



EgoAdapt: A Joint Distillation and Policy Learning Framework for Efficient Multisensory Egocentric Perception



Wed 22 Oct | 11:15 a.m. HST – 1:15 p.m. HST | Poster Session 3 | Exhibit Hall I #983

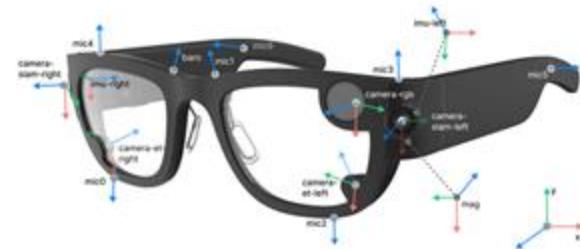
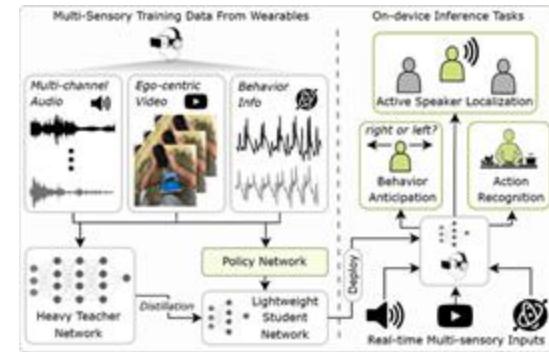
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¹University of Maryland, College Park, ²Meta, ³Worcester Polytechnic Institute, ⁴University of Toronto

Oct 19th 2025

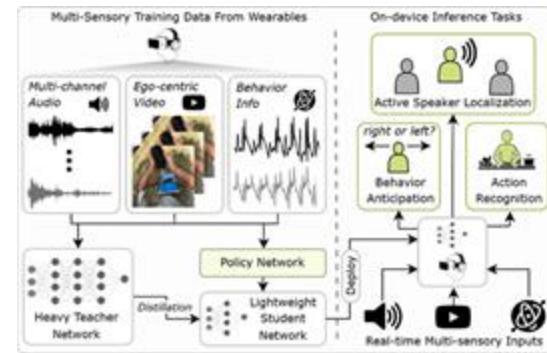
Motivation

- Egocentric multi-modal perception is challenging because:
 - Limited compute in wearable devices
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 - Wait, but performance is important too!!

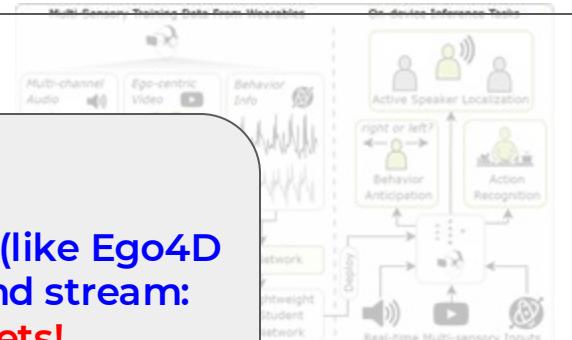


Motivation

- Egocentric multi-modal perception is challenging because:

- Limited context
- Needs reasoning
- Wait, but

Typical 3D CNN-based egocentric models (like Ego4D baselines) require >100 GMACs per second stream:
Infeasible for on-device AR headsets!



Motivation

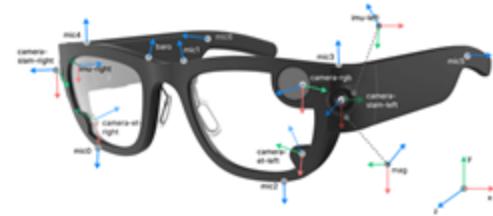
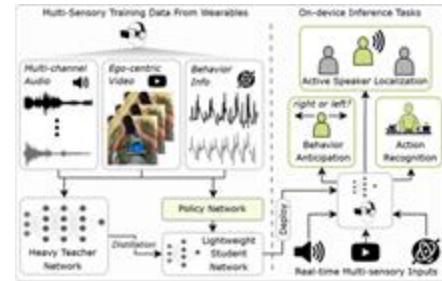
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- Limited compute in wearable devices
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- Key Questions?

- Are all of them important at all the time?
- What all modalities do we leverage for optimal efficiency?
- What is the smartest way to switch between the modalities at our disposal?



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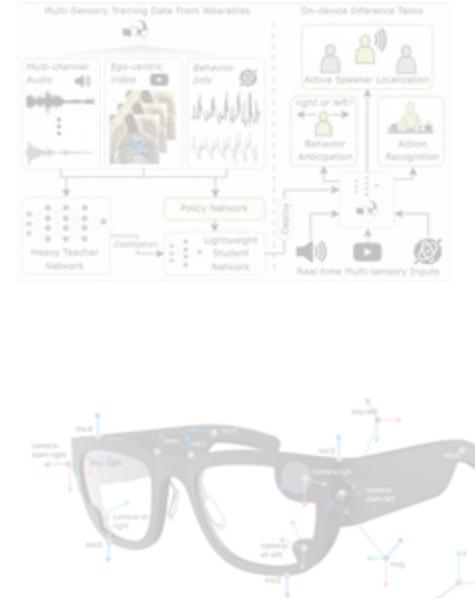
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- Limited compute in wearable devices
- Network latency
- Wearable battery life

Can we combine model distillation with policy learning?

