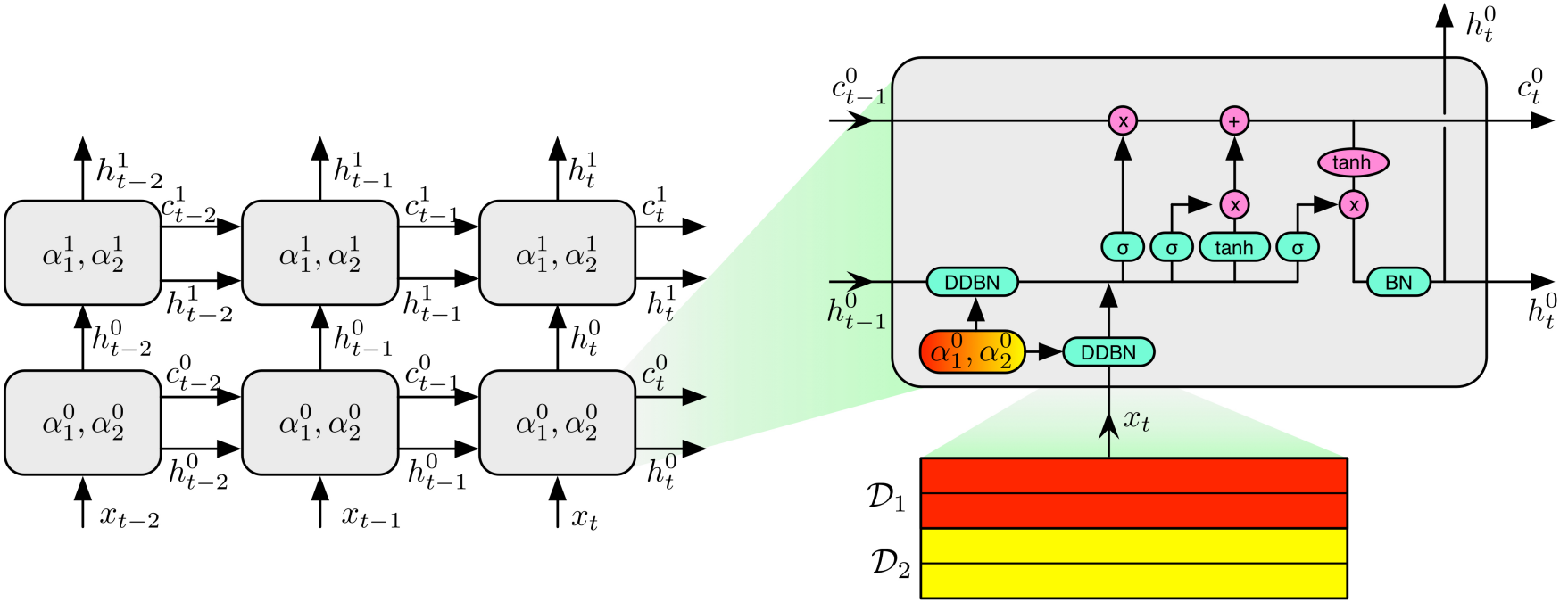


$$\tau_1(\alpha_1, j) = \frac{1 - \tanh(j - \alpha_1 N)}{2}$$

$$\tau_2(\alpha_2, j) = \frac{1 + \tanh(j - \alpha_2 N)}{2}$$

T Perrett, D Damen (2019). DDLSTM: Dual-Domain LSTM for Cross-Dataset Action Recognition. CVPR

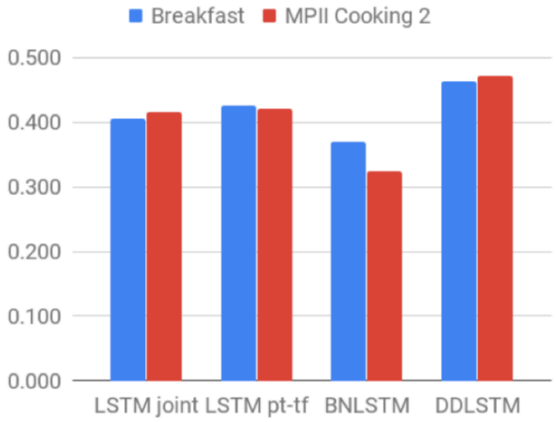
Dual-Domain LSTM for Cross-Dataset Action



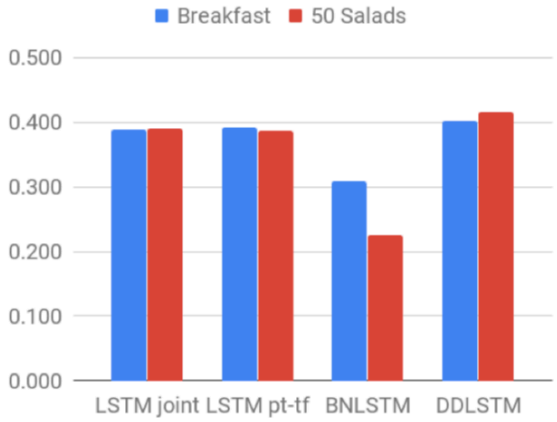
T Perrett, D Damen (2019). DDLSTM: Dual-Domain LSTM for Cross-Dataset Action Recognition. CVPR

Dual-Domain LSTM for Cross-Dataset Action

(a) Breakfast



(b) 50 Salads



(c) MPII Cooking 2

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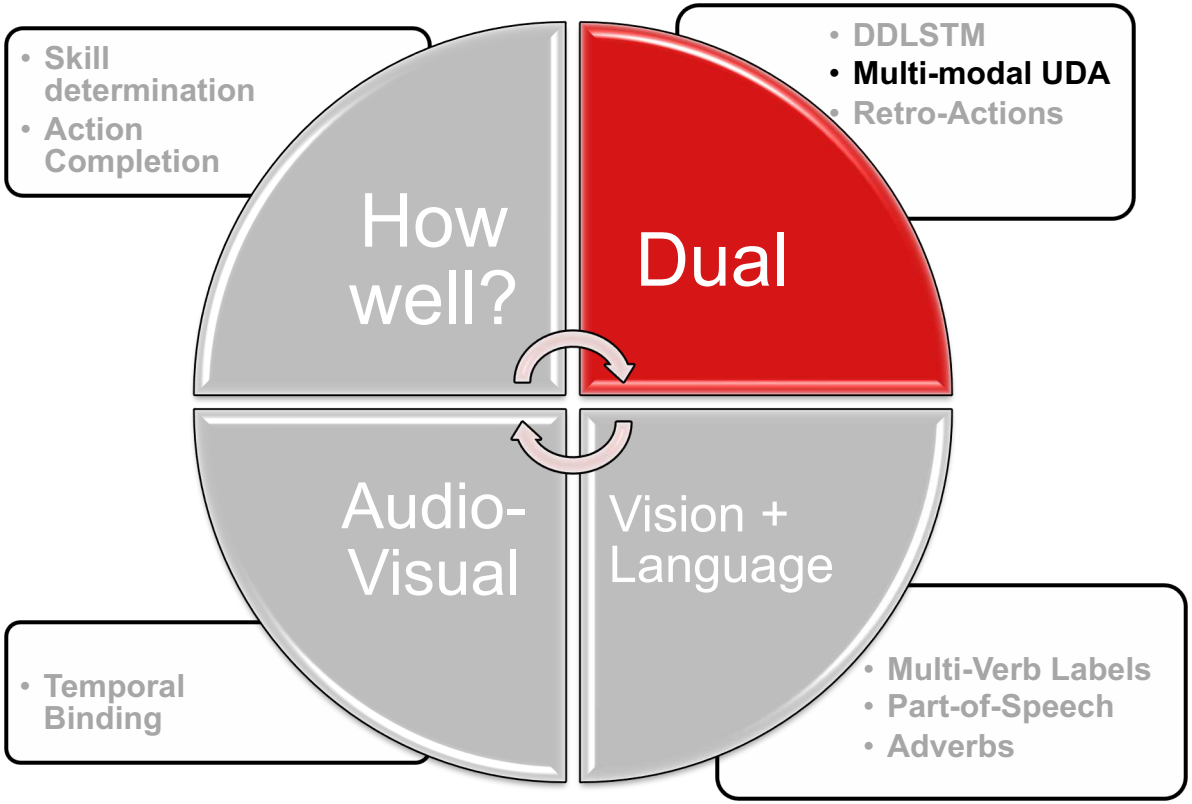
Dual-Domain LSTM for Cross-Dataset Action

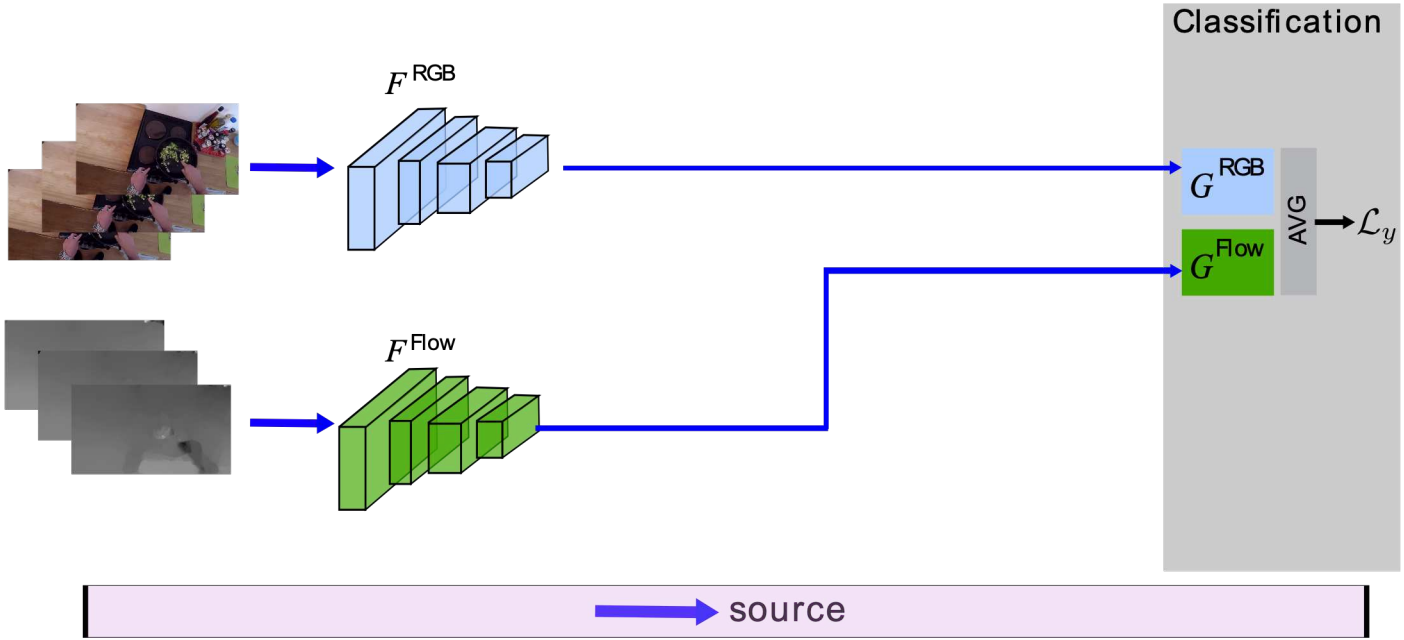
D1	D2	Training	LSTM Type	D1 Acc	D2 Acc
ActivityNet	50 Salads	Pt/ft	LSTM	44.4	42.1
ActivityNet	50 Salads	Joint	DDLSTM	44.3	42.2
Thumos	50 Salads	Pt/ft	LSTM	65.9	42.0
Thumos	50 Salads	Joint	DDLSTM	66.1	42.3
EPIC	50 Salads	Pt/ft	LSTM	31.5	**44.9**
EPIC	50 Salads	Joint	DDLSTM	33.1	**48.9**

T Perrett, D Damen (2019). DDLSTM: Dual-Domain LSTM for Cross-Dataset Action Recognition. CVPR

Fine(r)-grained?

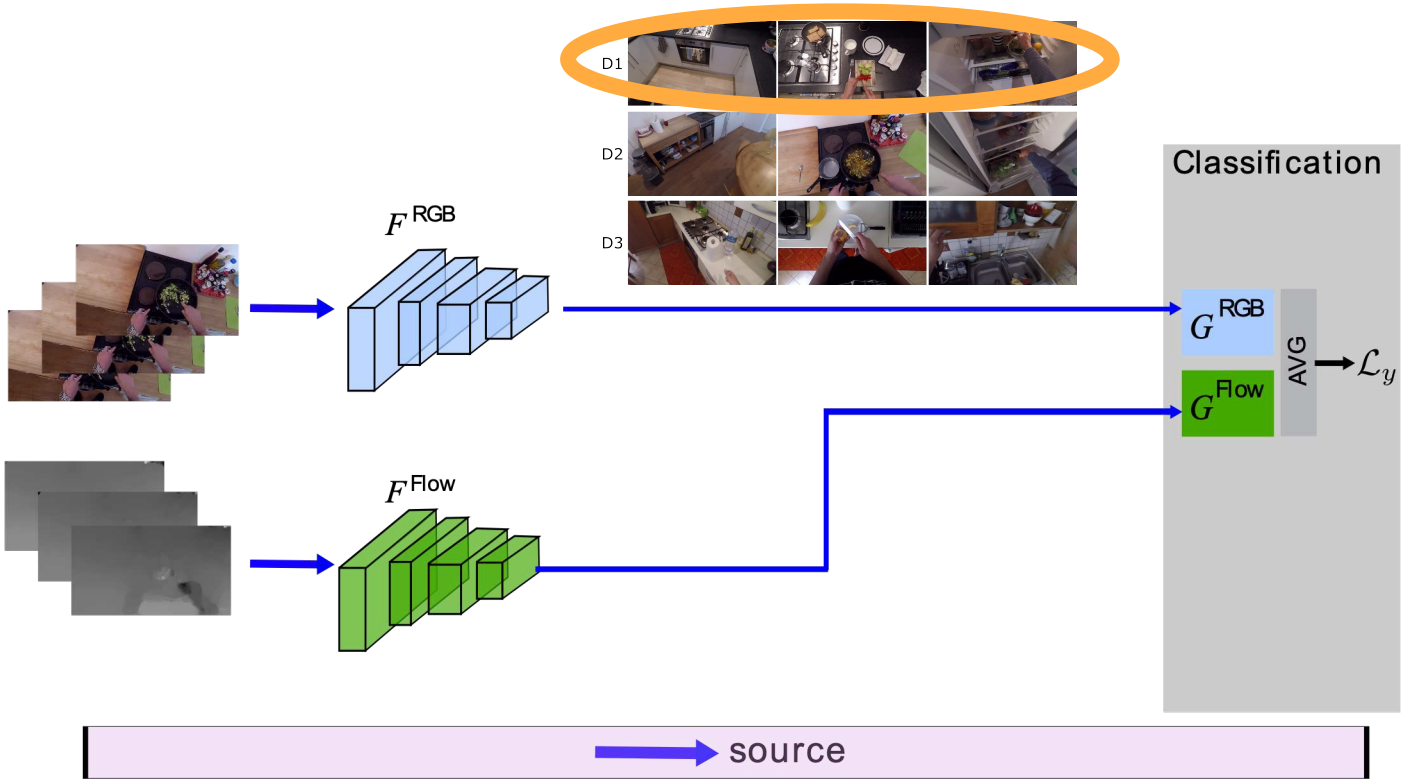


Multi-modal UDA



J Munro, D Damen (2020). Multi-Modal Domain Adaptation for Fine-Grained Action Recognition. *Computer Vision and Pattern Recognition (CVPR)*

