

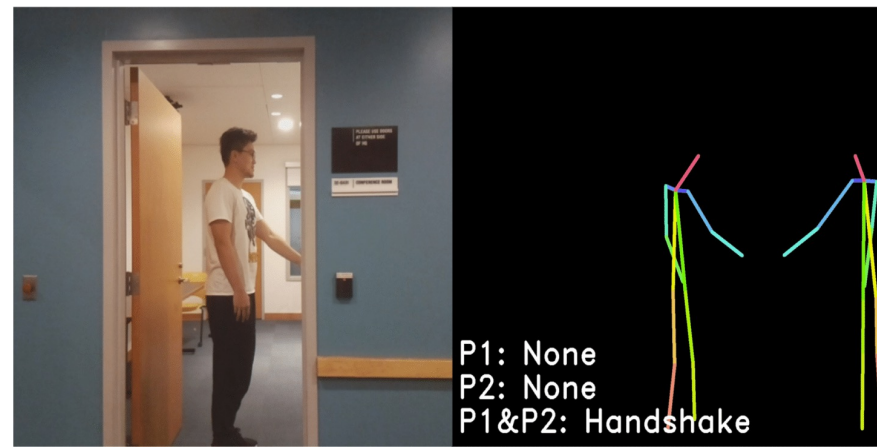
Unsupervised Learning for RF-based Vision

RF-based vision: RF signals traverse walls and occlusions; thus, they can sense humans through walls and occlusions.