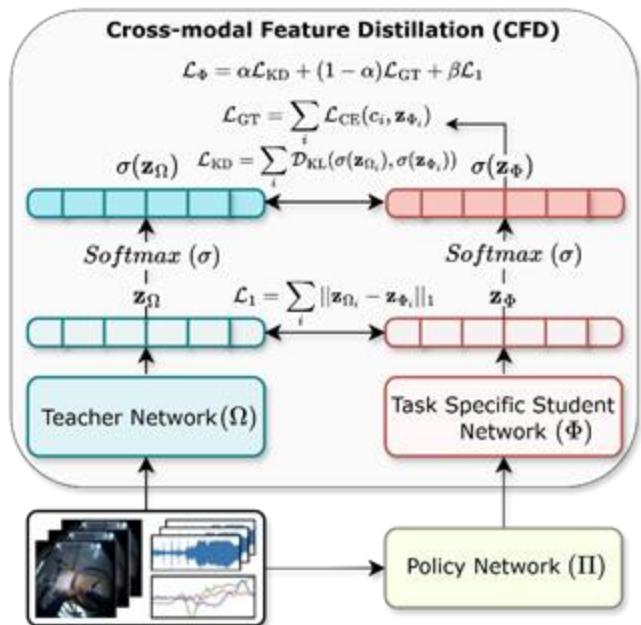
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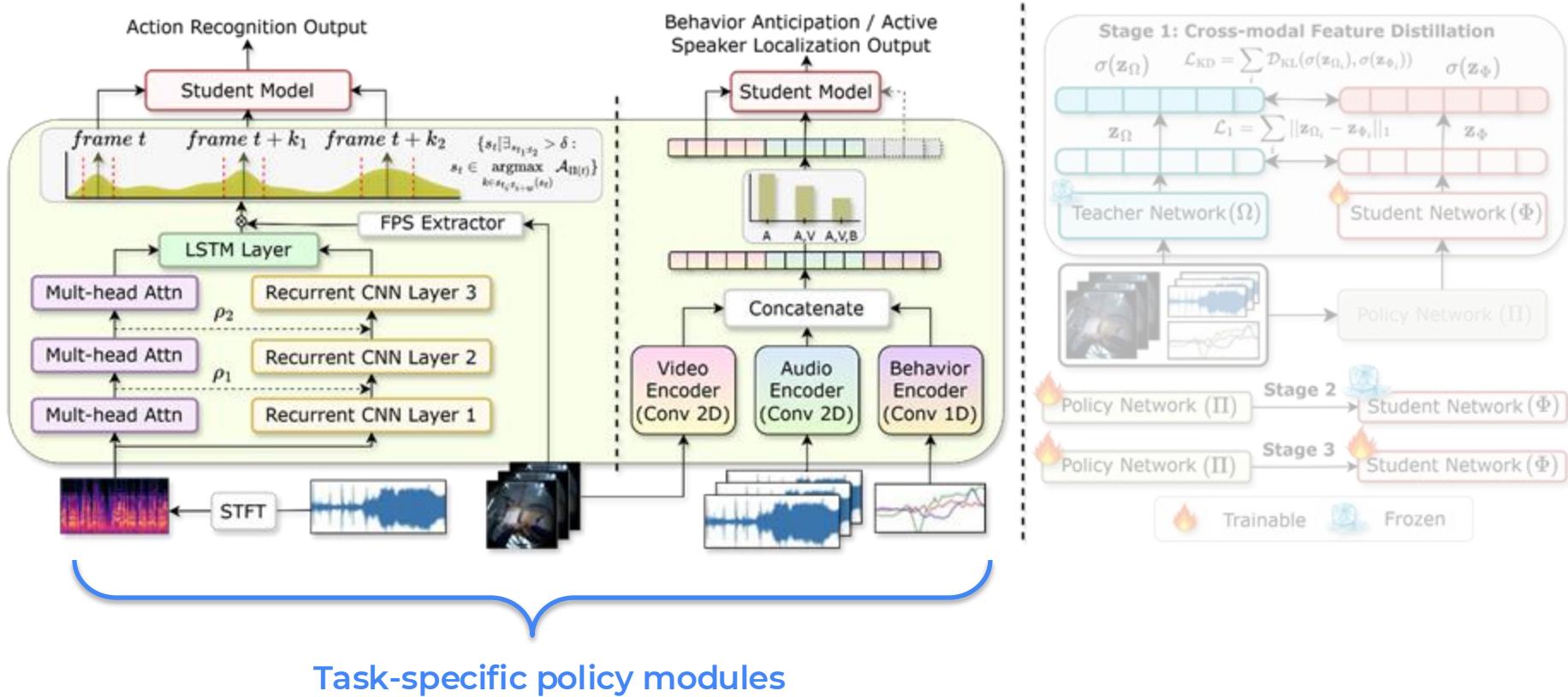


Distillation module

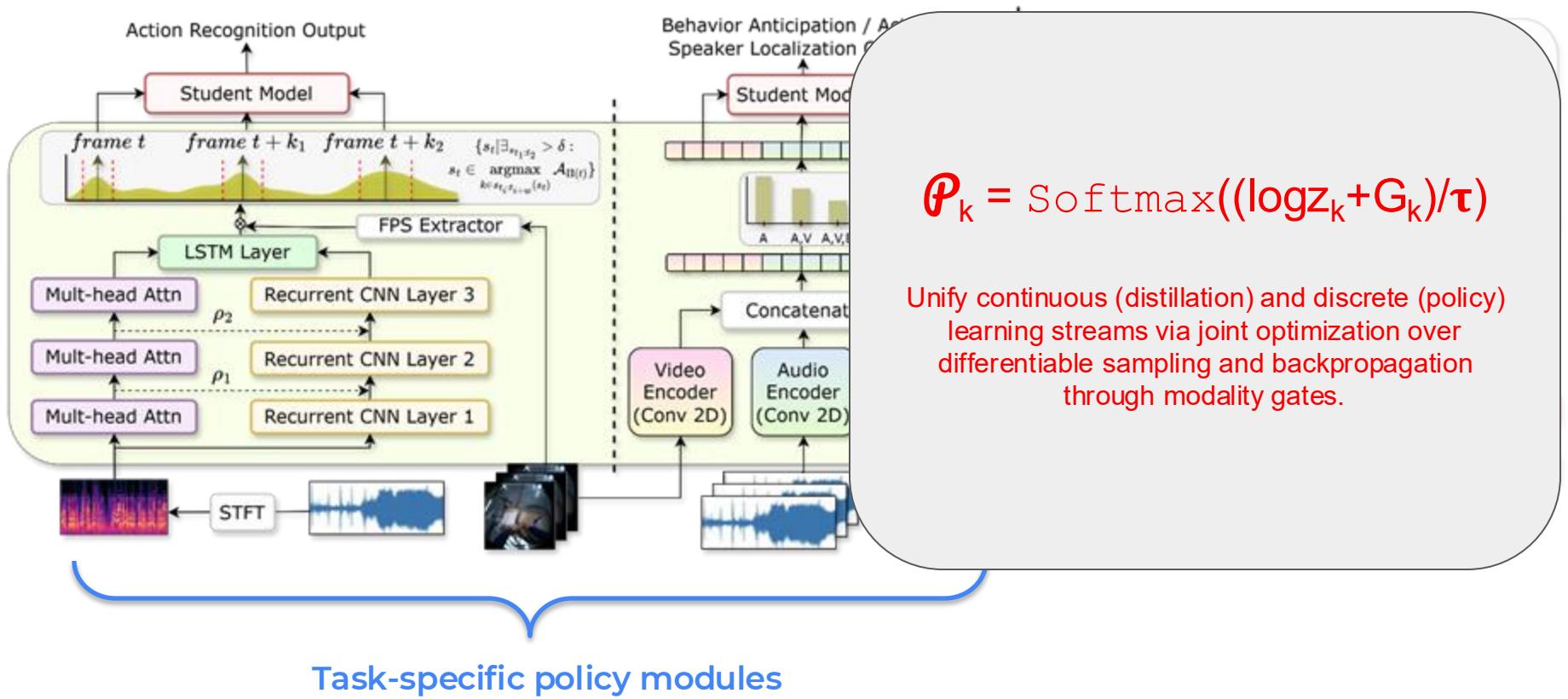
- \mathcal{L}_{KD} Aligns soft targets (semantic space)
- \mathcal{L}_I Aligns intermediate representations (feature space)
- \mathcal{L}_{GT} Anchors final task objective (logit space).