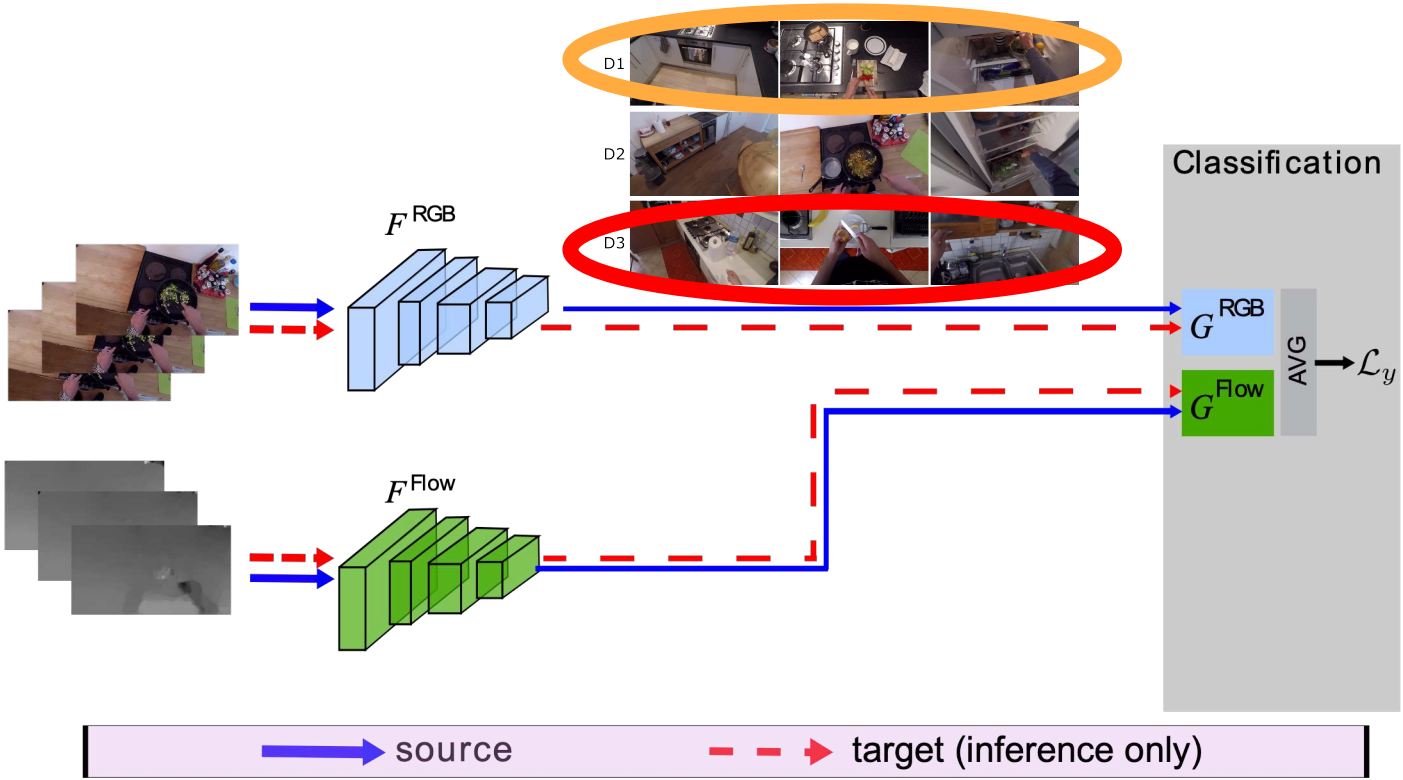
Multi-modal UDA



J Munro, D Damen (2020). Multi-Modal Domain Adaptation for Fine-Grained Action Recognition. *Computer Vision and Pattern Recognition (CVPR)*

Multi-modal UDA

with: Jonathan Munro



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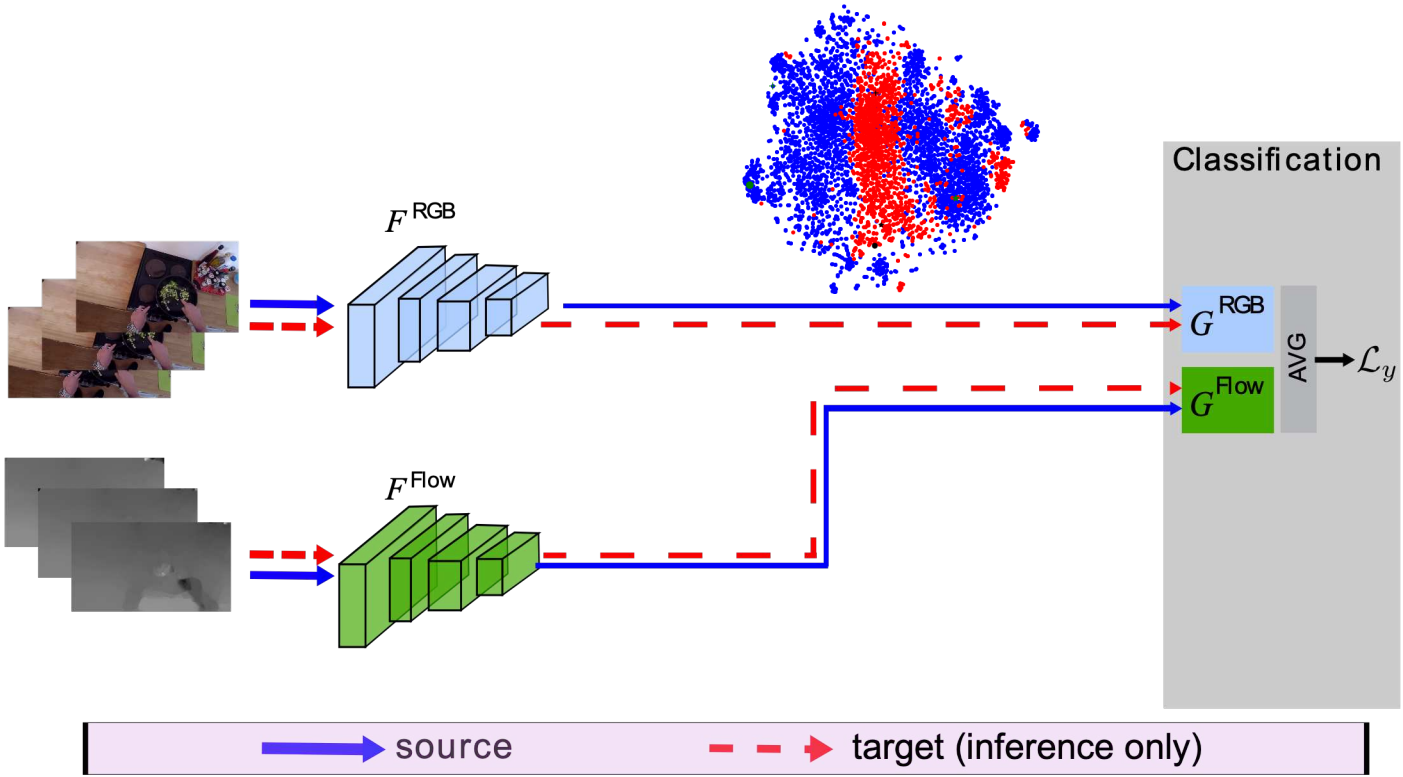
Multi-modal UDA



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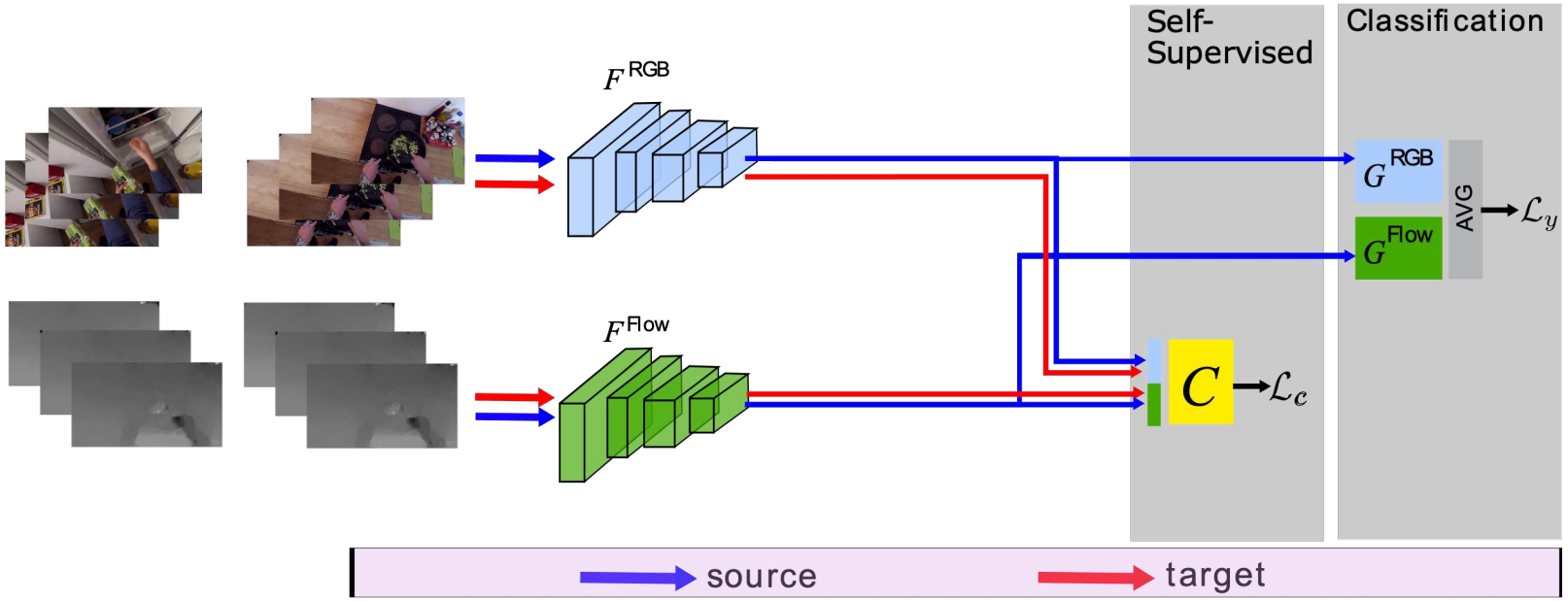
Multi-modal UDA



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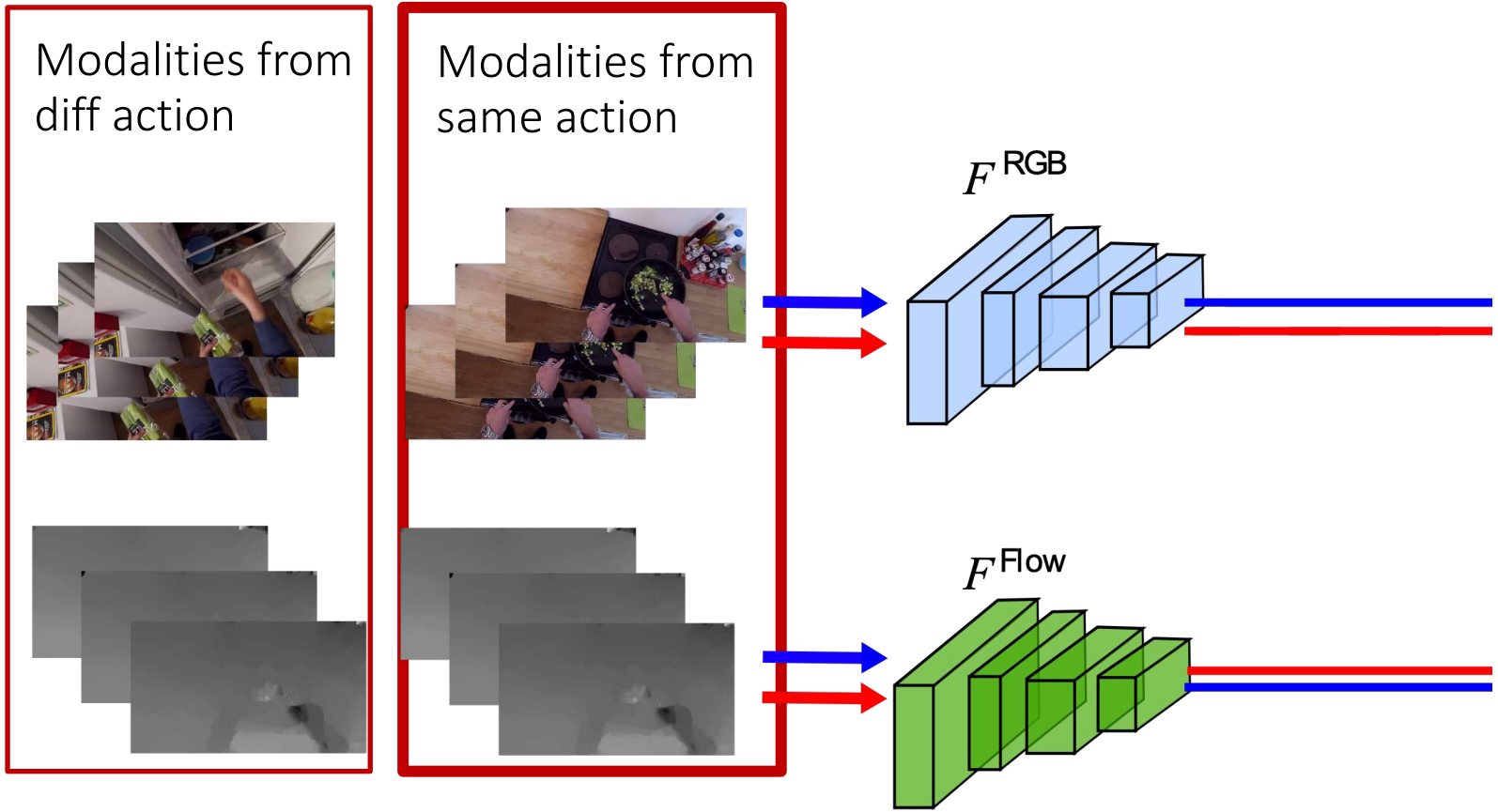
Multi-modal UDA



