







A backpack full of skills: Egocentric Video Understanding with diverse task perspective

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<u>What</u> can we learn from a single video?

Different video tasks = different, possibly complementary, perspectives

Actions Recognition (AR)



Object State Change Classification (OSCC)





Long Term Action Anticipation (LTA)



Point of No Return (PNR)



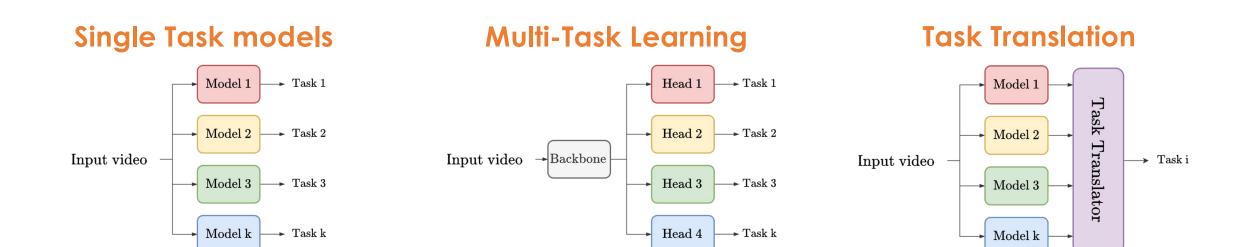






How can we learn from these perspectives?

Main approaches from the literature:







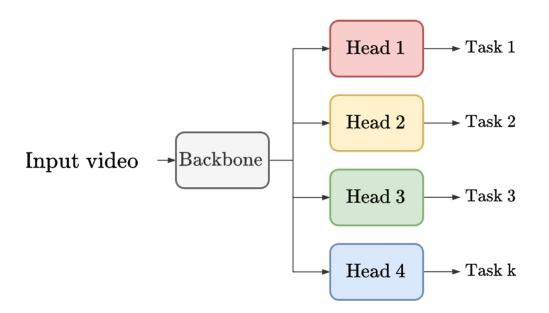




How can we learn from videos? - Multi-Task Learning

Jointly learn multiple tasks using a shared backbone and a set of task-specific heads

- + Same model is shared across different tasks
- Does not <u>explicitly</u> model task sinergies
- May suffer of negative transfer between tasks







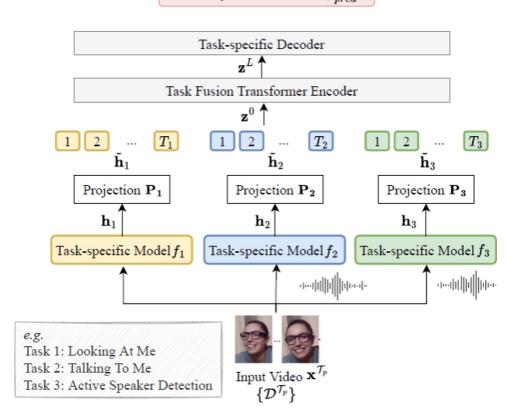




How can we learn from videos? - Cross-Task Translation

EgoT2 proposes an innovative approach to leverage cross-task sinergies by learning to "translate" features across different tasks

- + Combine perspectives from different tasks
- Need to know all the tasks before-hand
- One model for each task



Primary Task Prediction $y_{nred}^{T_p}$

Xue, Zihui, et al. "Egocentric Video Task Translation" (CVPR 2023)









<u>What</u> can we learn from different perspective?

Holistic perception of video stream:

- Correlate concepts from different tasks
- Collection of task-specific knowledge
- Exploit gained knowledge to learn novel skills