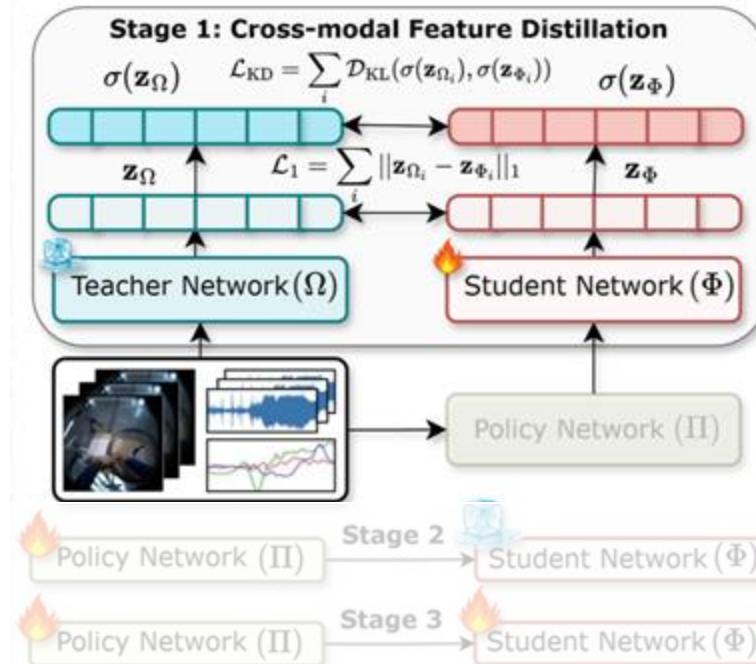
Policy module



Policy module



Stage 1: Distillation - stabilizes KT



Task specific student model is distilled from the heavy teacher model. The distillation objective optimizes three loss functions \mathcal{L} , \mathcal{L}_{KD} , \mathcal{L}_{GT}

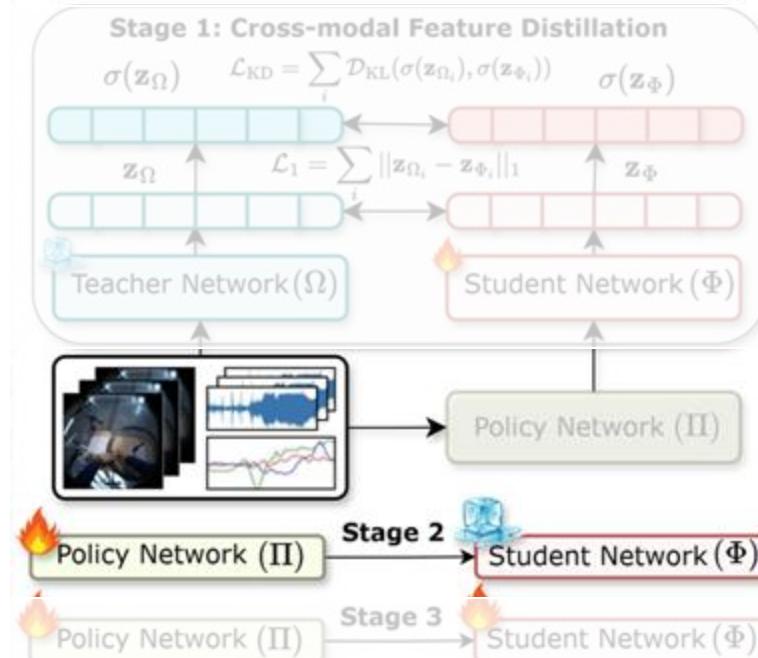


Trainable



Frozen

Stage 2: Policy learning with frozen student - isolates policy gradients, avoiding feature drift

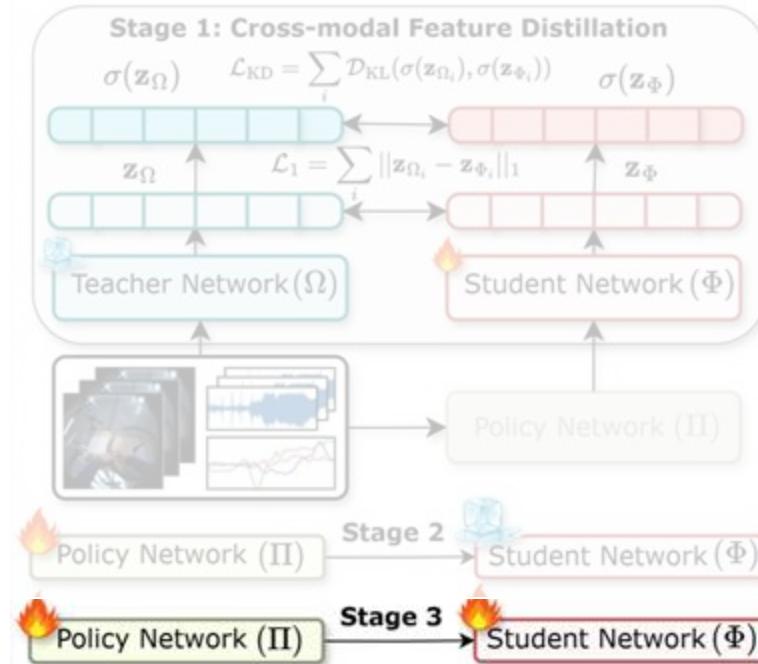


In this stage the policy module is trained keeping the distilled student model fixed. This results in stable training and quicker convergence!