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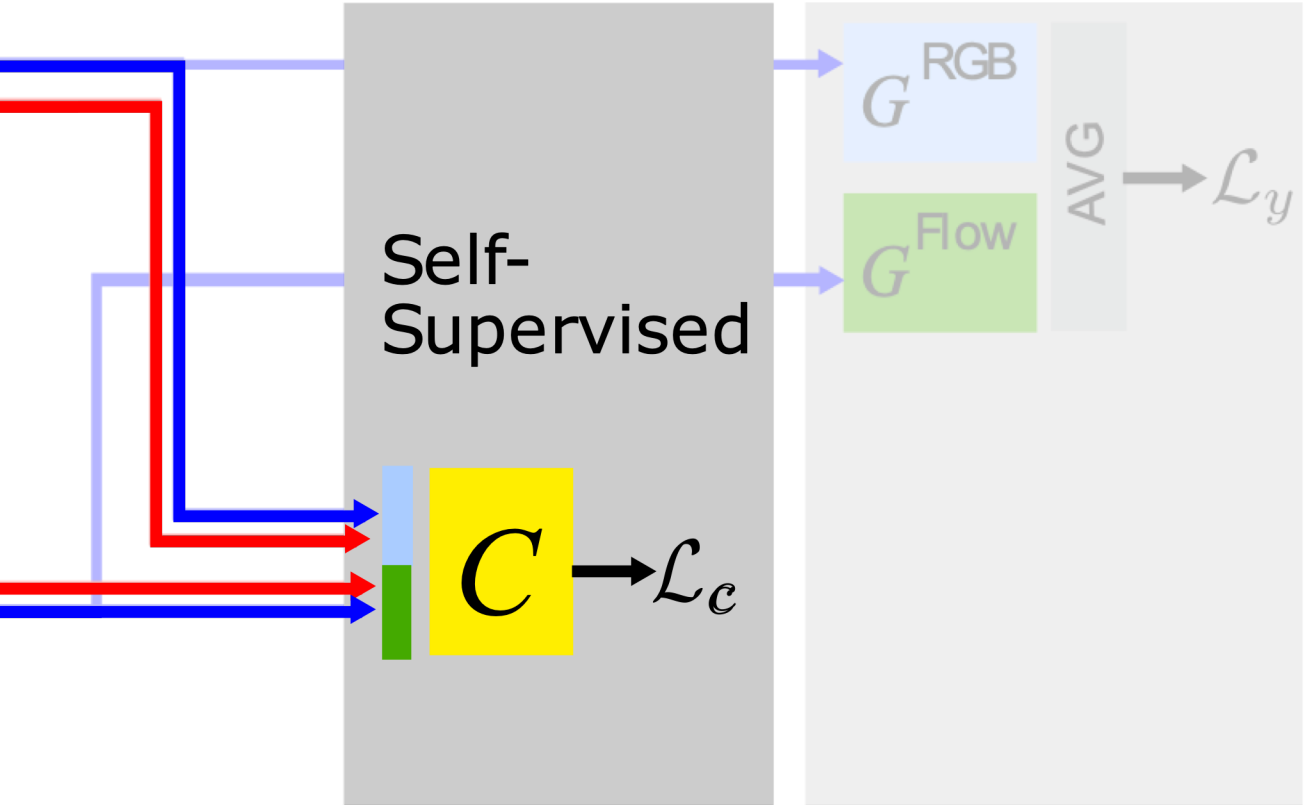
Multi-modal UDA



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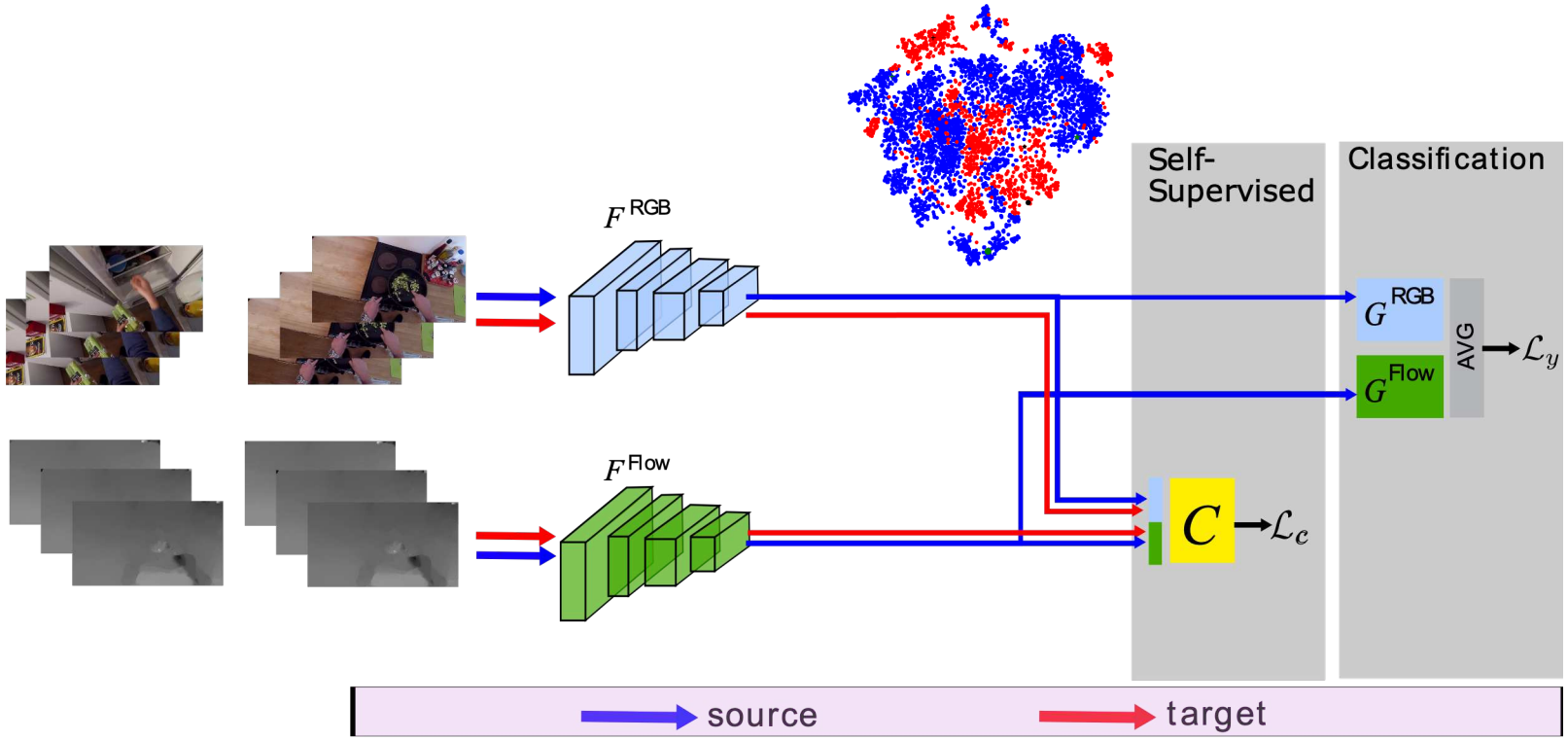
Multi-modal UDA



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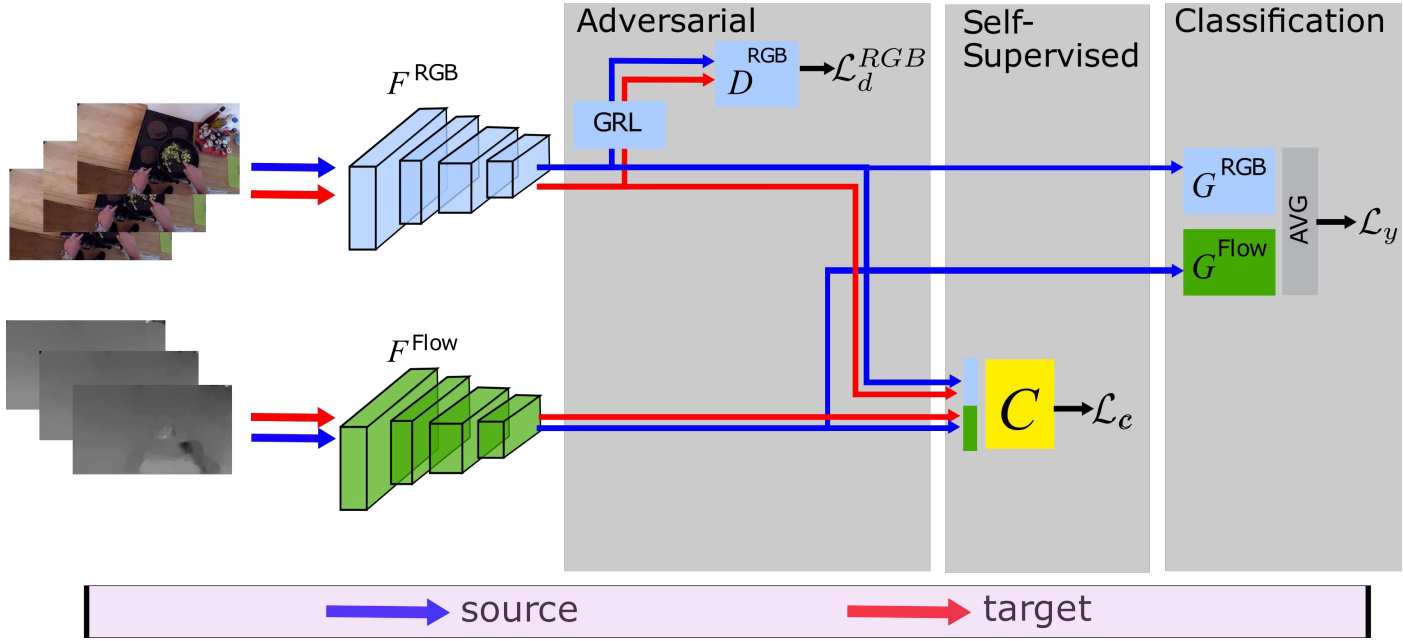
Multi-modal UDA



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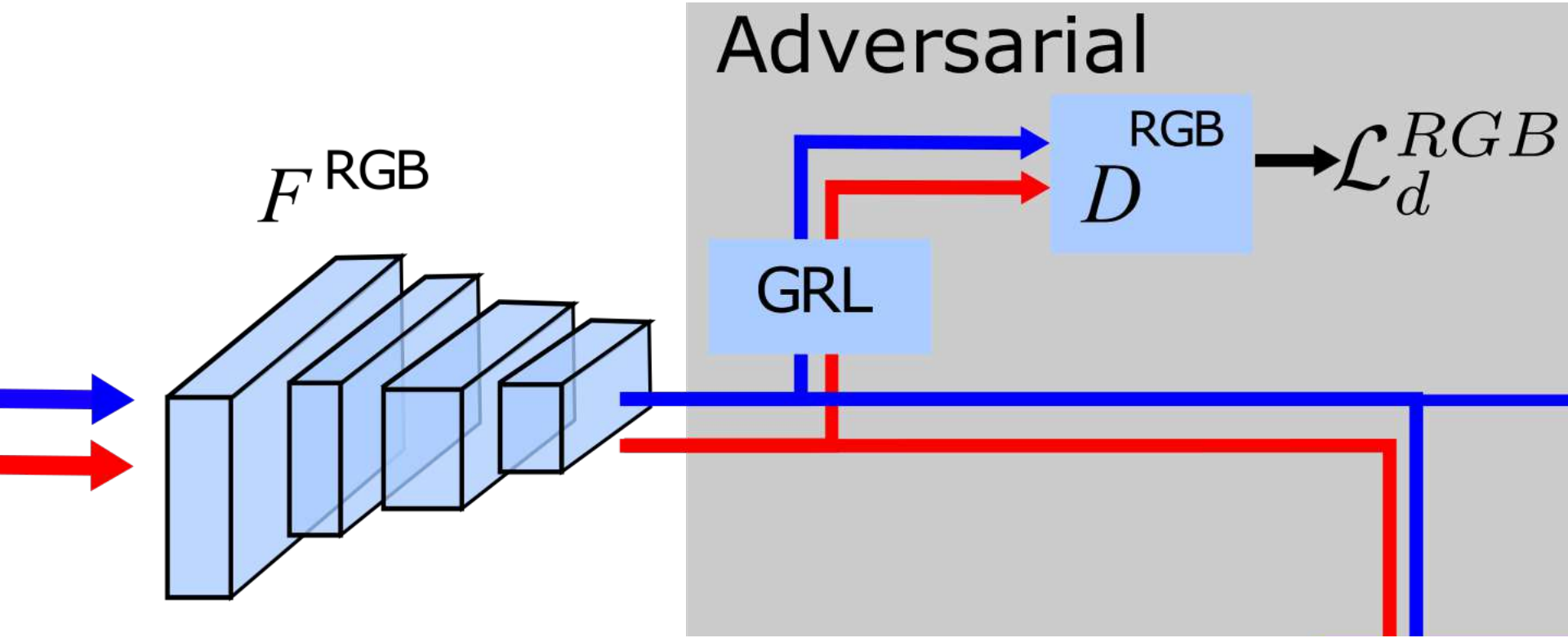
Multi-modal UDA