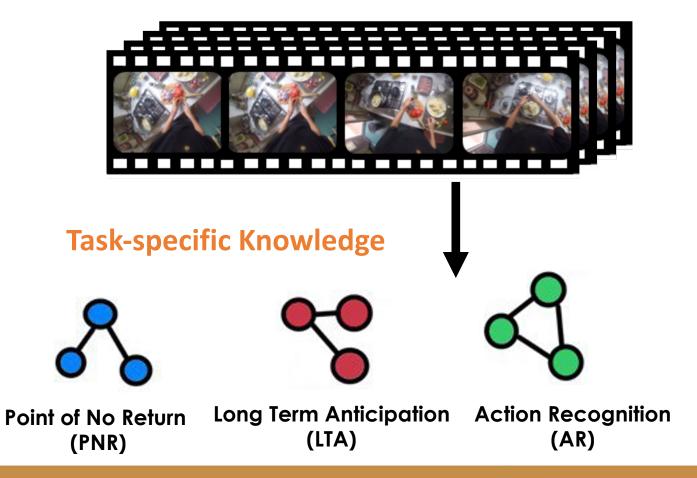








Our Goal: Recombining Task-specific Knowledge for a Novel Task



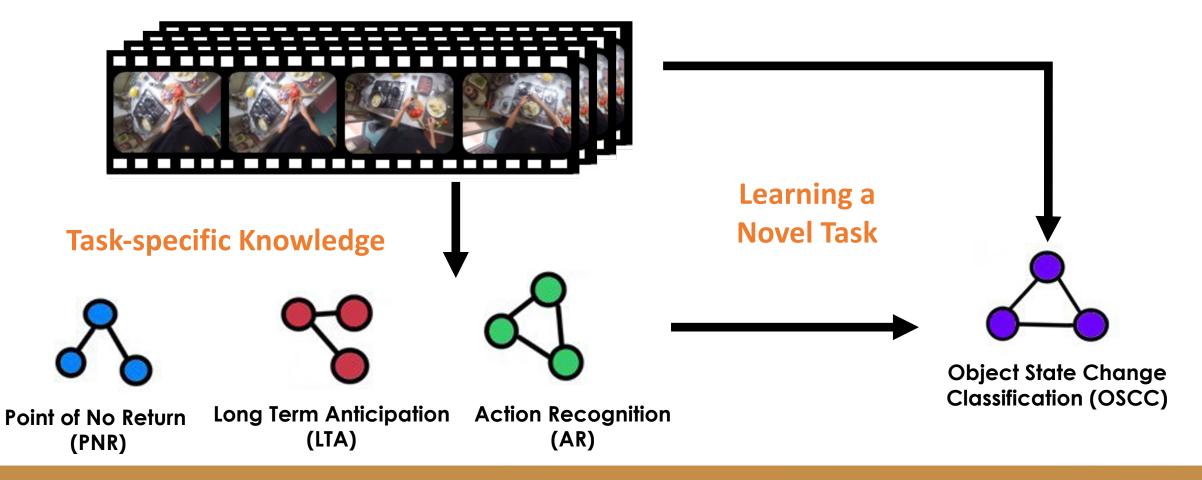








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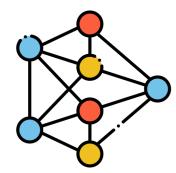