Trainable
Frozen

Stage 3: Policy and distillation update - $\mathcal{L}_\Theta = \eta_1 \mathcal{L}_\Pi + \eta_2 \mathcal{L}_\Phi$



In this stage both the policy module and the distilled student is trained in tandem. This is the final training stage!



Trainable



Frozen

Egocentric **Action Recognition Results**

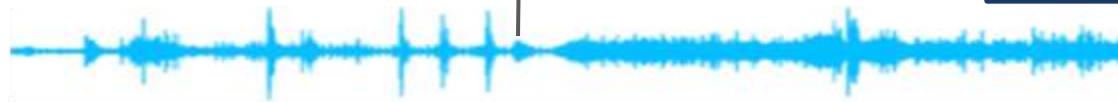


EPIC-Kitchens 100 example

Audio Preview



A person doing kitchen chores. Opens
the tap, washes dishes, cleans counter.

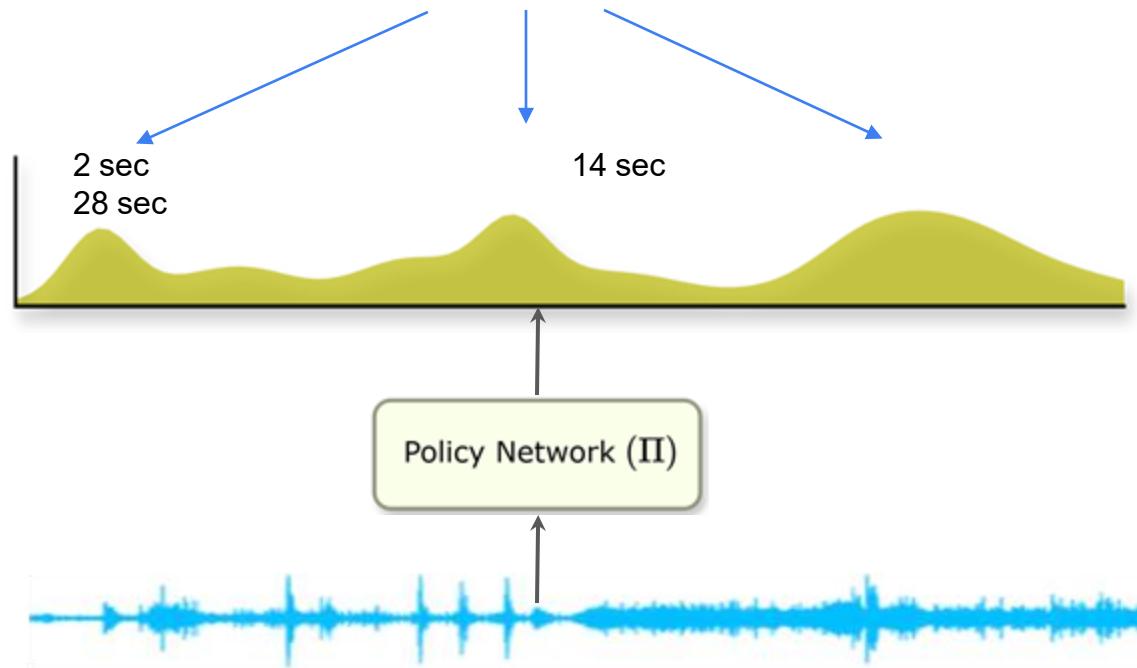


Policy Network (II)



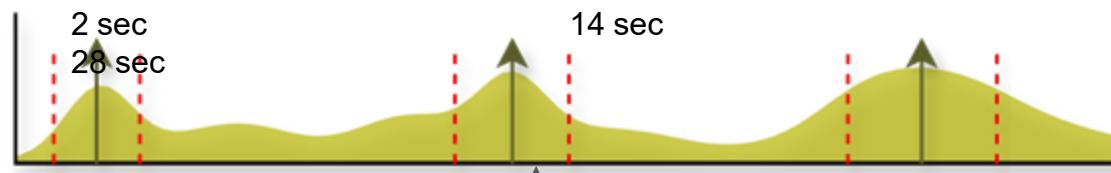
Only the audio is passed to the policy network. Which '**previews**' the audio signal to identify potentially distinct events in the video!

Distinct audio event prediction by audio previewing



Most salient K frames selected

$$\{s_t | \exists_{s_{t_1:t_2}} > \delta : s_t \in \operatorname{argmax}_{k \in s_{t_i:t_{i+w}}(s_t)} \mathcal{A}_{\Pi(t)}\}$$



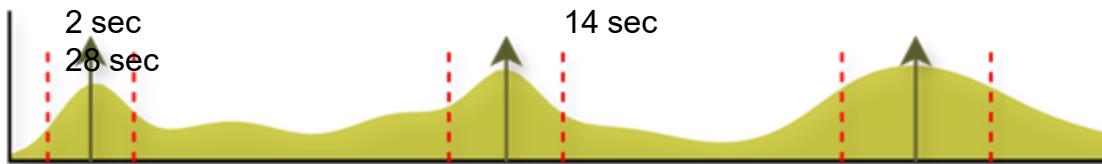
Policy Network (Π)