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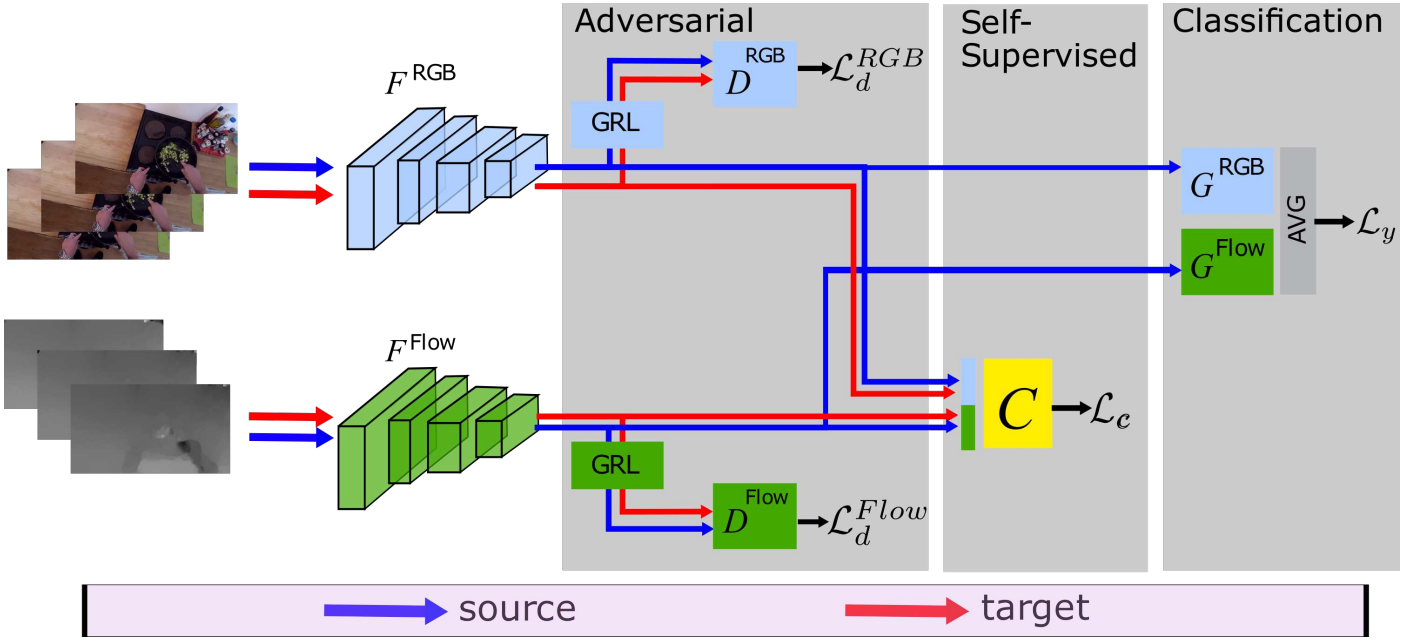

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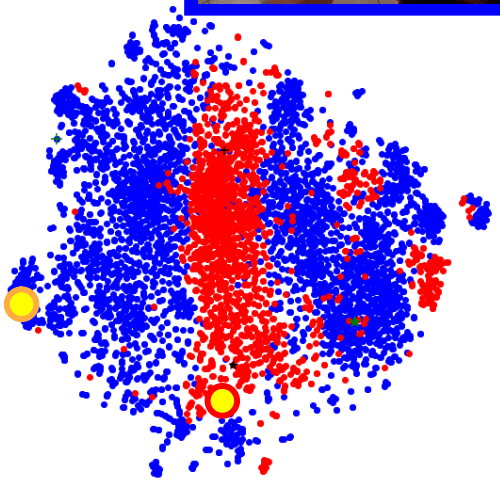
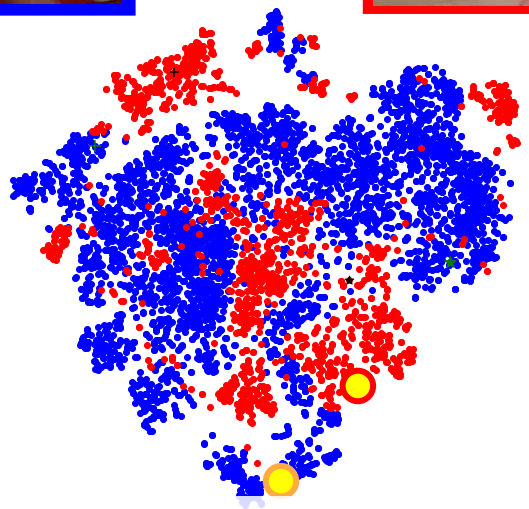
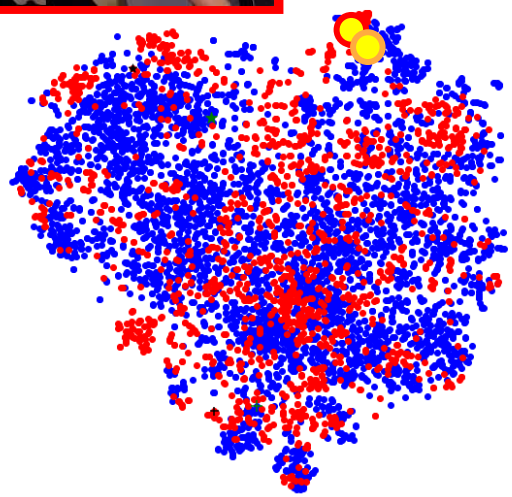


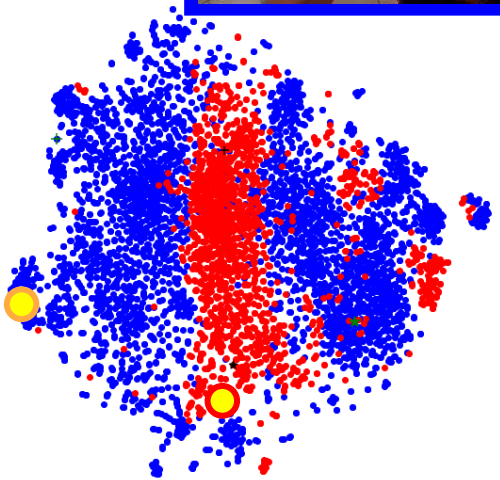


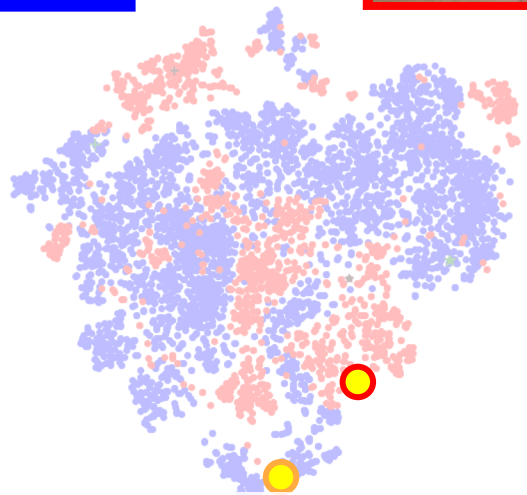


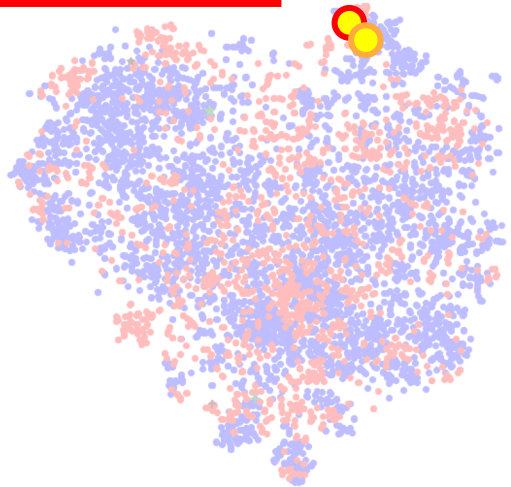
Source-Only Self-Supervision **MM-SADA**

J Munro, D Damen (2020). Multi-Modal Domain Adaptation for Fine-Grained Action Recognition. *Computer Vision and Pattern Recognition (CVPR)*

Multi-modal UDA







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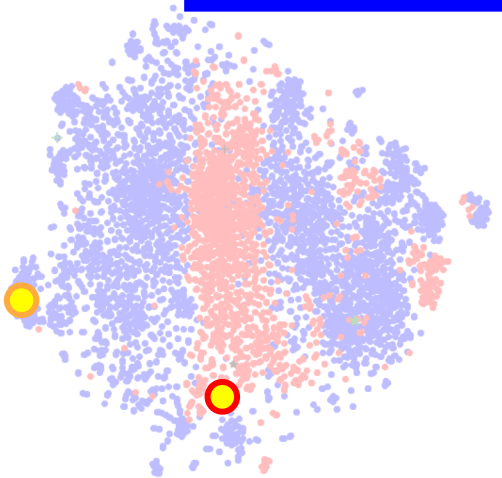
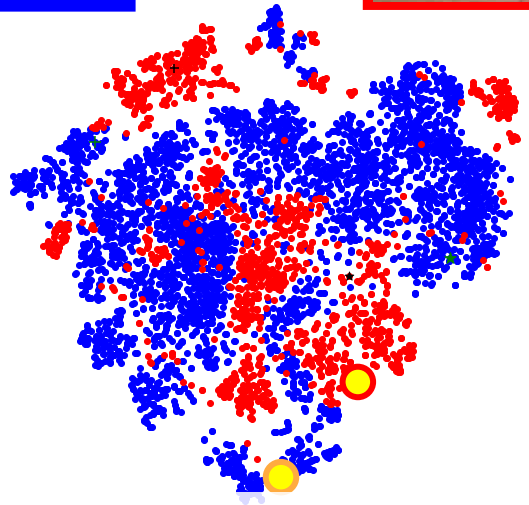
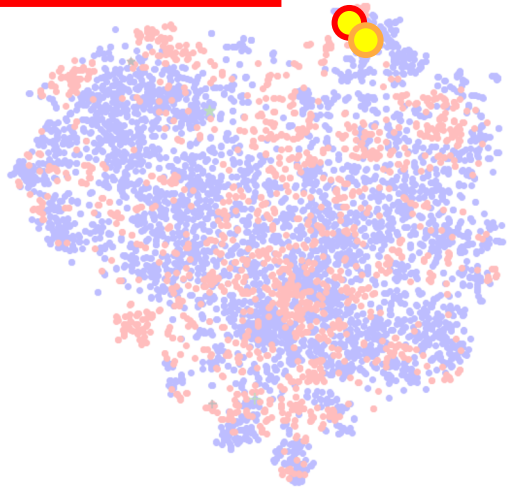
Multi-modal UDA





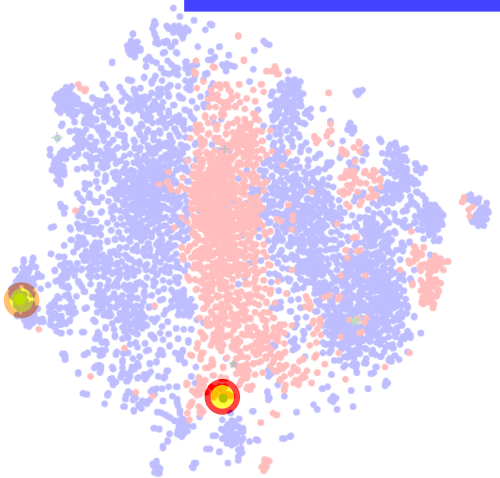


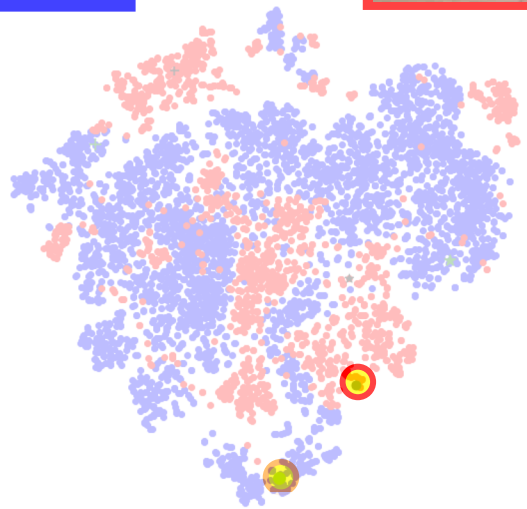
Source-Only Self-Supervision **MM-SADA**

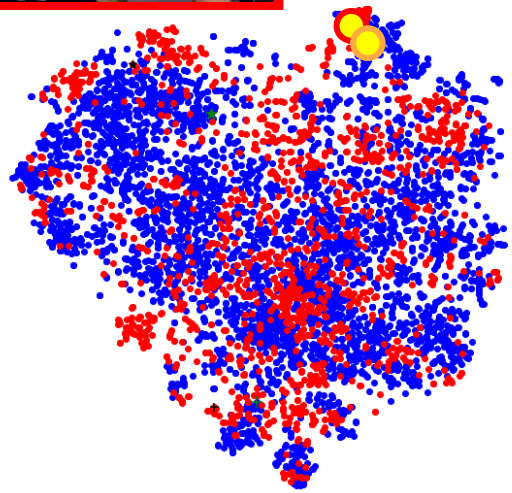
J Munro, D Damen (2020). Multi-Modal Domain Adaptation for Fine-Grained Action Recognition. *Computer Vision and Pattern Recognition (CVPR)*

Multi-modal UDA

with: Jonathan Munro







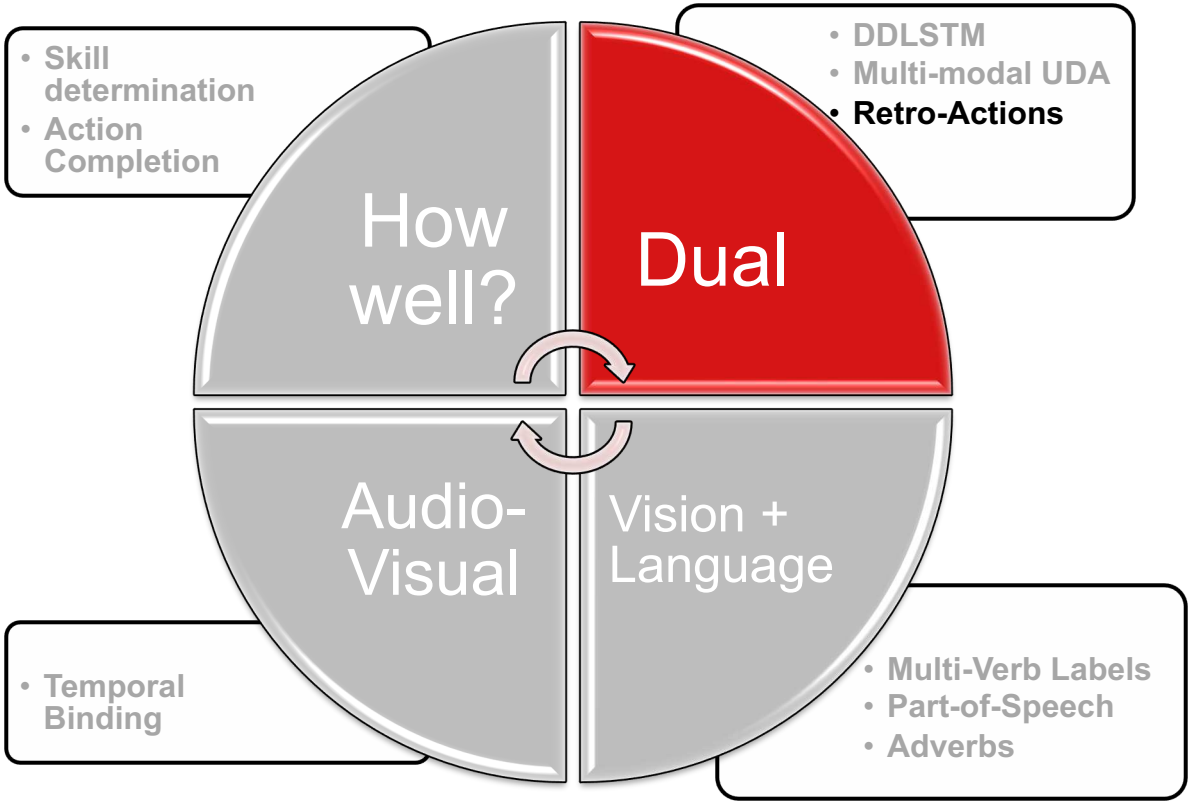
Source-Only

Self-Supervision

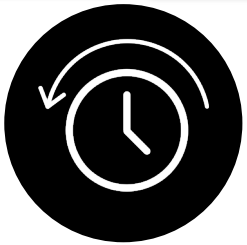
MM-SADA

J Munro, D Damen (2020). Multi-Modal Domain Adaptation for Fine-Grained Action Recognition. *Computer Vision and Pattern Recognition (CVPR)*

Fine(r)-grained?

