

across different video tasks.

Is she looking at me?



Egocentric Video Task Translation

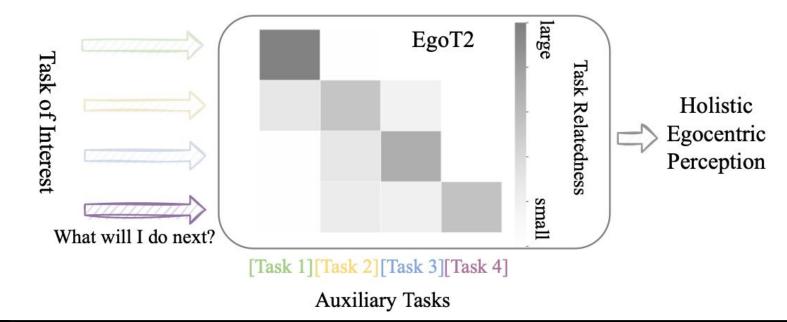
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new learning paradigm to leverage synergies What am I doing? What will I do next?

The attention maps produced by EgoT2 offer good interpretability on inherent task relations.

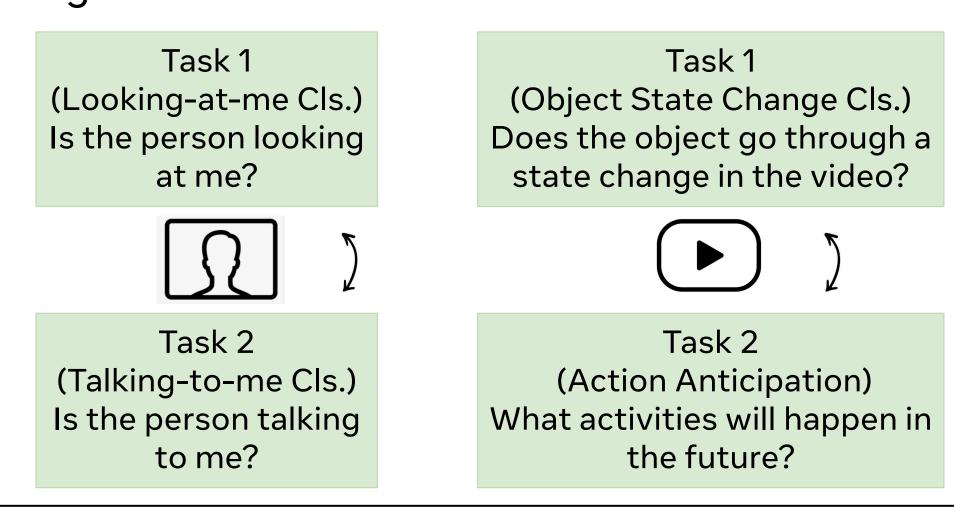
Did the object go

Main idea: We propose task translation as a



Motivation:

- Traditionally, third-person video understanding tasks are studied in isolation;
- Recent egocentric datasets provide suites of tasks associated with various human-human and human-object interactions;
- Strong synergies exist among these egocentric tasks.



Approach: Given K video tasks, we propose two designs with distinct advantages: EgoT2-s & EgoT2-g. Conventional approaches EgoT2-s (task-specific translation) EgoT2-g (task-general translation) Objective: improve all K tasks at the Objective: improve 1 primary task with K-1 auxiliary tasks (resembles TL) same time (resembles MTL) **Transfer Layers** Primary Task Prediction $y_{nred}^{\mathcal{T}_p}$ Backbone pretrained on Task A Task-specific Decoder $[ask\ Prompt]\ Task\ Output\ \ y_{pred_{sea}}^{\mathcal{T}_k}]$ <u>Transfer</u> Task Fusion Transformer Encoder Unified Sequence Decoder <u>Learning (TL)</u> 1 2 T_2 Task Fusion Transformer Encoder ... T_2 1 2 $1 \quad 2 \quad \cdots \quad T_3$ Projection P₂ Projection P₃ Projection P₁ Head B Head C Head A Projection P₁ Projection P₂ Task-specific Model f_1 Task-specific Model f_2 Task-specific Model f_3 Shared Task-specific Model f_1 Task-specific Model f_2 Task-specific Model f_3 Backbone <u>Multi-task</u> <u>Learning (MTL)</u> Input Video x Input Video $\mathbf{x}^{\mathcal{T}_k}$ $\{\mathcal{D}^{\mathcal{T}_1}, \mathcal{D}^{\mathcal{T}_2}, \mathcal{D}^{\mathcal{T}_3}\}$

EgoT2:

- "Flipped" design: multiple task-specific (TS) backbones & a single task translator;
- Two-stage training: 1) optimize K TS backbones \rightarrow 2) optimize the task-specific/task-general translator. Key advantages:
- Backbones and inputs (modality / temporal resolutions) can be selected optimally for each task;
- Do not require a common training set for all tasks;
- Leverage multiple auxiliary tasks simultaneously (unlike TL);
- Mitigate negative transfer when tasks are not strongly related (unlike MTL).



EgoT2-s: leads to top performance as the task translator is individually optimized for each primary task. EgoT2-g: a unified framework for all task translation simultaneously, providing added flexibility.

For more details, our released code and model checkpoints see our website →





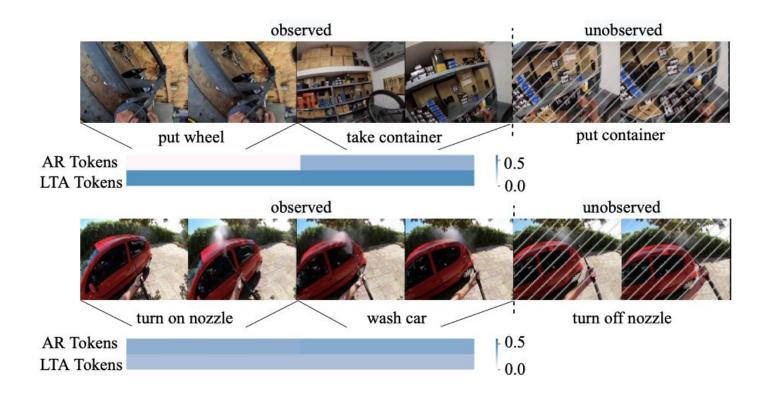
EgoT2-s reliably adapts the auxiliary tasks to suit the primary task, consistently improving performance across all tasks.

	PNR↓	OSCC ↑	AR↑	LTA ↓	TTM ↑	ASD↑
TS model	0.615	68.22	21.87	0.768	58.91	79.05
TL (best)	0.611	70.98	14.81	0.776	63.59	71.06
Late Fusion	0.610	72.10	20.17	0.766	64.29	77.54
EgoT2-s	0.610	72.69	23.16	0.750	66.54	79.38



EgoT2-s achieves 1st place in TTM and 3rd place in PNR at the 2022 Ego4D ECCV challenge.

EgoT2-s selectively activates auxiliary task feature tokens for the primary task (Primary task: LTA, Auxiliary task: AR).



EgoT2-g is flexible, accurate and mitigates negative transfer.

	PNR↓	OSCC ↑	AR↑	LTA ↑	LAM ↑	TTM↑	ASD↑
TS model	0.615	68.2	21.87	21.31	77.79	58.91	79.05
MTL	0.617	66.0	N/A	N/A	60.53	61.91	N/A
EgoT2-g	0.611	71.7	22.33	22.76	77.63	64.49	79.06

EgoT2-g activates task tokens conditioned on the task prompt.