RF 3D Pose Estimation



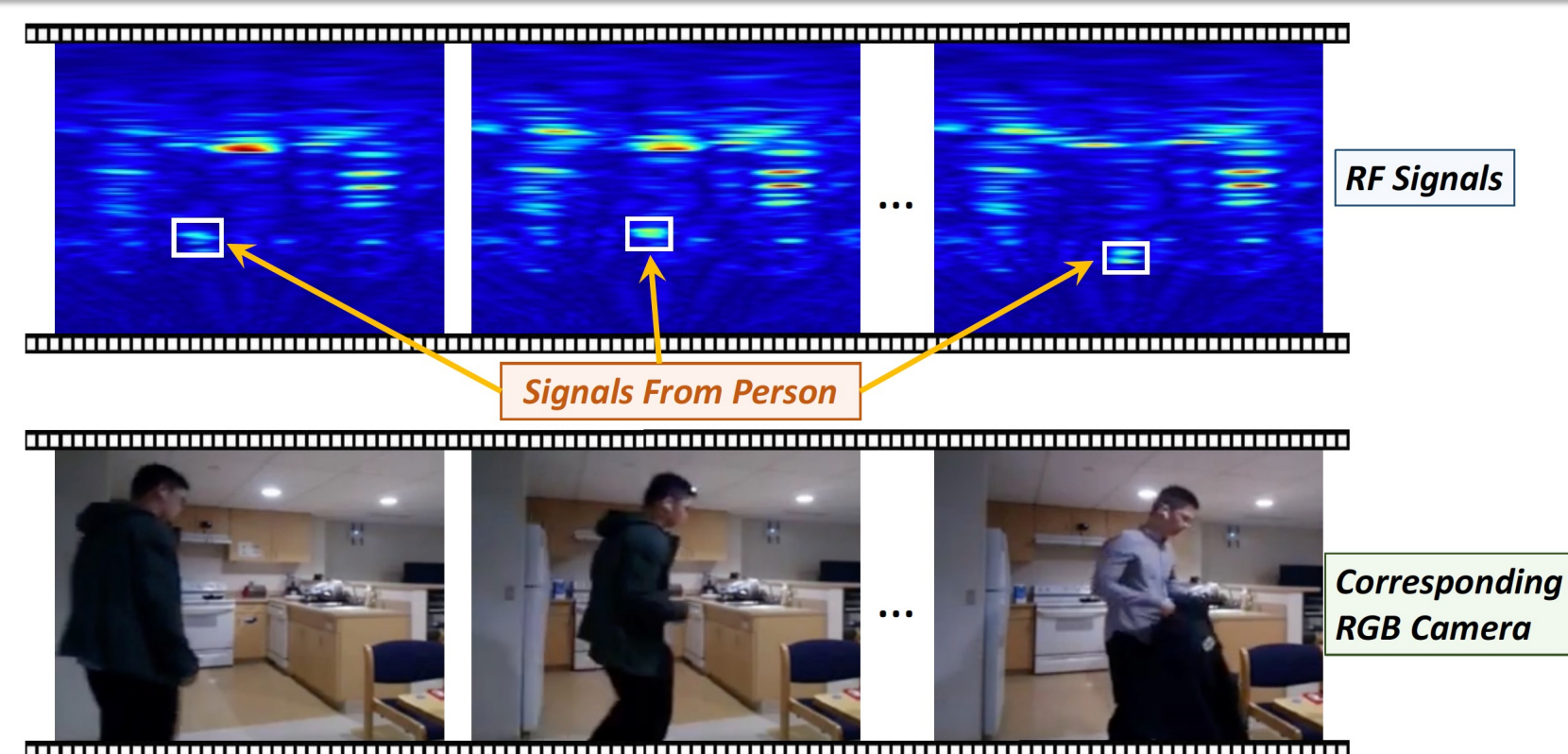
RF Action Recognition



Motivation:

- Labeling RF signals is a daunting task because RF signals are not human interpretable.
- Leveraging large-scale unlabeled radio signals may improve the performance.

Challenge I: Human-Relevant Information Sparsity



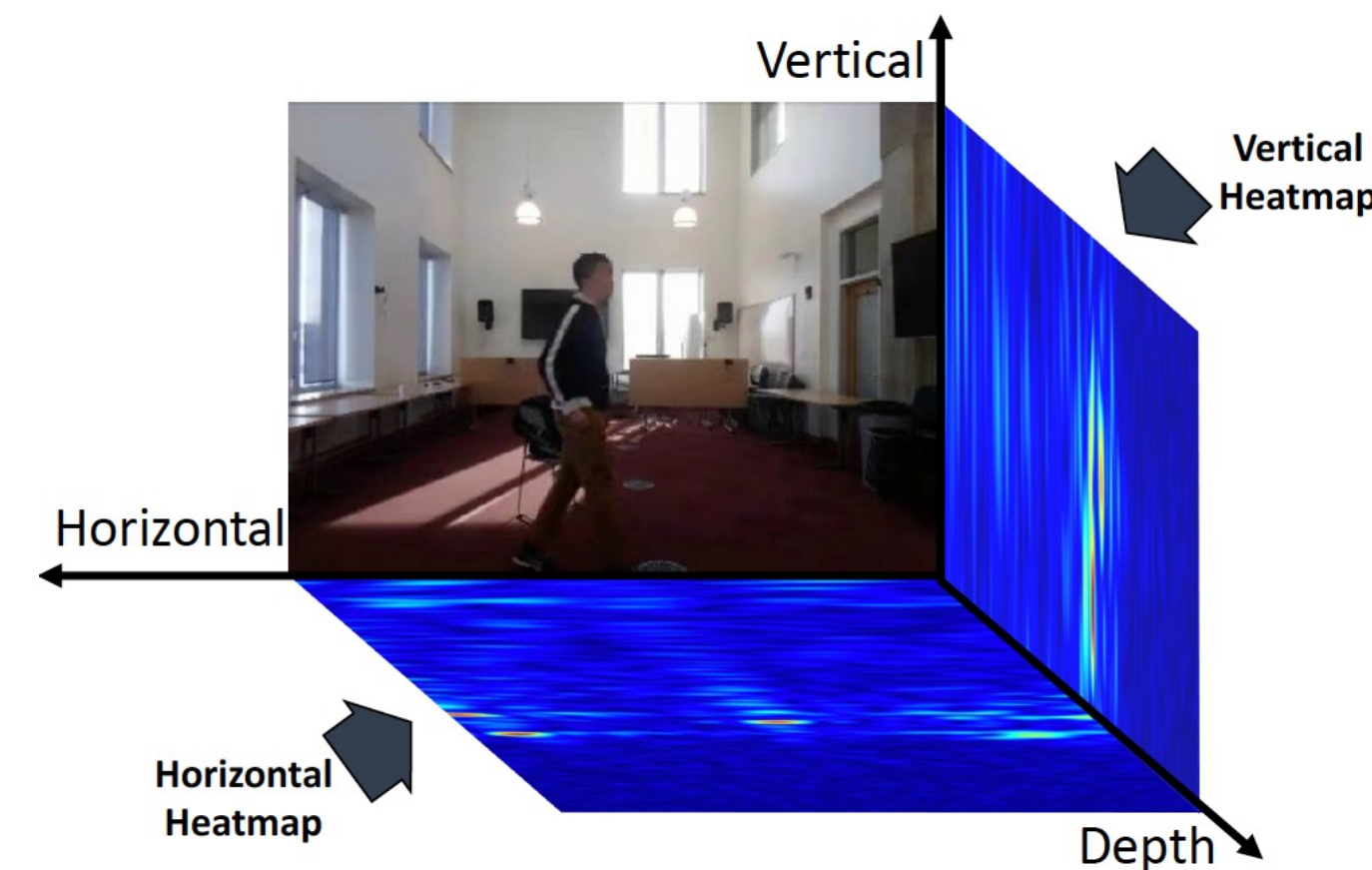
Compared with RGB data:

- The information region in RF signals that corresponds to a person could be extremely small (<1%).
- RF signals carry much information that is irrelevant to the person or task, e.g., some signals that reflect off walls, signals that reflect other objects in the environment.

Solution:

- In most indoor scenarios, people are the only large moving objects. Therefore, we can adapt radar detection algorithms to detect and localize the person.
- Zoom in on radio signals which contain the person by cropping horizontal and vertical heatmaps based on their trajectory.

Challenge II: Augmentation is not applicable to RF signals



Self-supervised learning typically depends on data augmentation and pretext tasks.

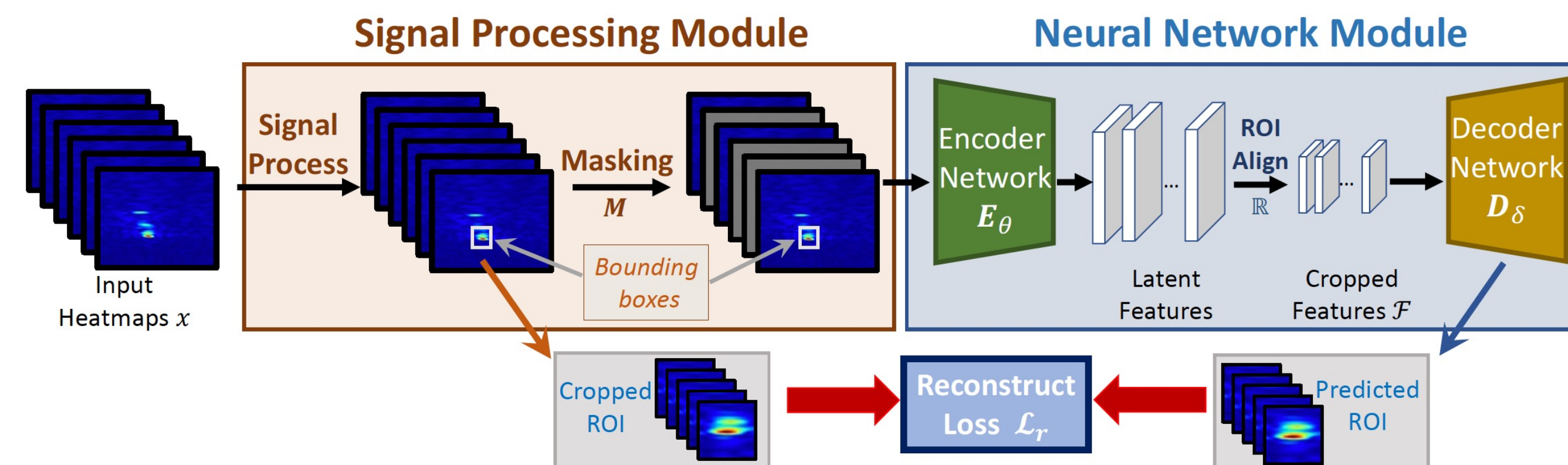
RGB specific augmentations and tasks cannot be directly applied to RF signals, e.g.,

- No color information in RF signals
- RF signal is not invariant to rotation transformation