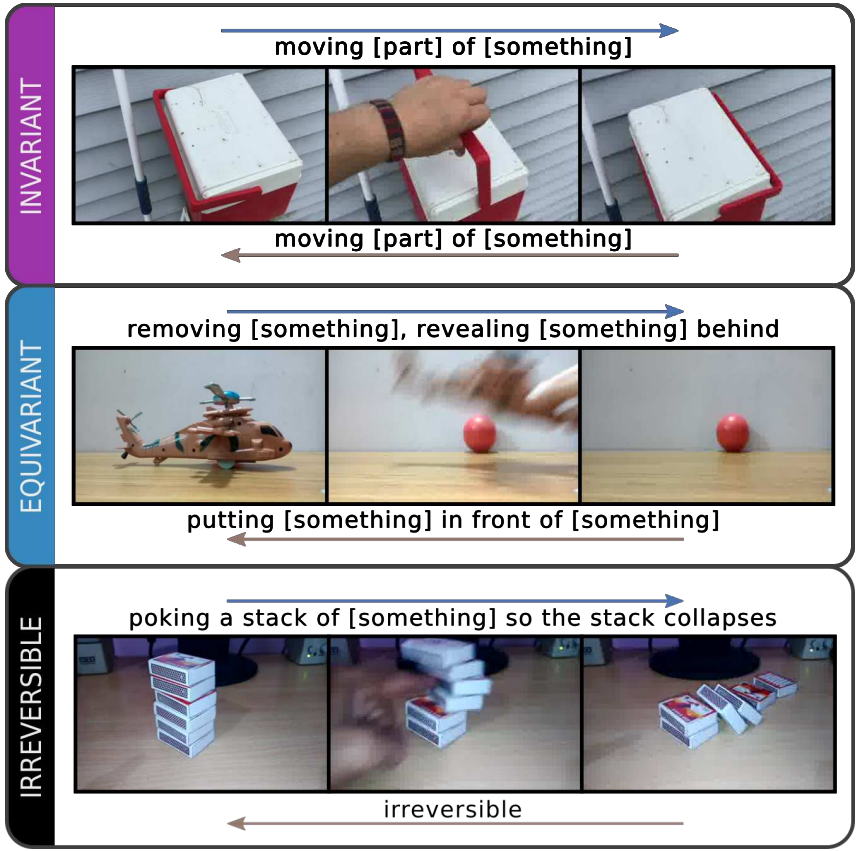


Retro-Actions



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

Retro-Actions



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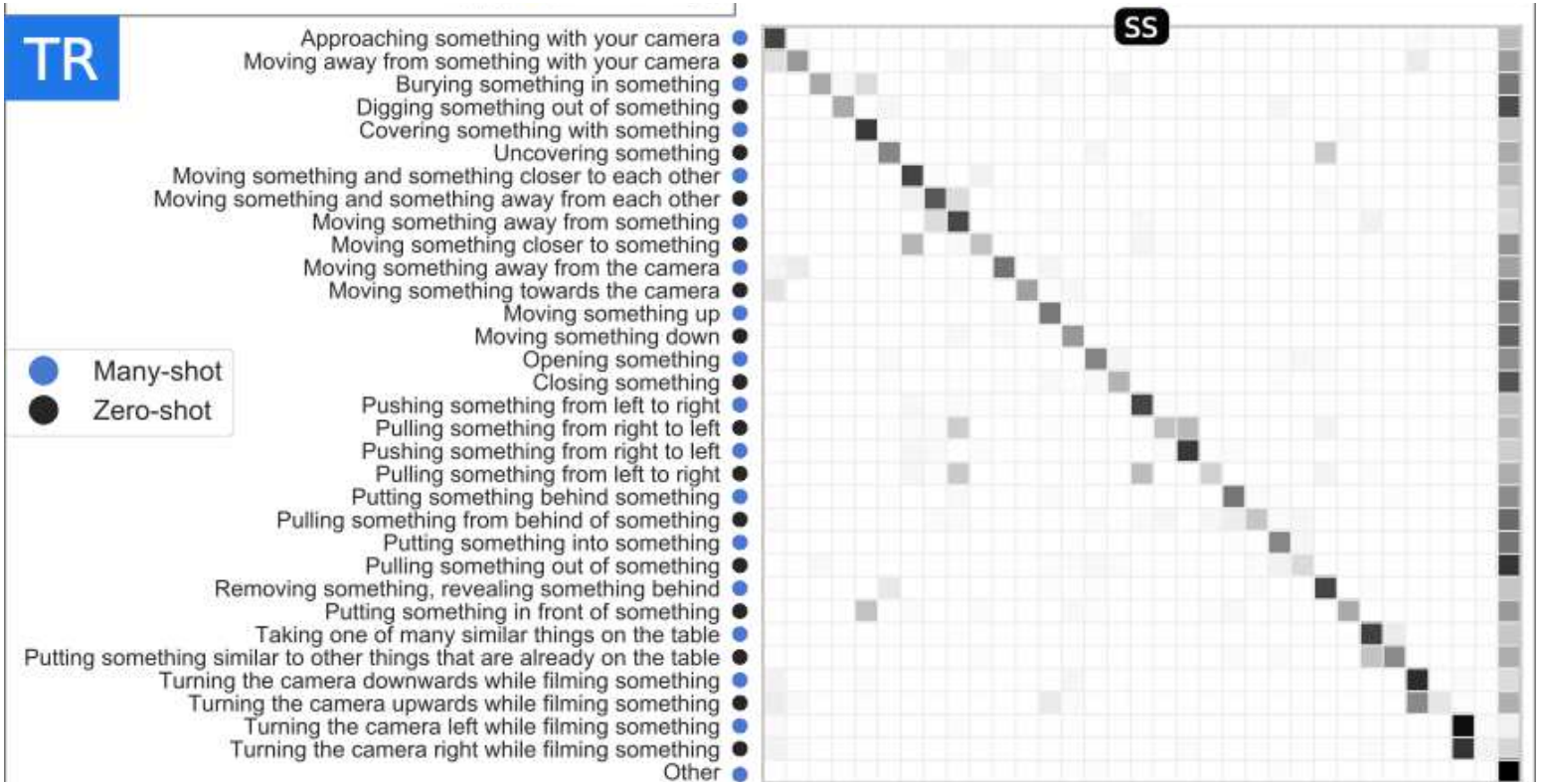
Retro-Actions



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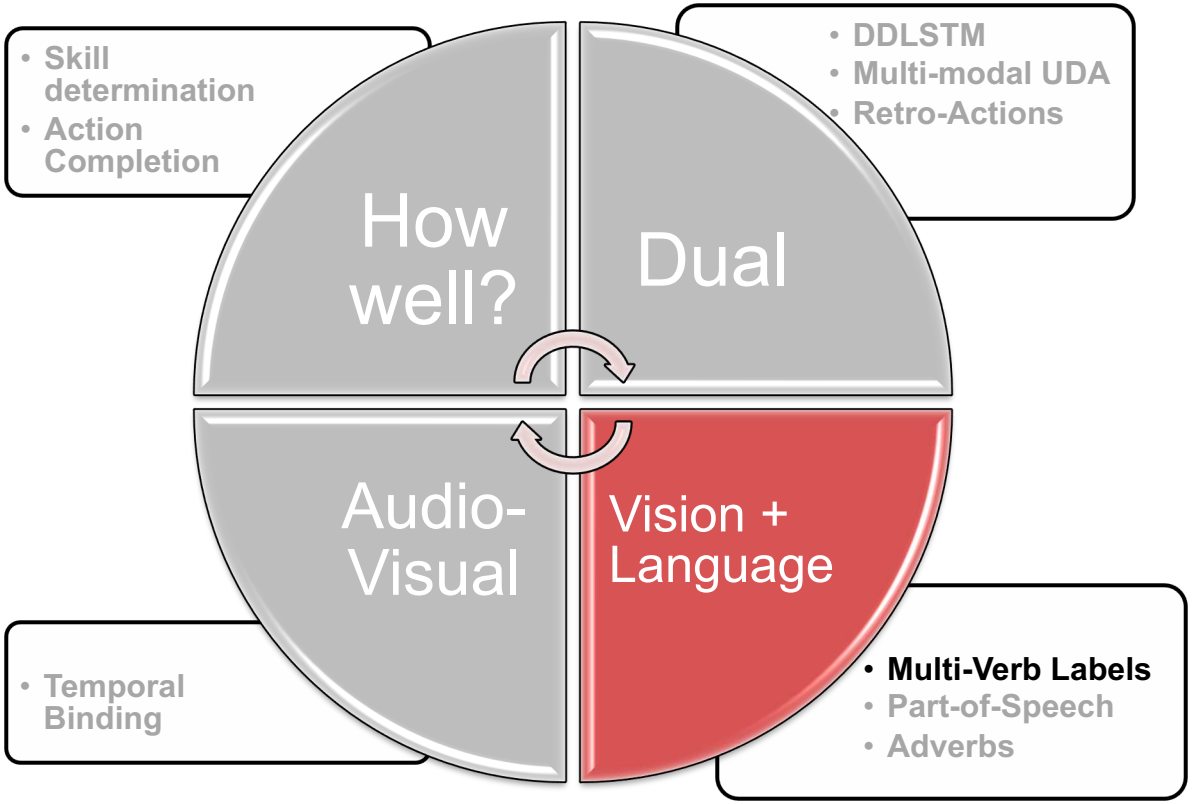
Fine(r)-grained?



The *Verbs* Dilemma

with: Michael Wray

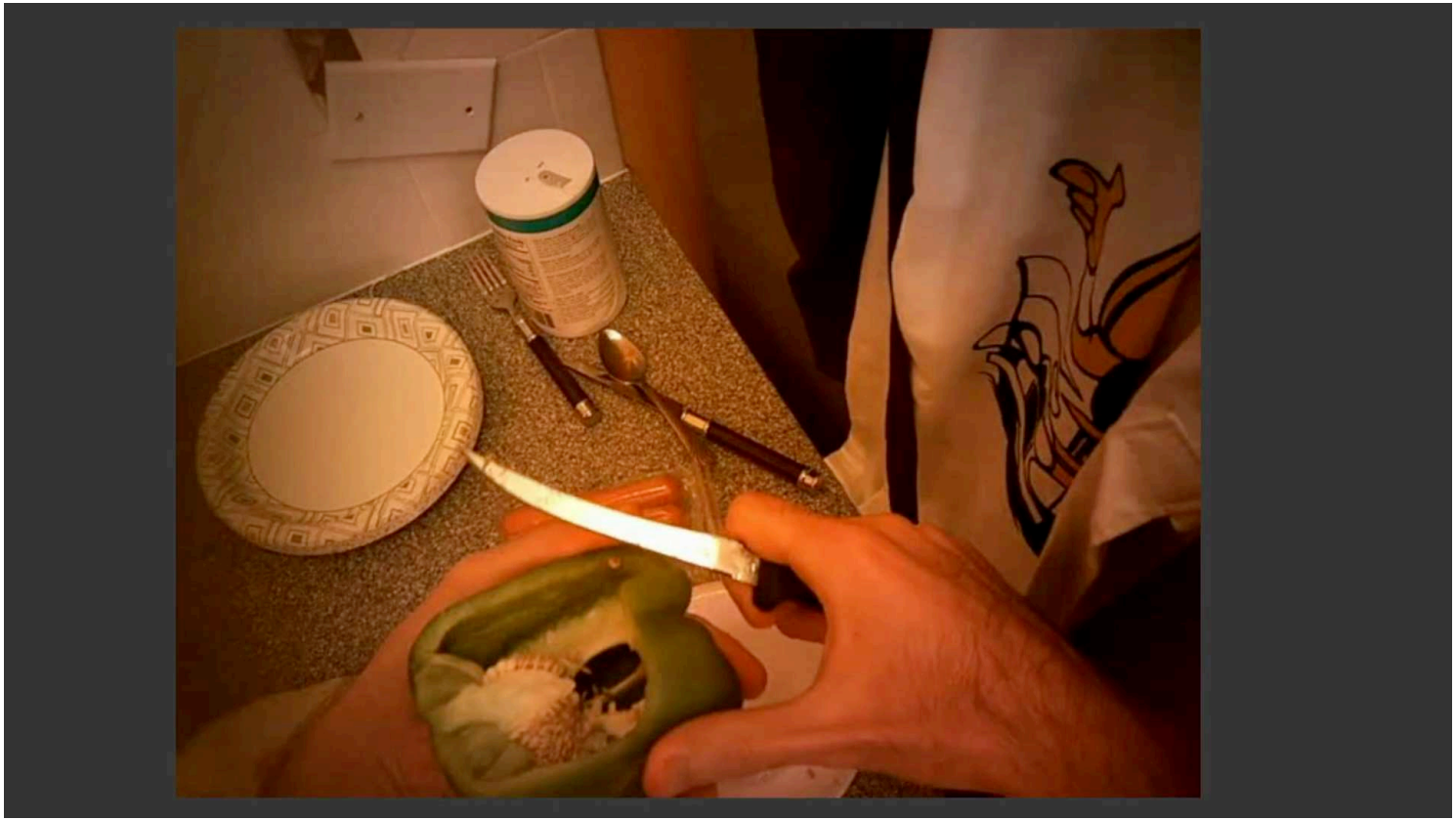
M Wray and D Damen (2019). Learning Visual Actions Using Multiple Verb-Only Labels. BMVC

The *Verbs* Dilemma

Open

M Wray and D Damen (2019). Learning Visual Actions Using Multiple Verb-Only Labels. BMVC

The *Verbs* Dilemma



M Wray and D Damen (2019). Learning Visual Actions Using Multiple Verb-Only Labels. BMVC