Predicted action: *Place cup in the sink*

The selected frames are fed to the student model for Action Recognition

Student Model

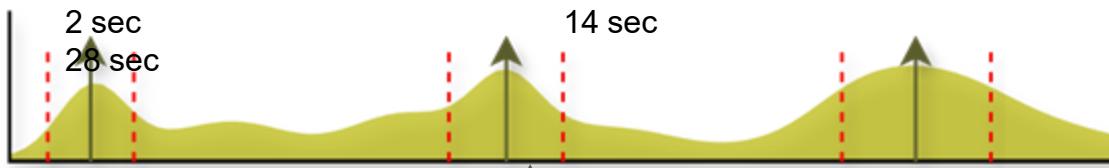


Policy Network (II)



Predicted action: *Start tap*

The selected frames are fed to the student model for Action Recognition



Policy Network (II)



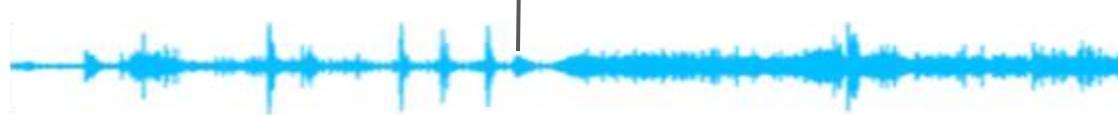
Predicted action: **Wash towel**

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Student Model

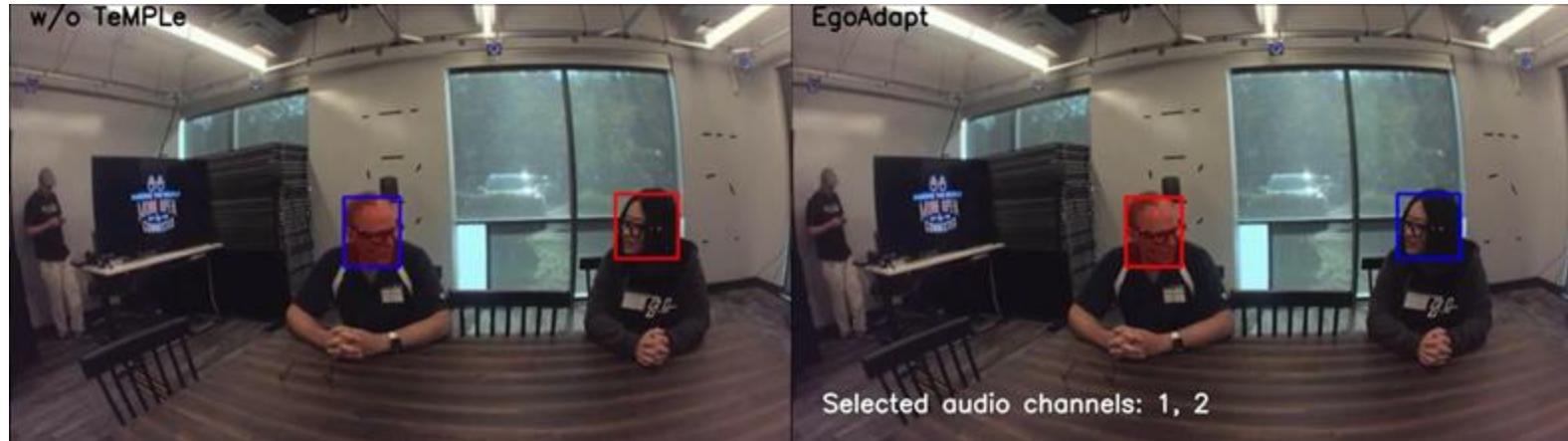


Policy Network (II)



Active Speaker Localization Results

Frame-wise Comparison Results



Non-active speaker



Active speaker



Model prediction

Results: Performance

| Method | Input resolution ↓ | Verb↑ | Noun↑ | Action↑ | GMACs↓ |
|---------------------|--------------------|--------------|--------------|--------------|-------------|
| MoViNet-A6 [37] | 320 × 320 | 72.24 | 57.31 | 47.79 | 79.35 |
| TBN [36] | 224 × 224 | 66.03 | 47.24 | 36.72 | 75.73 |
| AdaFuse [48] | 224 × 224 | 65.52 | 55.75 | 50.16 | 95.84 |
| Ego-only [68] | 224 × 224 | 73.33 | 59.48 | 52.59 | 507.39 |
| ListenToLook [18] | 224 × 224 | 61.27 | 52.52 | 39.85 | 380.46 |
| AdaMML [50] | 224 × 224 | 64.95 | 55.27 | 41.73 | 277.76 |
| VS-VIO [78] | 224 × 224 | 61.37 | 52.21 | 38.07 | 106.97 |
| TIM AV [5] | 224 × 224 | 77.19 | 67.22 | 57.57 | 26.62 |
| EGOADAPT w/o TeMPLe | 224 × 224 | 68.34 | 59.02 | 50.88 | 5.79 |
| EGOADAPT | 224 × 224 | 76.65 | 66.83 | 56.74 | 7.14 |

Table 1. Egocentric action recognition performance of baselines and other other SOTA on EPIC-Kitchens. We report the top-1 accuracy for verb, noun, and action (%).

| Method | mAP↑ | GMACs↓ | Params (M)↓ | Energy (J)↓ |
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| MAVSLoss [35] | 86.32 | 6.852 | 16.13 | 0.698 |
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| VS-VIO [78] | 72.31 | 7.873 | 5.97 | 0.266 |
| MÜST [80] | 89.88 | 0.642 | 2.17 | 0.029 |
| EGOADAPT w/o TeMPLe | 78.59 | 0.077 | 0.36 | 0.003 |
| EGOADAPT | 89.74 | 0.070 | 0.39 | 0.003 |

Table 2. Performance of active speaker localization on Easy-Com. We compare the mAPs (in %) of various baselines in the visual field of view. Most of these tests use 4-channel audio. EGOADAPT can dynamically choose optimal number of channels.