A new paradigm for Egocentric Video Understanding



Shared model for all the tasks



Knowledge reuse across tasks



Outperform single and multi-task baselines



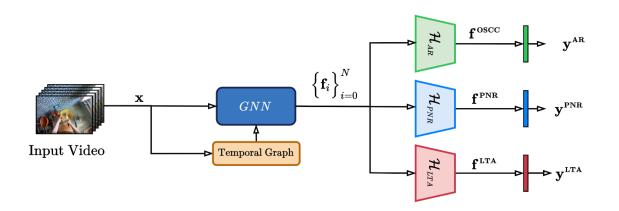




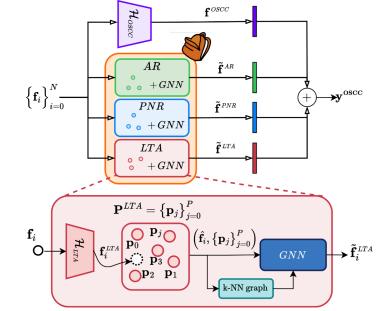


The EgoPack approach

Step 1: MTL Pre-training step



Multi-task pre-training on a set of known task Step 2: Novel Task Learning



Fine-tuning on a novel task with EgoPack's cross-task interaction



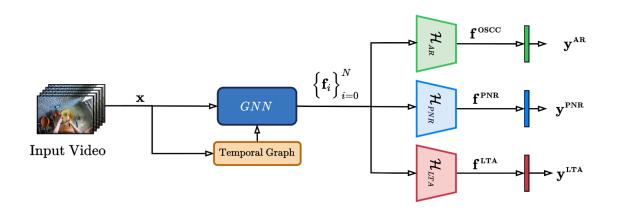




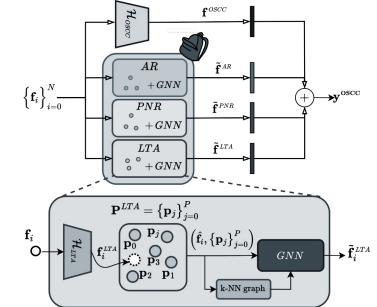


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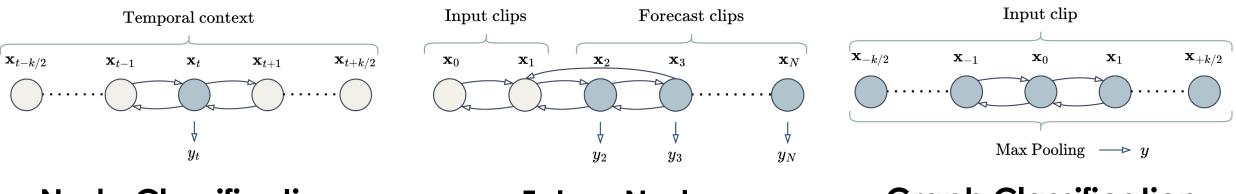




Step 1: A graph-based temporal model



We can model many egocentric vision tasks with a shared graph-based structure...



Node Classification (AR, PNR) Future Node Classification (LTA) Graph Classification

Each node is a temporal segment and egocentric video tasks become different graph operations

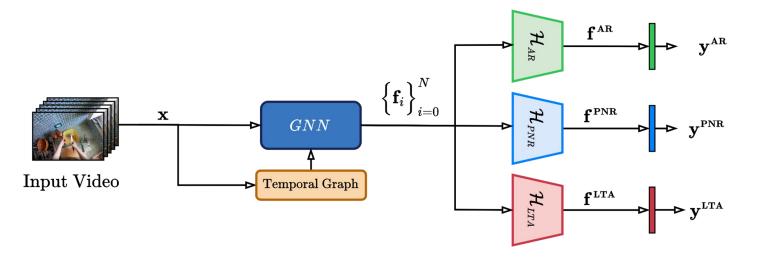








Step 1: Temporal Multi-Task Pre-Training



The output of the Temporal Model is specialized into task-specific features using a set of **task-specific heads**

The output are the task logits $\mathbf{y}_i^k \in \mathbb{R}^{D_o^k}$





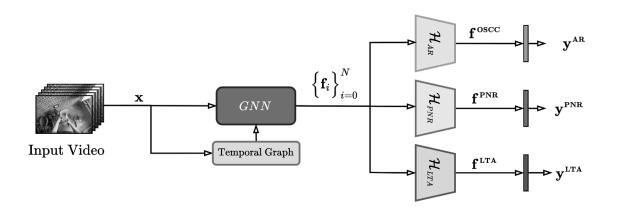




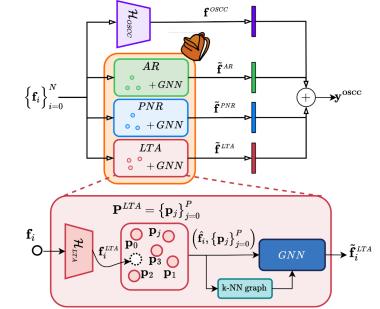


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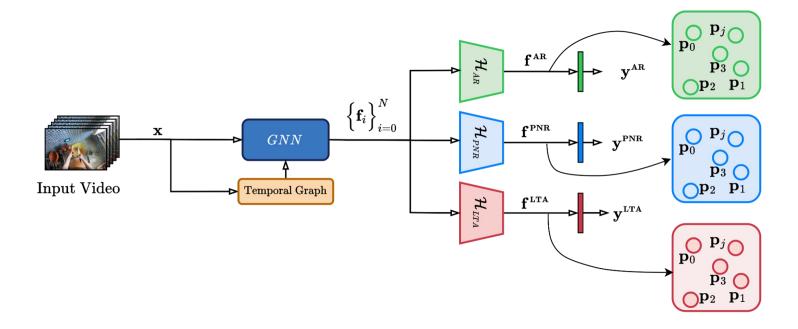




Step 2: Novel Task Learning with EgoPack



Given as input the same video, the model's heads express different and complementary perspectives on the content of the video