The *Verbs* Dilemma

Open

Cut

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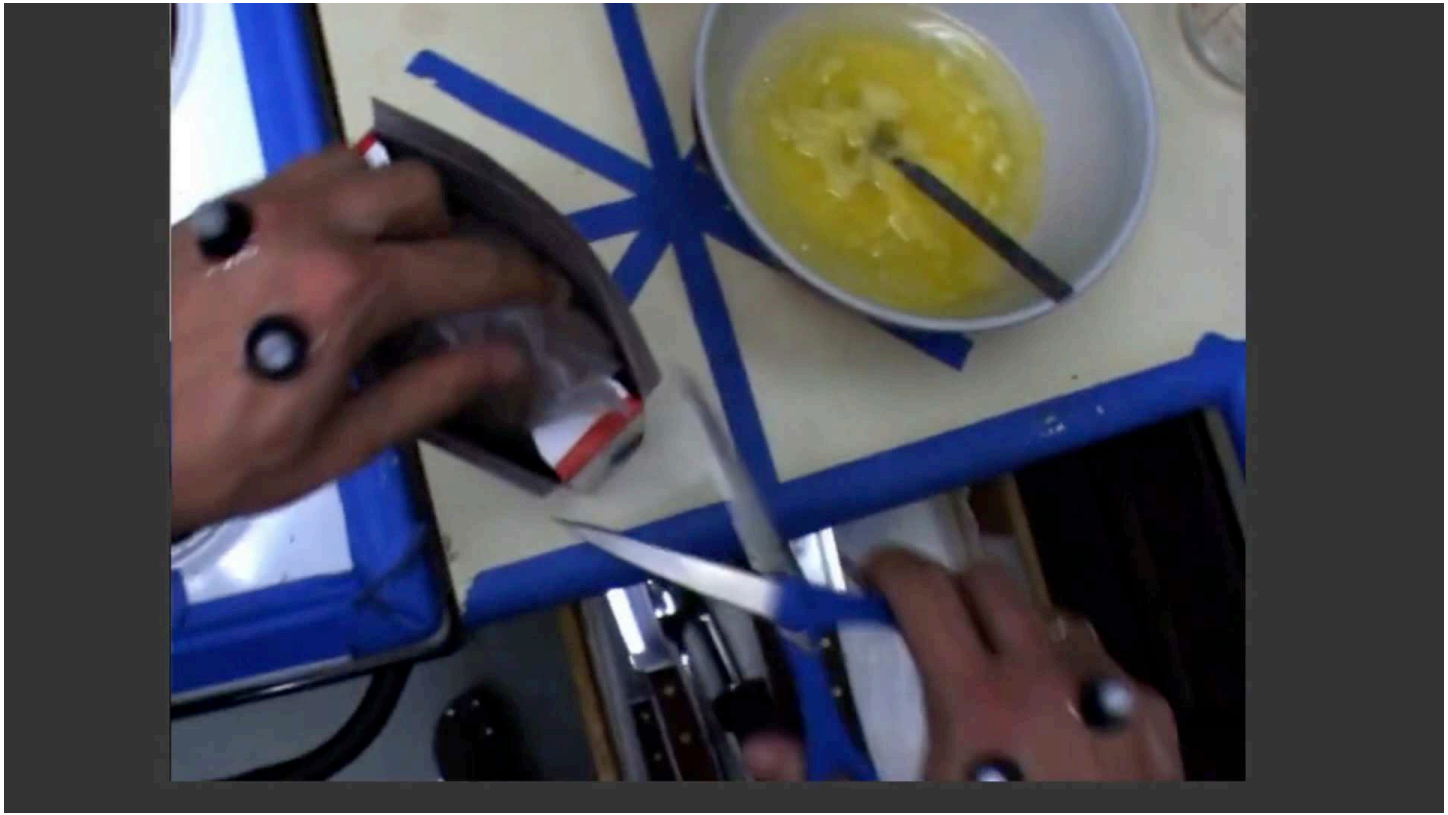
The *Verbs* Dilemma

with: Michael Wray



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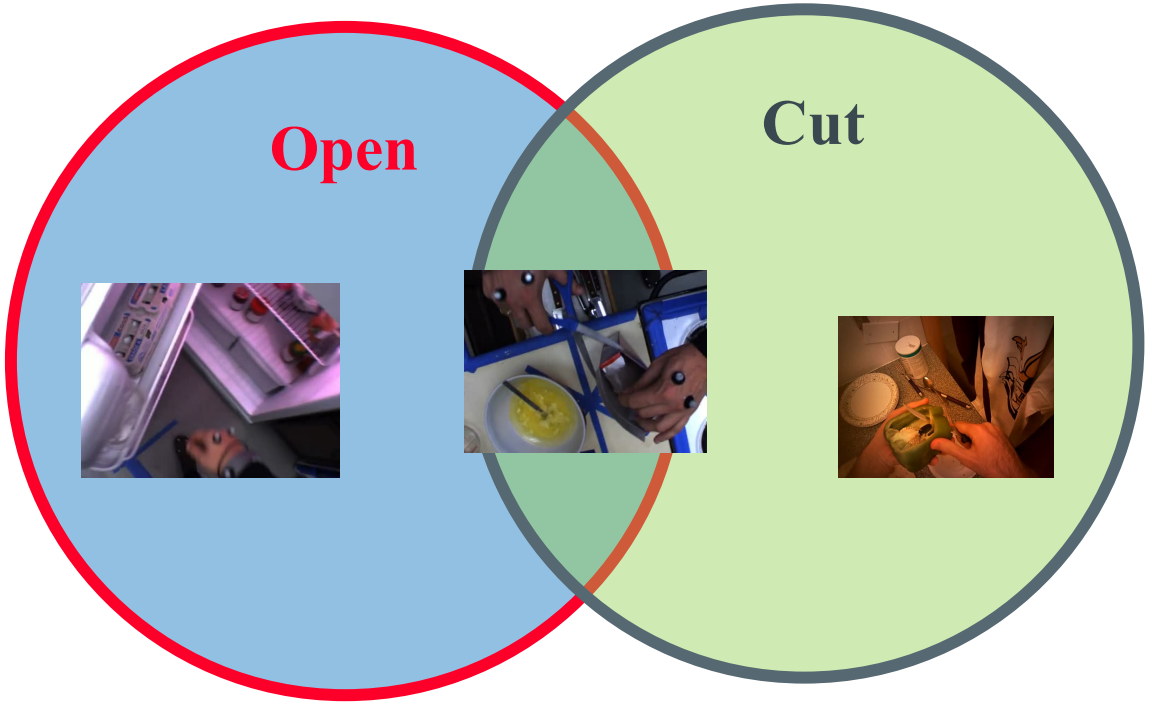
The *Verbs* Dilemma



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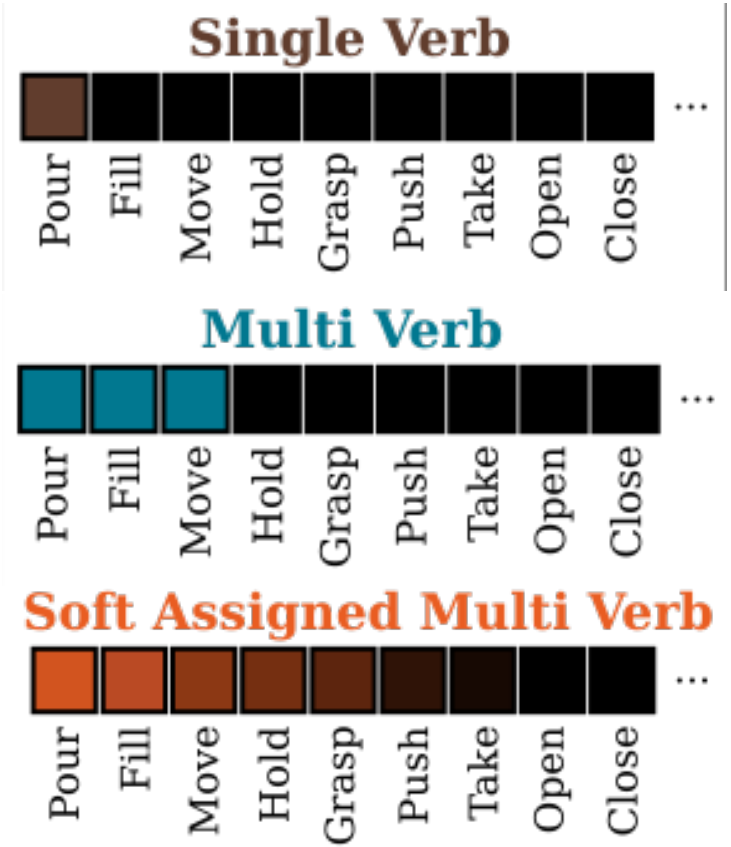
The *Verbs* Dilemma

- 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

M Wray and D Damen (2019). Learning Visual Actions Using Multiple Verb-Only Labels. BMVC

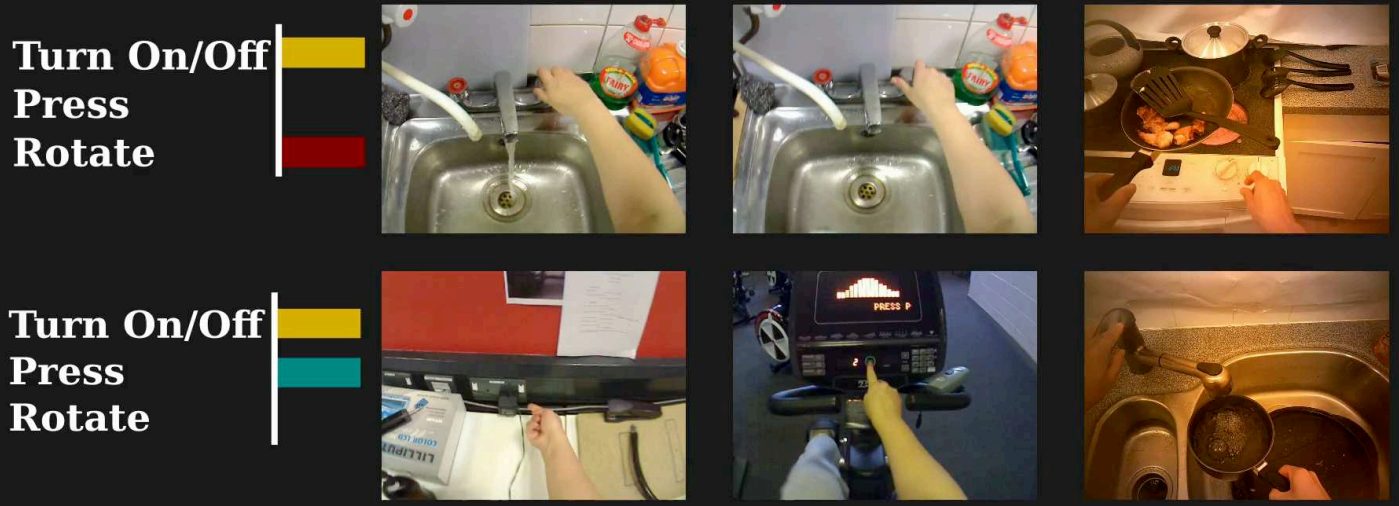
The *Verbs* Dilemma



M Wray and D Damen (2019). Learning Visual Actions Using Multiple Verb-Only Labels. BMVC

The *Verbs* Dilemma

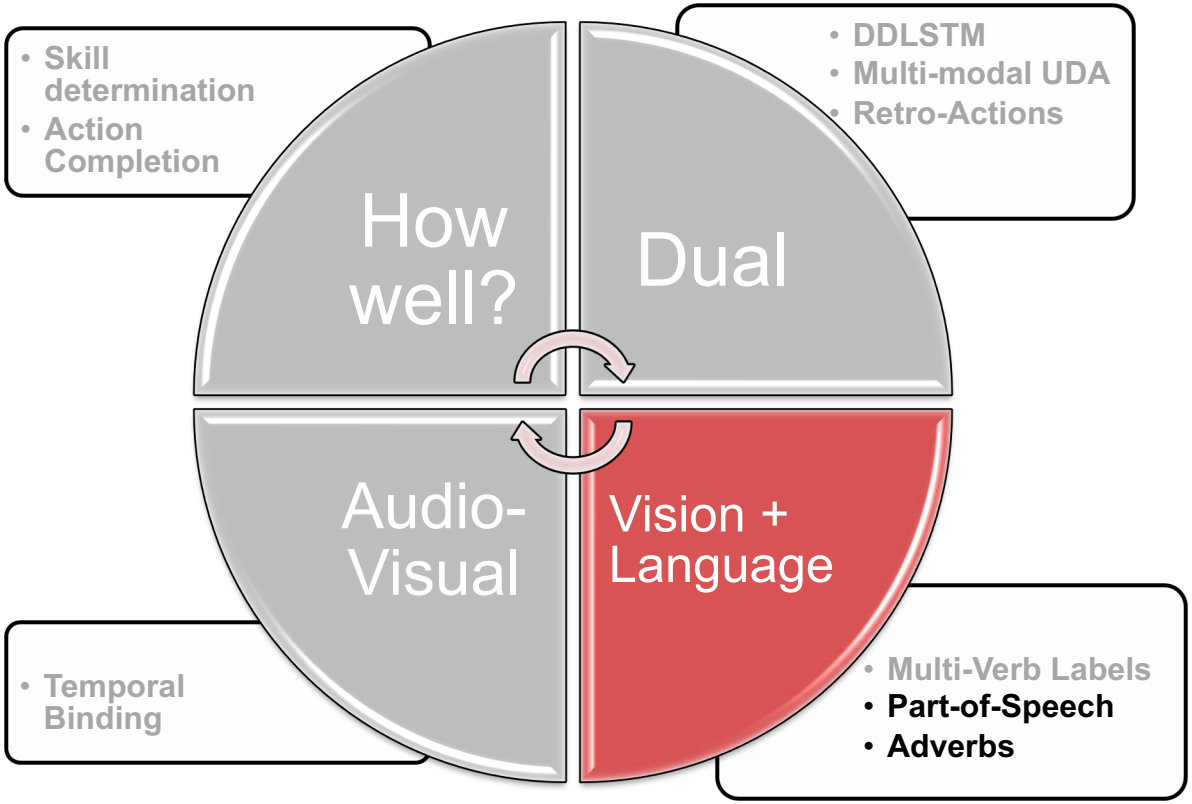
Top 3 retrieved classes across all datasets.