| Method | Gaze | | | Orientation | | | Trajectory | | | Energy (J) ↓ |
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| | $T_{300 \text{ ms}}$ | $T_{500 \text{ ms}}$ | $T_{700 \text{ ms}}$ | $T_{300 \text{ ms}}$ | $T_{500 \text{ ms}}$ | $T_{700 \text{ ms}}$ | $T_{300 \text{ ms}}$ | $T_{500 \text{ ms}}$ | $T_{700 \text{ ms}}$ | |
| MultitaskGP [20] | 11.42 | 15.59 | 18.40 | 4.70 | 9.28 | 12.27 | 13.75 | 17.86 | 20.02 | 0.056 |
| GazeMLE [40] | 10.74 | 14.37 | 18.14 | 4.68 | 9.11 | 12.03 | 14.33 | 16.02 | 18.64 | 1.371 |
| GLC [39] | 10.21 | 14.66 | 17.80 | 4.76 | 8.98 | 11.20 | 13.15 | 15.39 | 17.41 | 0.972 |
| ListenToLook [18] | 13.68 | 17.24 | 19.02 | 5.47 | 8.92 | 11.36 | 13.54 | 15.11 | 17.02 | 0.512 |
| AdaMML [50] | 12.16 | 16.70 | 18.31 | 5.41 | 8.76 | 11.24 | 13.27 | 14.10 | 16.28 | 0.296 |
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| EGOADAPT | 8.53 | 11.93 | 14.58 | 4.61 | 7.39 | 9.91 | 9.58 | 11.97 | 13.36 | 0.003 |

Table 3. Comparison of behavior anticipation errors on the AEA Dataset. The energy values (in J) are reported by aggregating over three time windows ($T_{300 \text{ ms}}$, $T_{500 \text{ ms}}$, and $T_{700 \text{ ms}}$).

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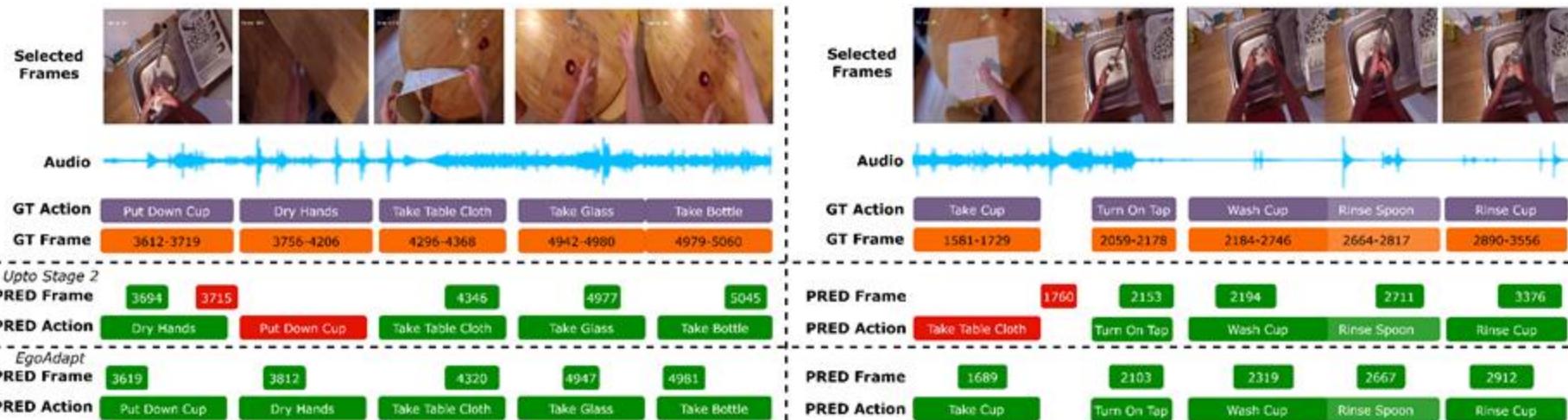
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Ablation Results

Qualitative Results: Action Recognition



The **green** and **red** boxes represent correct and incorrect predictions, respectively. EgoAdapt picks the most informative frame to predict the 'Noun' classes, which is subsequently used to predict the action

Qualitative Results: Active Speaker Localization

w/o TeMPLe



Audio
Channel
Selection

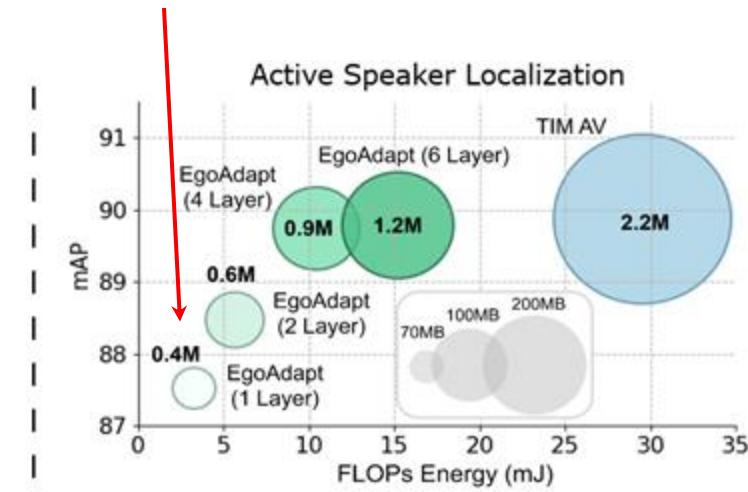
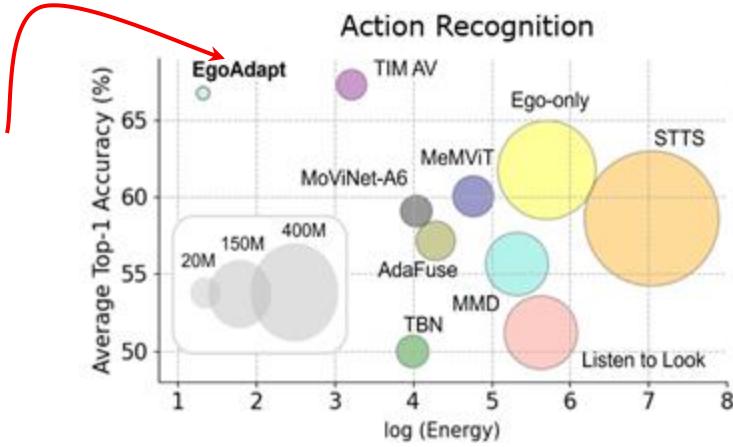


EgoAdapt



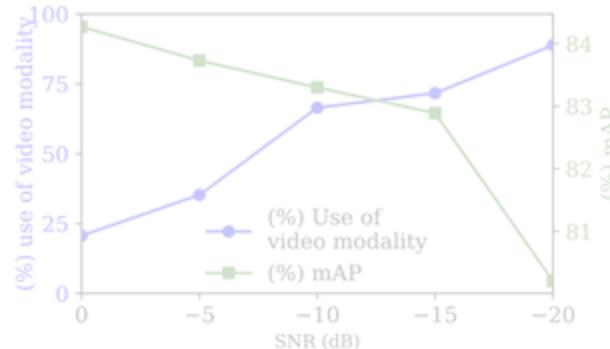
The red/blue boxes indicate active/non-active speakers, and the red heatmap indicates model prediction. EgoAdapt can make correct predictions for scenes with motion blur (col. 4), partial vision (col. 5), and multi-speakers (col. 2, 5). The red/green circles represent the discarded and selected audio channels.