Step 2.1: Prototypes collection

We collect action-wise task-specific prototypes by feeding the model with AR videos

$$\mathbf{P}^k = \{\mathbf{p}_0^k, \mathbf{p}_2^k, \dots, \mathbf{p}_P^k\} \in \mathbb{R}^{P imes D_k}$$

for each task





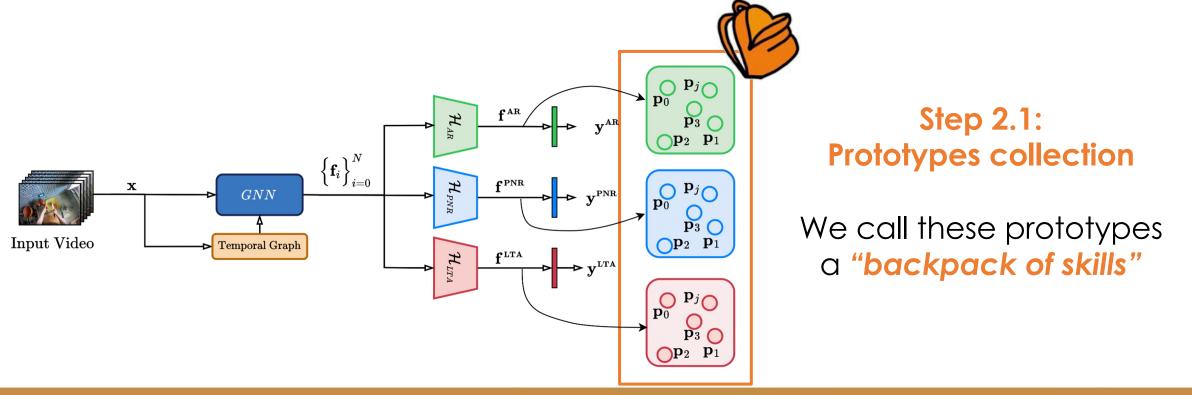




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Step 2: Novel Task Learning with EgoPack



To learn a **novel task**, e.g., **Object State Change Classification**, we add the corresponding head and exploit the synergies with the previous tasks.

 \mathbf{f}^{OSCC} New head trained for the \mathcal{H}_{oscc} novel task (OSCC) $\mathbf{\tilde{f}}^{\scriptscriptstyle{AR}}$ AR $\circ \circ + GNN$ $\left\{\mathbf{f}_{i}\right\}_{i=0}^{N}$ →y^{oscc} Knowledge reuse from PNR $\mathbf{\tilde{f}}^{PNR}$ previous tasks using the $\circ \circ + GNN$ prototypes from AR, PNR and $\mathbf{ ilde{f}}^{LTA}$ LTALTA +GNN0



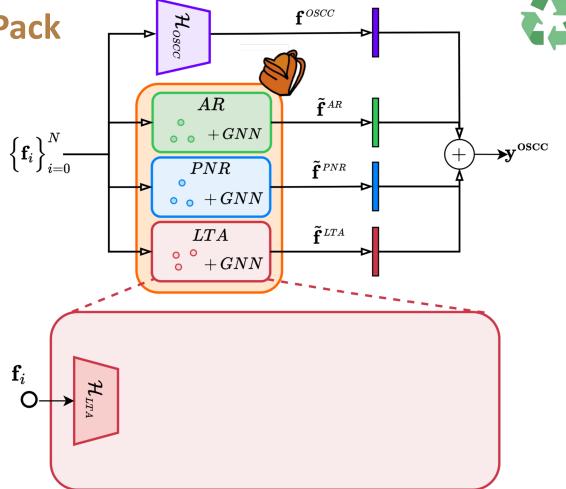






Step 2: Novel Task Learning with EgoPack

We feed the temporal features through the task-specific heads of the pretraining tasks to obtain **f**_i^k.







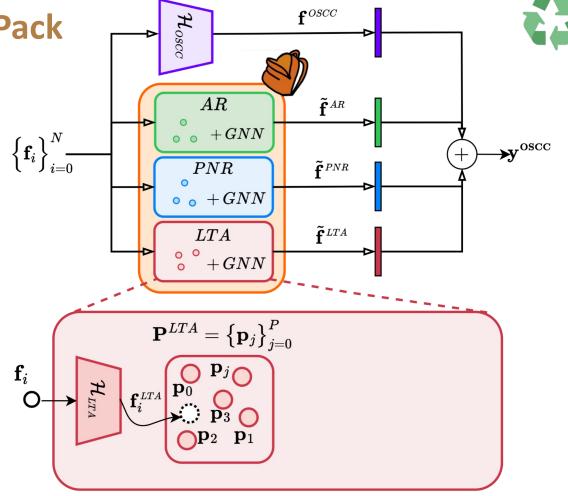




Step 2: Novel Task Learning with EgoPack

We feed the temporal features through the task-specific heads of the pretraining tasks to obtain f^k.

These features act as queries to look for the **closest matching prototypes** using k-NN in the features space.