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

M Wray and D Damen (2019). Learning Visual Actions Using Multiple Verb-Only Labels. BMVC

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

M Wray, D Larlus, G Csurka, D Damen (2019). Fine-Grained Action Retrieval through Multiple Parts-of-Speech Embeddings. ICCV

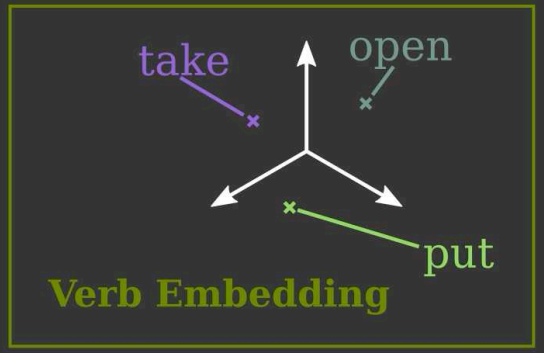
Fine-Grained Action Retrieval

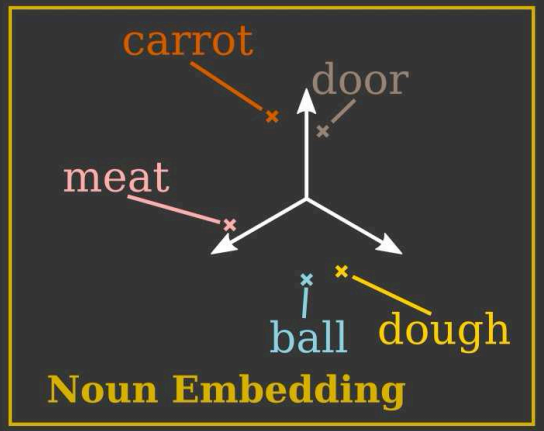
with: Michael Wray
Gabriela Csurka
Diane Larlus

We embed the video and representations

[put]

[meat, ball, dough]





M Wray, D Larlus, G Csurka, D Damen (2019). Fine-Grained Action Retrieval through Multiple Parts-of-Speech Embeddings. ICCV

Fine-Grained Action Retrieval

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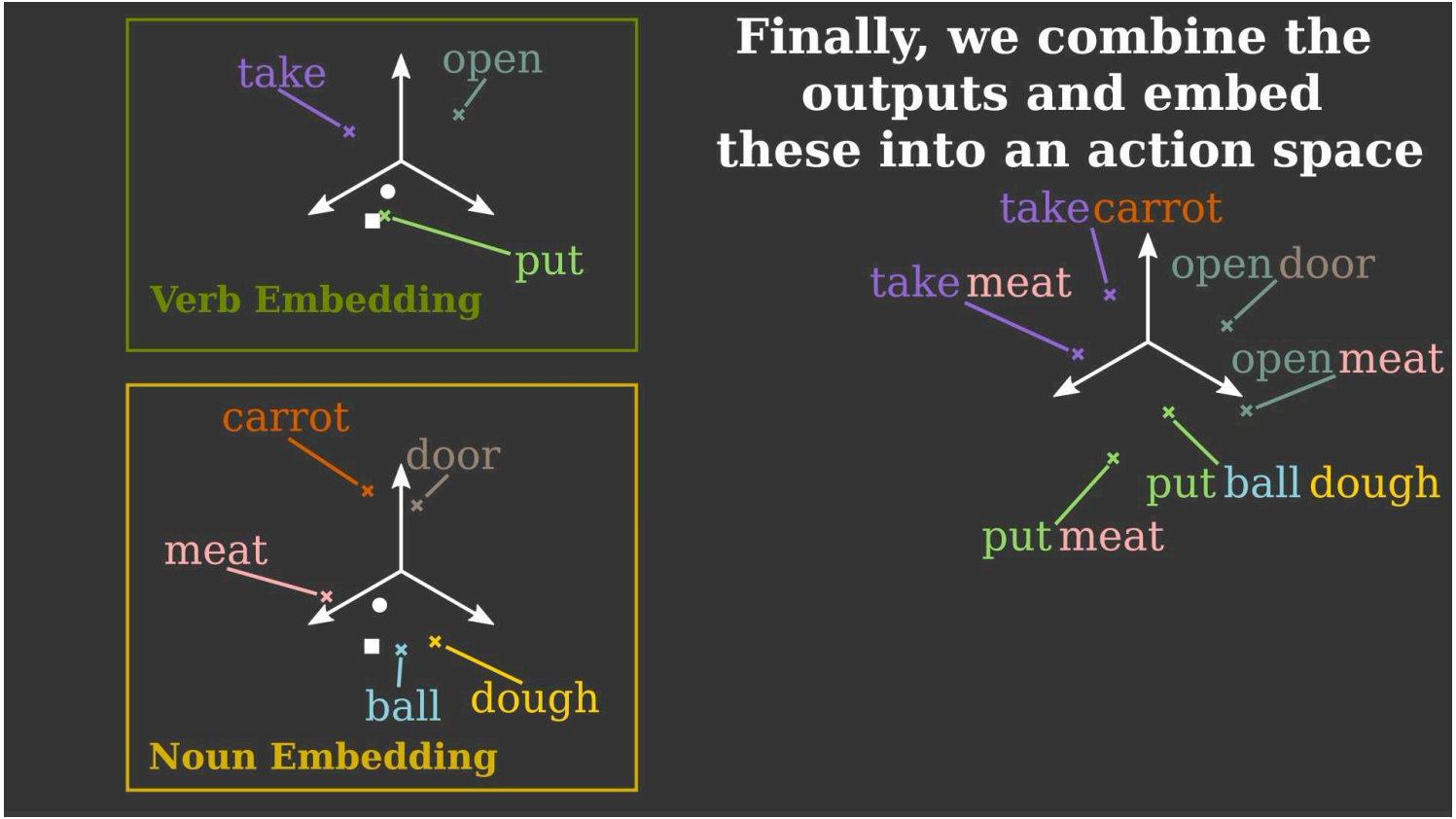

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Fine-Grained Action Retrieval

with: Michael Wray
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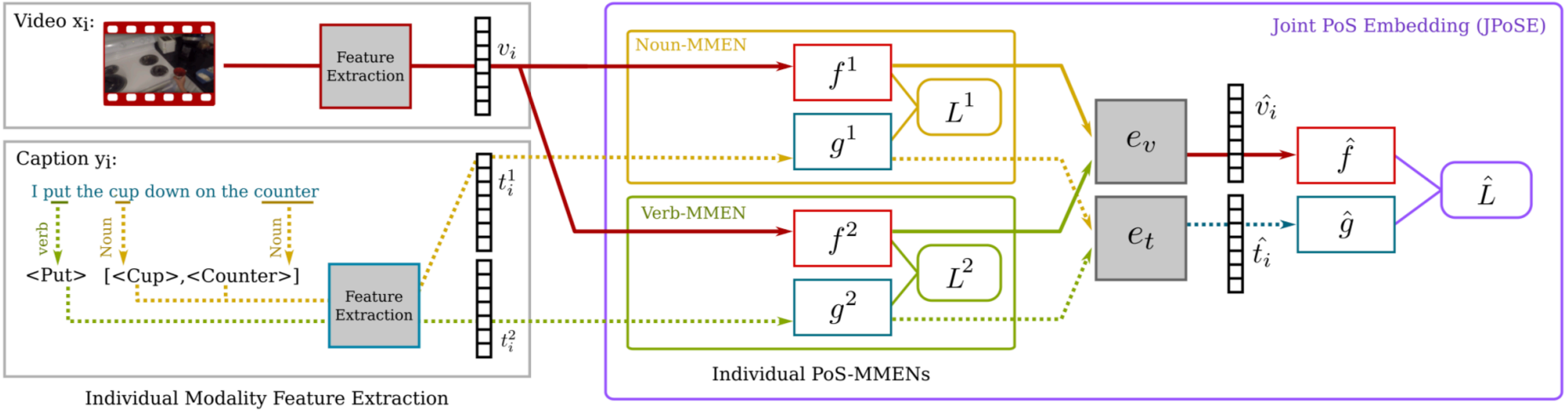
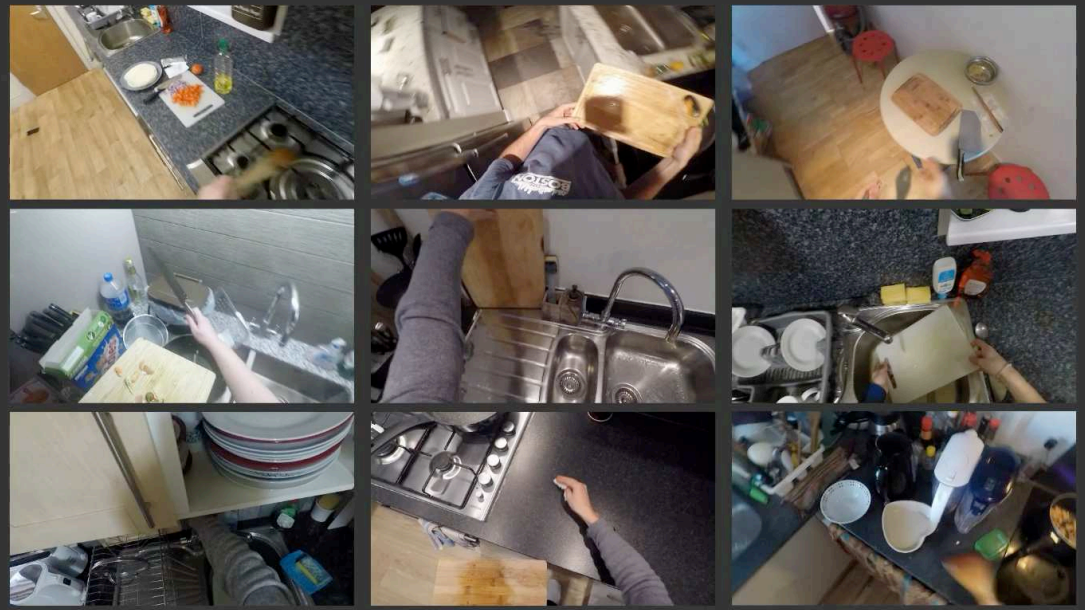


M Wray, D Larlus, G Csurka, D Damen (2019). Fine-Grained Action Retrieval through Multiple Parts-of-Speech Embeddings. ICCV

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



M Wray, D Larlus, G Csurka, D Damen (2019). Fine-Grained Action Retrieval through Multiple Parts-of-Speech Embeddings. ICCV

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

H Doughty, I Laptev, W Mayol-Cuevas, D Damen (2020). Action Modifiers: Learning from Adverbs in Instructional Videos. Computer Vision and Pattern Recognition (CVPR)

Action Modifiers: Learning from Adverbs

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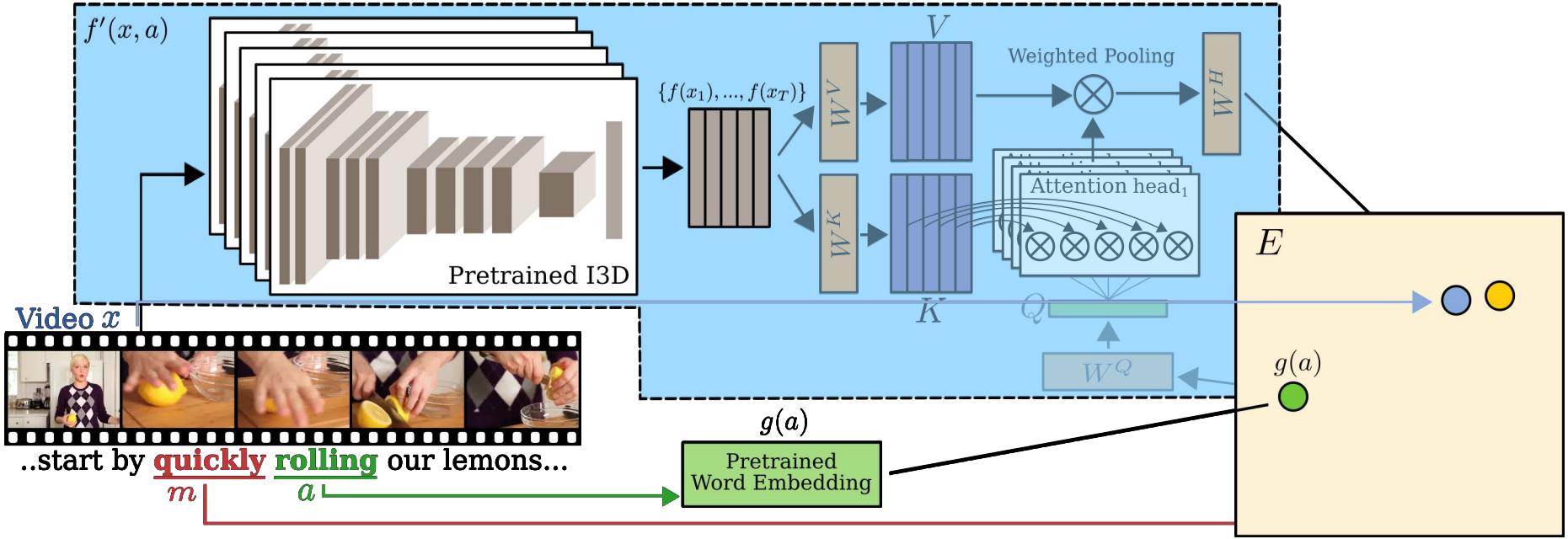


H Doughty, I Laptev, W Mayol-Cuevas, D Damen (2020). Action Modifiers: Learning from Adverbs in Instructional Videos. Computer Vision and Pattern Recognition (CVPR)