Results: Efficiency

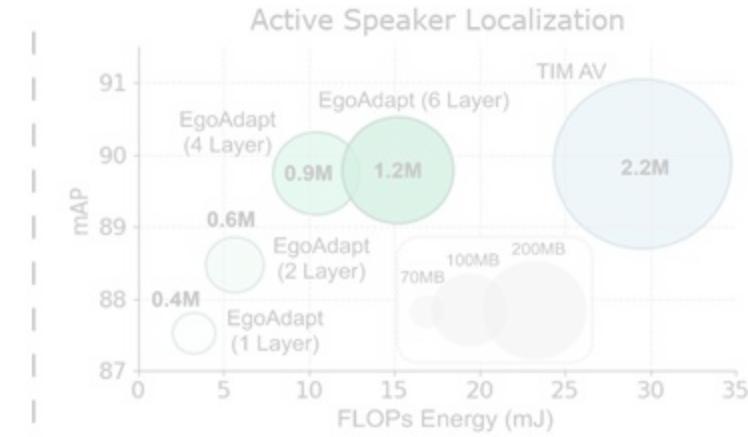
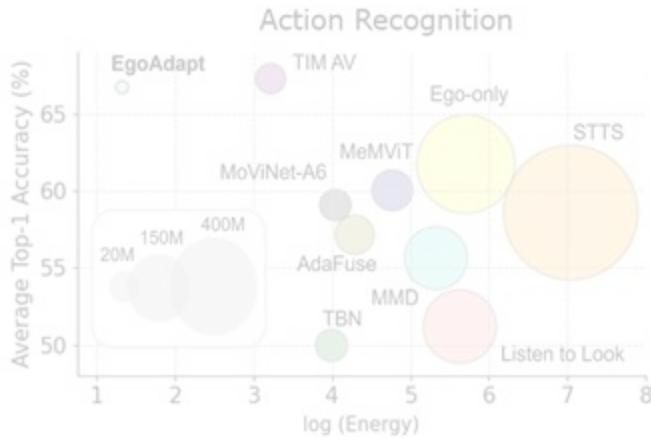


| Precision Level | Modality | | mAP ↑ | Power (mW) ↓ | Exec. Time ↓ |
|-----------------|----------|---|-------|--------------|--------------|
| | A | V | | | |
| 4 bit | ✓ | ✗ | 77.14 | 7.38 | 0.12 |
| | ✓ | ✓ | 78.92 | 9.94 | 0.21 |
| 8 bit | ✓ | ✗ | 80.56 | 11.37 | 0.33 |
| | ✓ | ✓ | 81.13 | 14.90 | 0.42 |
| 16 bit | ✓ | ✗ | 84.39 | 19.11 | 0.59 |
| | ✓ | ✓ | 85.74 | 23.06 | 0.68 |
| 32 bit | ✓ | ✗ | 83.22 | 29.71 | 0.89 |
| | ✓ | ✓ | 89.74 | 34.39 | 1.00 |

On device implementation

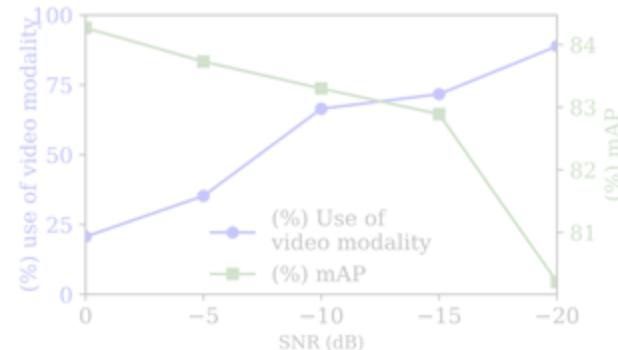


Results: Efficiency

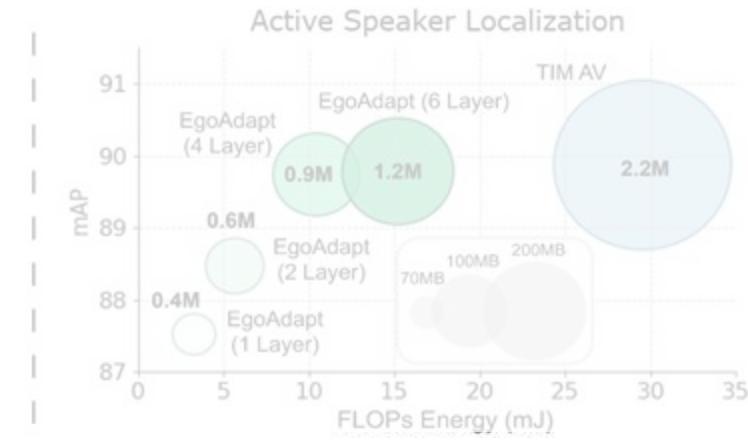
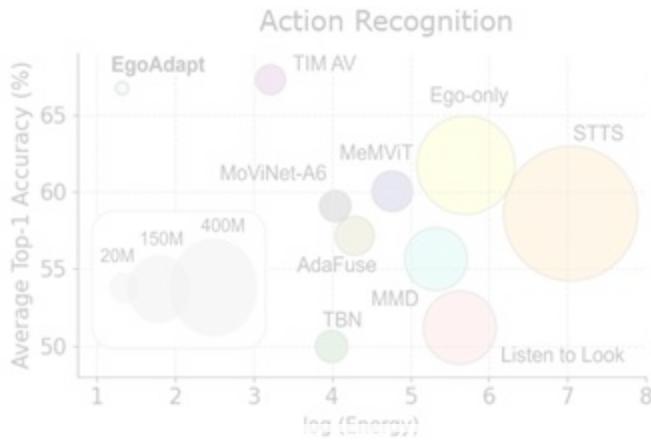