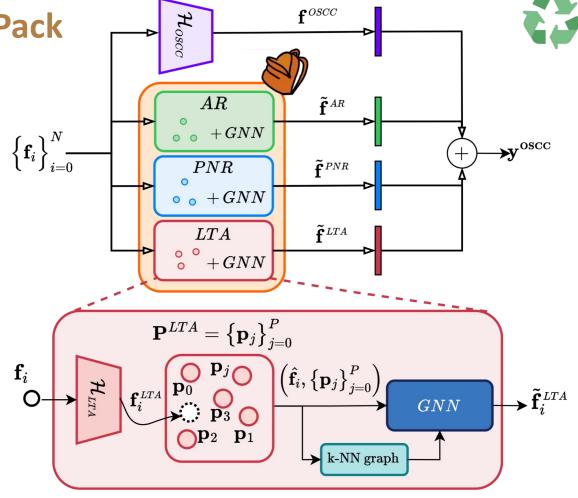
Step 2: Novel Task Learning with EgoPack

We feed the temporal features through the task-specific heads of the pretraining tasks to obtain f^k_i.

These features act as queries to look for the closest matching prototypes using k-NN in the features space.

We refine the task features using **Message Passing with task prototypes**.

$$\mathbf{f}_{i}^{(l+1),k} = \mathbf{W}_{r}^{(l)}\mathbf{f}_{i}^{(l),k} + \mathbf{W}^{(l)} \cdot \max_{\mathbf{p}_{j}^{k} \in \mathcal{N}_{i}^{(l),k}} \mathbf{p}_{j}^{k}$$











Experimental Results - Ego4D HOI Tasks



We validate EgoPack on AR, OSCC, PNR and LTA from Ego4D.

	Trained on frozen features	AR		OSCC	LTA		PNR
		Verbs Top-1 (%)	Nouns Top-1 (%)	Acc. (%)	Verbs ED (\downarrow)	Nouns ED (\downarrow)	Loc. Err. (s) ()
Ego4D Baselines [25]	×	22.18	21.55	68.22	0.746	0.789	0.62
EgoT2s [68]	×	23.04	23.28	72.69	0.731	0.769	0.61
MLP	1	24.08	30.45	70.47	0.763	0.742	1.76
Temporal Graph	✓	24.25	30.43	71.26	0.754	0.752	0.61
Multi-Task Learning	✓	22.05	29.44	71.10	0.740	0.746	0.62
Task Translation [†]	1	23.68	28.28	71.48	0.740	0.756	0.61
EgoPack	1	25.10	31.10	71.83	0.728	0.752	0.61

MLP: graph nodes are processed individually, with no temporal modelling

Temporal Graph: MLP + Temporal Graph model of EgoPack

Multi-Task Learning: all tasks are trained together with our Temporal Graph model

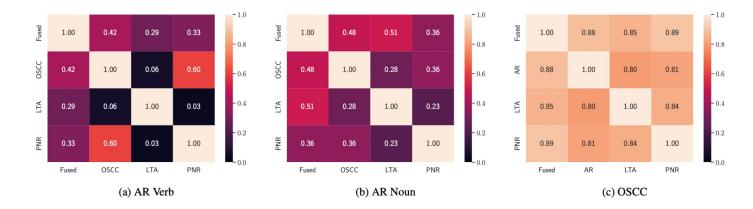
Task Translation: re-implementation of EgoT2 using pre-extracted (frozen) features









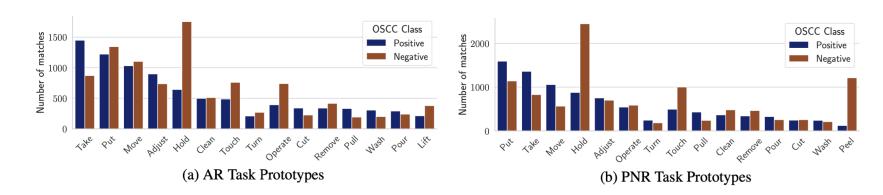


Cross-tasks agreement ratio

How much different "perspectives" bring complementary information?

Queried prototypes

When the novel task is OSCC, what are the closest prototypes from the AR and PNR tasks?











Thank you for your attention!

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Egocentric Video Understanding with EgoPack

Shared model: model all tasks using a shared graph-based structure

Knowledge Reuse: collect the knowledge learnt from a set of tasks in a backpack of skills ready to be reused when learning a new task

Simone Alberto Peirone, <u>Francesca Pistilli</u>, Antonio Alliegro, Giuseppe Averta "A backpack full of skills: Egocentric Video Understanding with diverse task perspective" (CVPR 2024) Can you spot an object state change?