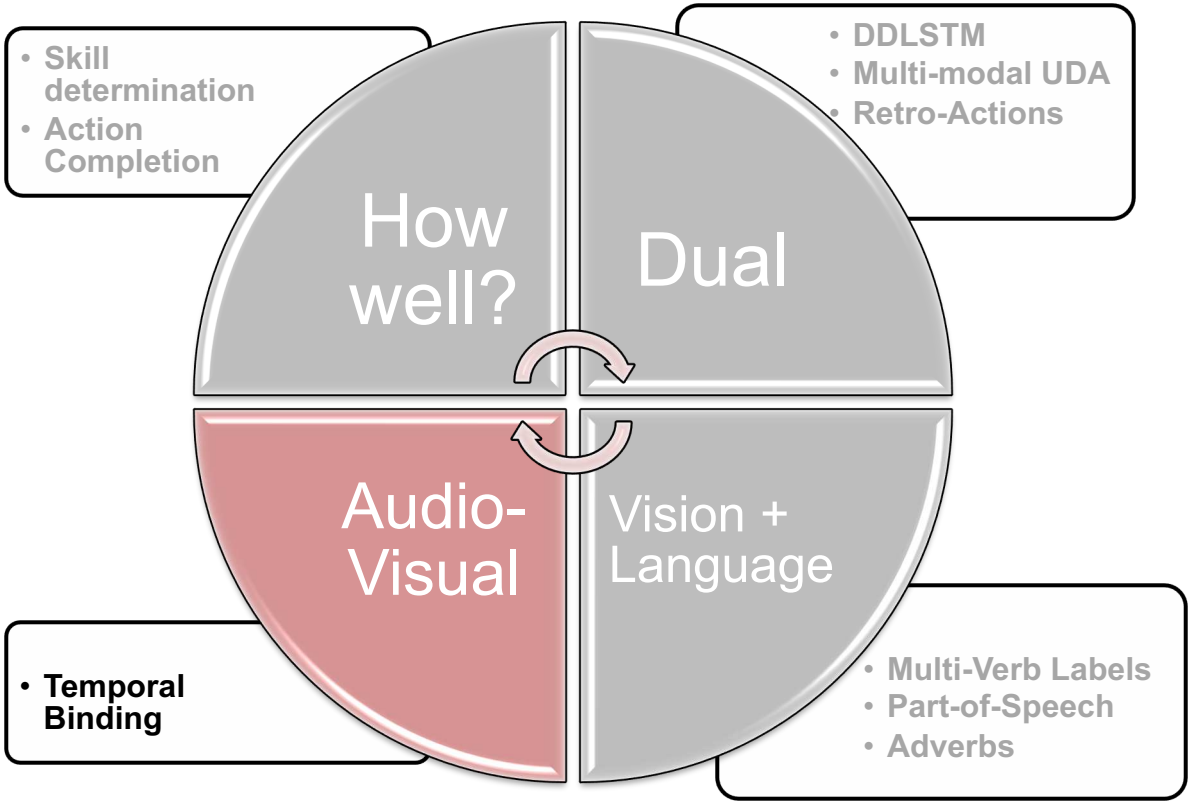
Action Modifiers: Learning from Adverbs

with: Hazel Doughty
Ivan Laptev
Walterio Mayol-Cuevas

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

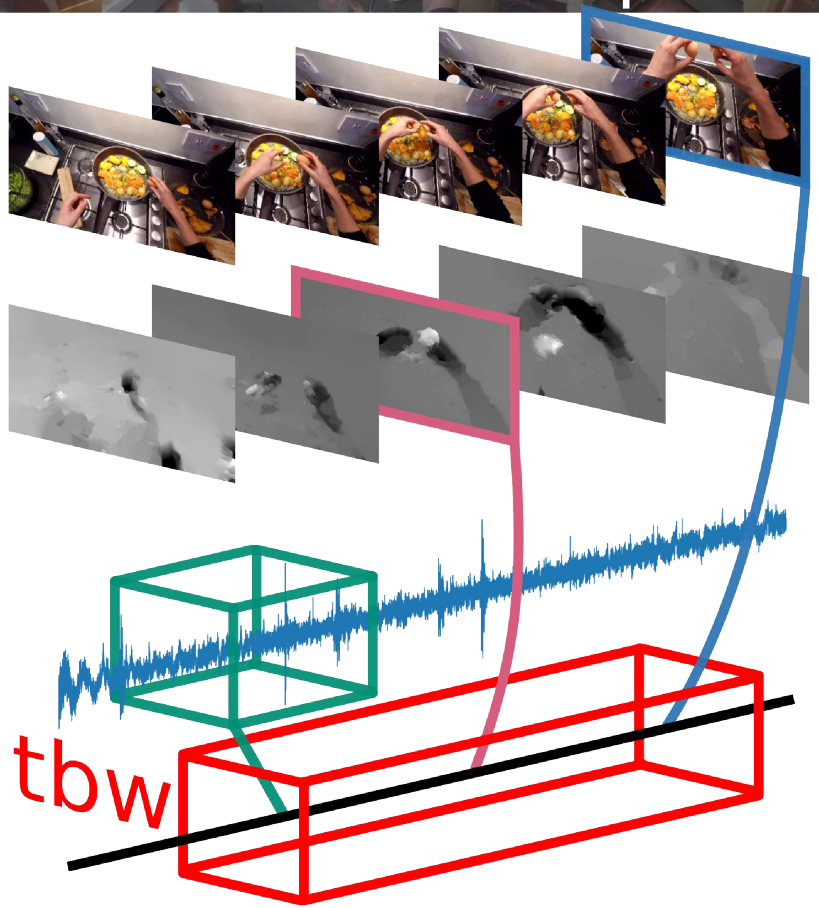
H Doughty, I Laptev, W Mayol-Cuevas, D Damen (2020). Action Modifiers: Learning from Adverbs in Instructional Videos. Computer Vision and Pattern Recognition (CVPR)

Fine(r)-grained?



Audio-Visual Temporal Binding

with: Vangelis Kazakos
Arsha Nagrani
Andrew Zisserman



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Audio-Visual Temporal Binding

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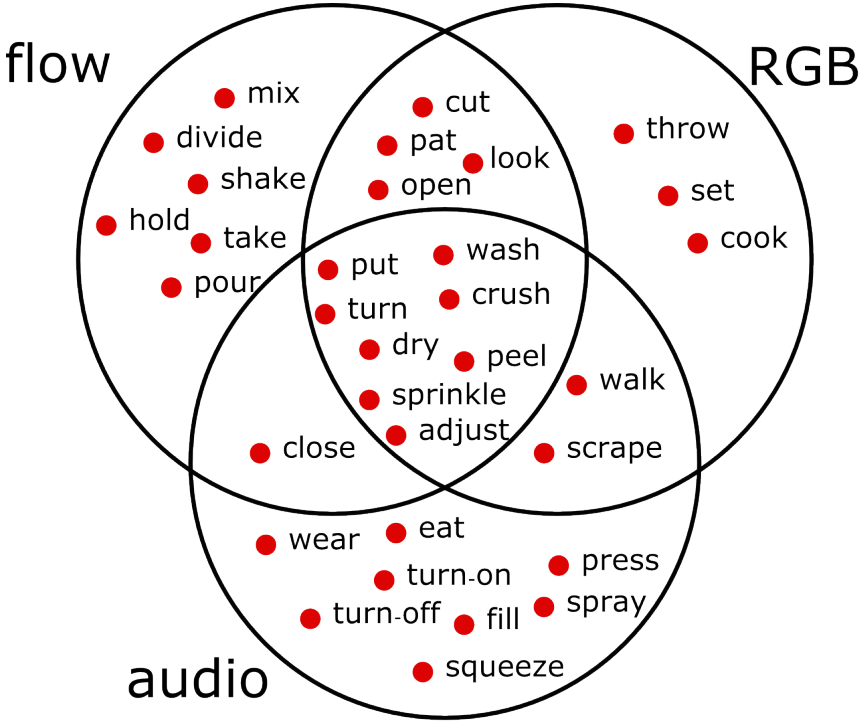
Andrew Zisserman



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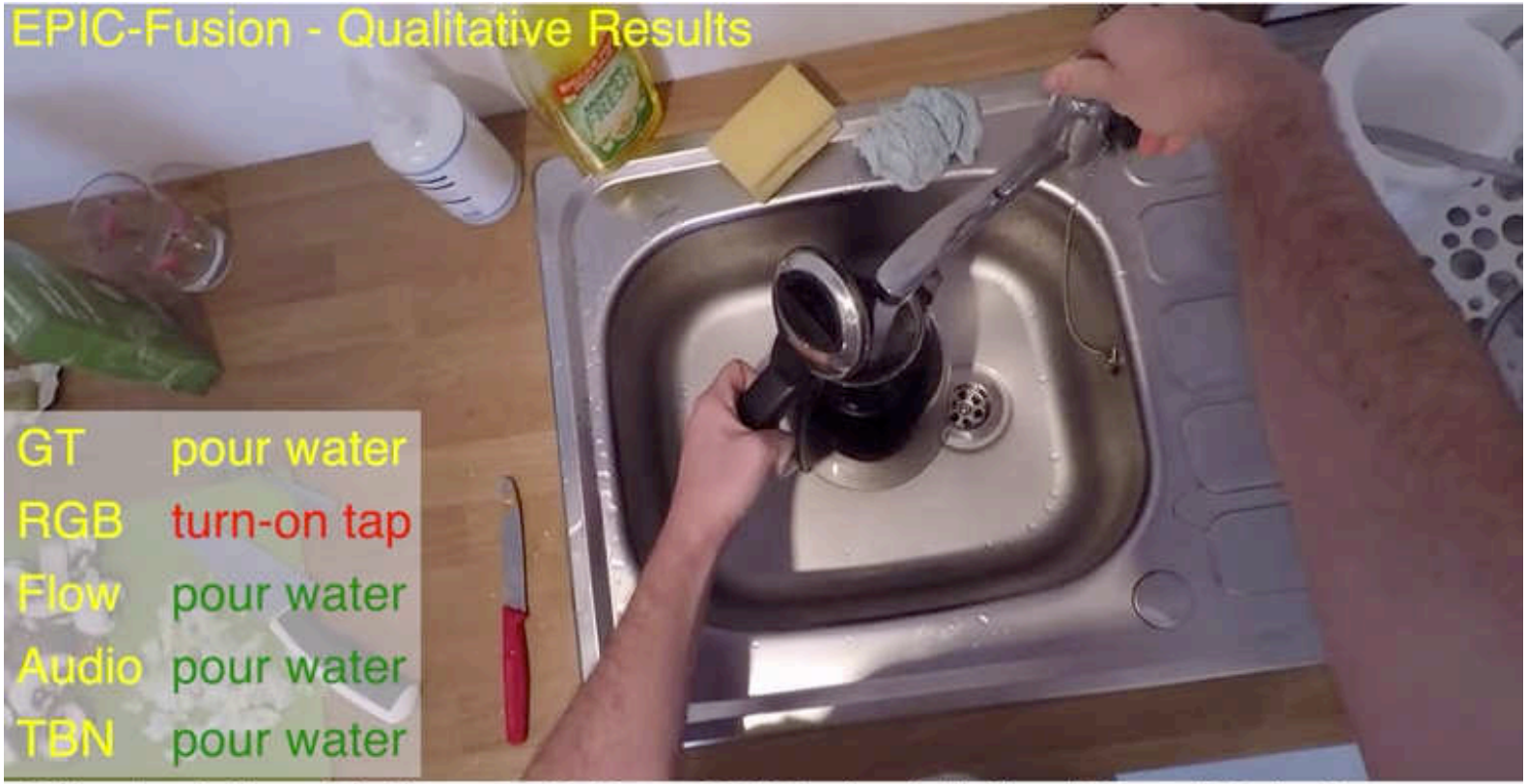


E. Kazakos, A. Nagrani, A. Zisserman, D. Damen, EPIC-Fusion: Audio-Visual Temporal Binding for Egocentric Action Recognition, ICCV 2019

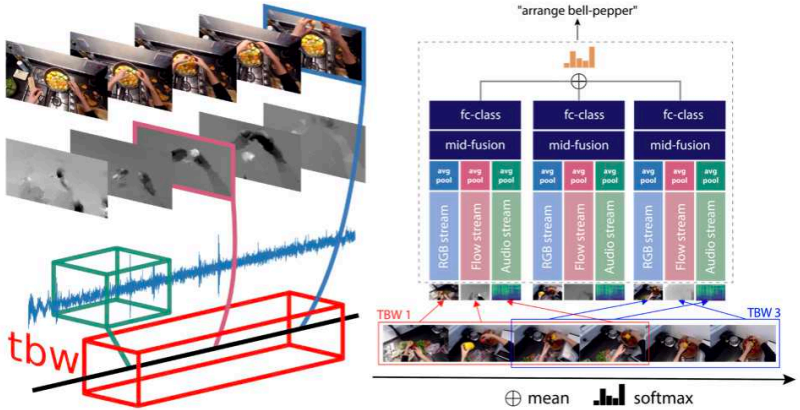
Audio-Visual Temporal Binding

with: Vangelis Kazakos
Arsha Nagrani
Andrew Zisserman

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

Evangelos Kazakos[1], Arsha Nagrani[2], Andrew Zisserman[2] and Dima Damen[1]

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



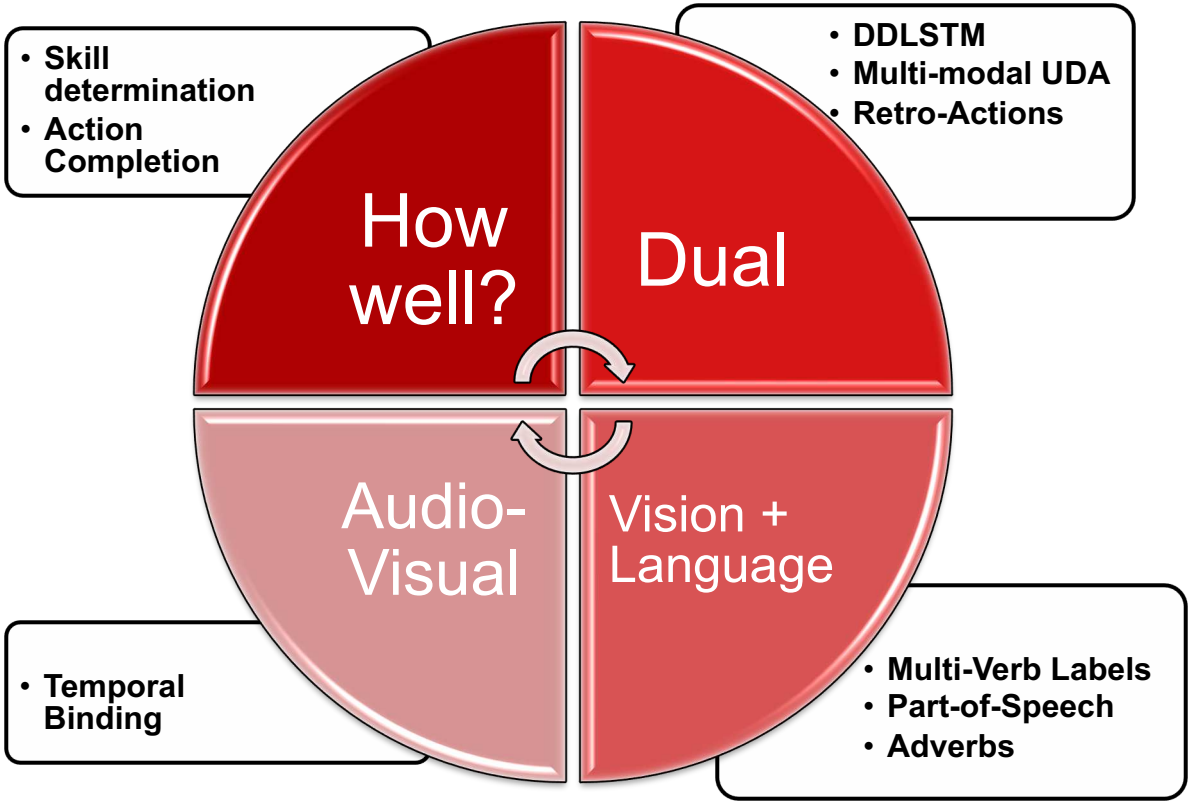
Abstract

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?



The Team

Thank you

For further info, datasets, code, publications…

http://dimadamen.github.io


@dimadamen


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

Q&A