| Precision Level | Modality | | mAP ↑ | Power (mW) ↓ | Exec. Time ↓ |
|-----------------|----------|---|--------------|--------------|--------------|
| | A | V | | | |
| 4 bit | ✓ | ✗ | 77.14 | 7.38 | 0.12 |
| | ✓ | ✓ | 78.92 | 9.94 | 0.21 |
| 8 bit | ✓ | ✗ | 80.56 | 11.37 | 0.33 |
| | ✓ | ✓ | 81.13 | 14.90 | 0.42 |
| 16 bit | ✓ | ✗ | 84.39 | 19.11 | 0.59 |
| | ✓ | ✓ | 85.74 | 23.06 | 0.68 |
| 32 bit | ✓ | ✗ | 83.22 | 29.71 | 0.89 |
| | ✓ | ✓ | 89.74 | 34.39 | 1.00 |

On device implementation

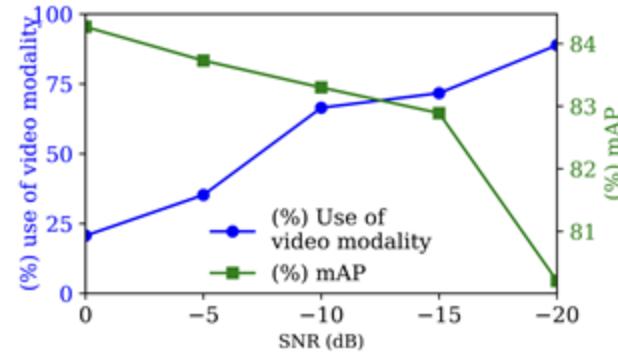


Results: Efficiency

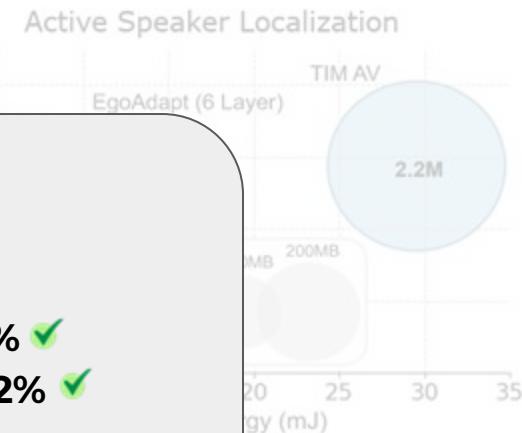
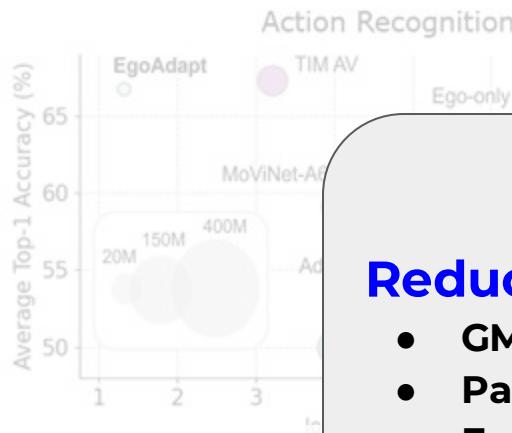


| Precision Level | Modality | | mAP ↑ | Power (mW) ↓ | Exec. Time ↓ |
|-----------------|----------|---|-------|--------------|--------------|
| | A | V | | | |
| 4 bit | ✓ | ✗ | 77.14 | 7.38 | 0.12 |
| | ✓ | ✓ | 78.92 | 9.94 | 0.21 |
| 8 bit | ✓ | ✗ | 80.56 | 11.37 | 0.33 |
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| 16 bit | ✓ | ✗ | 84.39 | 19.11 | 0.59 |
| | ✓ | ✓ | 85.74 | 23.06 | 0.68 |
| 32 bit | ✓ | ✗ | 83.22 | 29.71 | 0.89 |
| | ✓ | ✓ | 89.74 | 34.39 | 1.00 |

On device implementation



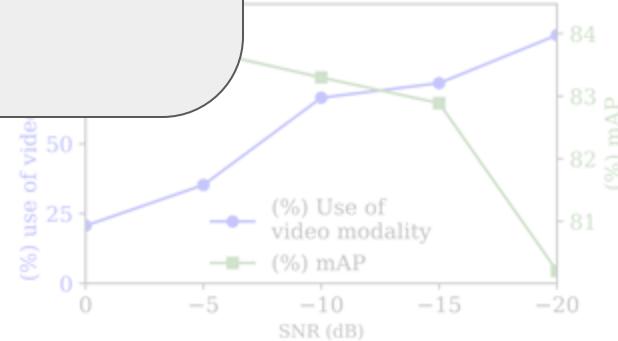
Results: Efficiency



Reduction in:

- GMACs by up to 89.09% ✓
- Parameters up to 82.02% ✓
- Energy up to 9.6× ✓

| Precision Level | Modality | | mAP | | |
|-----------------|----------|---|-------|--------|--------|
| | A | V | 8 bit | 16 bit | 32 bit |
| 4 bit | ✓ | ✗ | 77.1 | 84.39 | 83.22 |
| | ✓ | ✓ | 78.92 | 85.74 | 89.74 |
| 8 bit | ✓ | ✗ | 80.56 | 11.37 | 29.71 |
| | ✓ | ✓ | 81.13 | 14.90 | 34.39 |
| 16 bit | ✓ | ✗ | 84.39 | 19.11 | 0.89 |
| | ✓ | ✓ | 85.74 | 23.06 | 1.00 |
| 32 bit | ✓ | ✗ | 83.22 | 29.71 | 0.89 |
| | ✓ | ✓ | 89.74 | 34.39 | 1.00 |





Project Page

Questions?

Thank you!