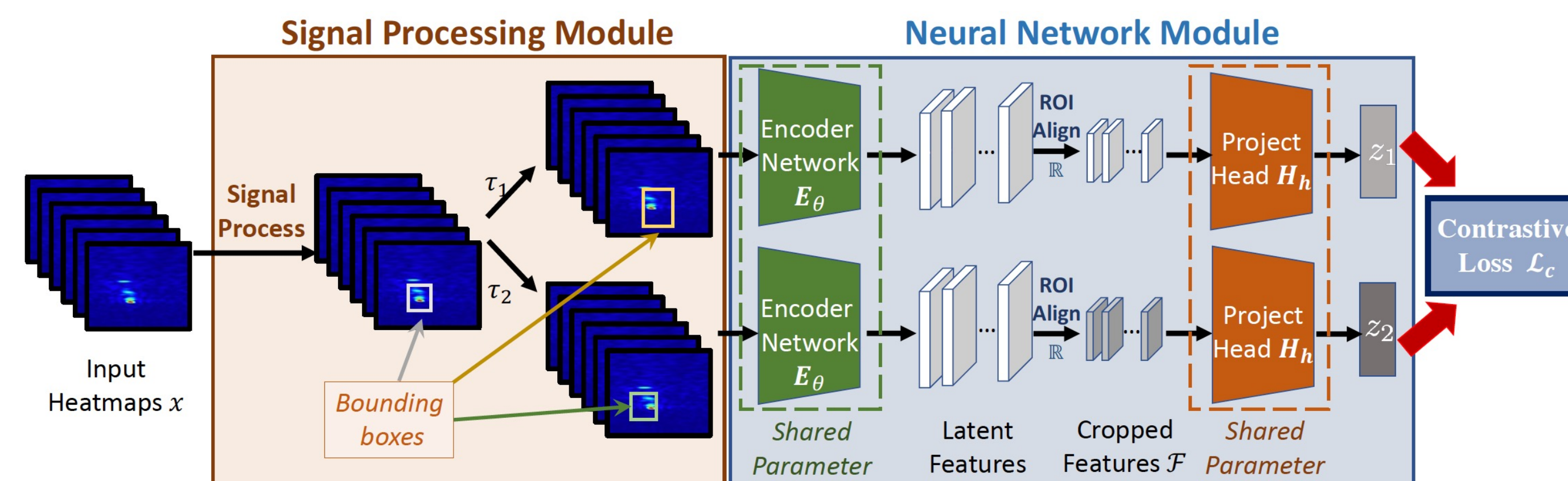
Solution: Predictive unsupervised learning is more suitable than contrastive unsupervised learning. Use adaptive reconstruction loss for RF data unsupervised learning.

Network Structure: Trajectory Guided Unsupervised Learning (TGUL)

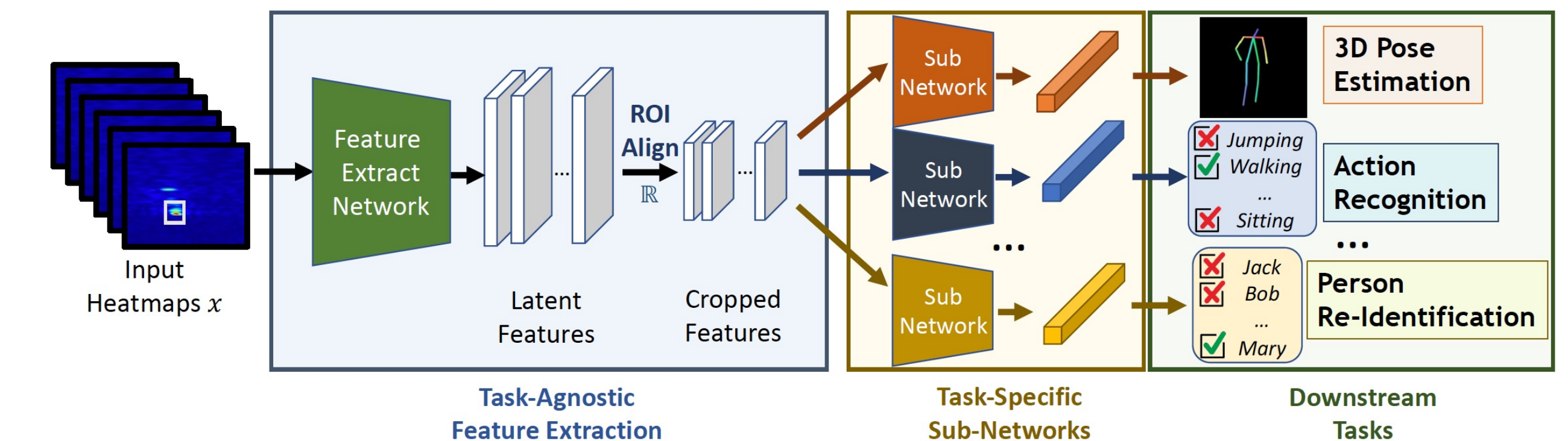
Predictive Unsupervised Learning (PL)



Contrastive Unsupervised Learning (CL)



Experimental Results



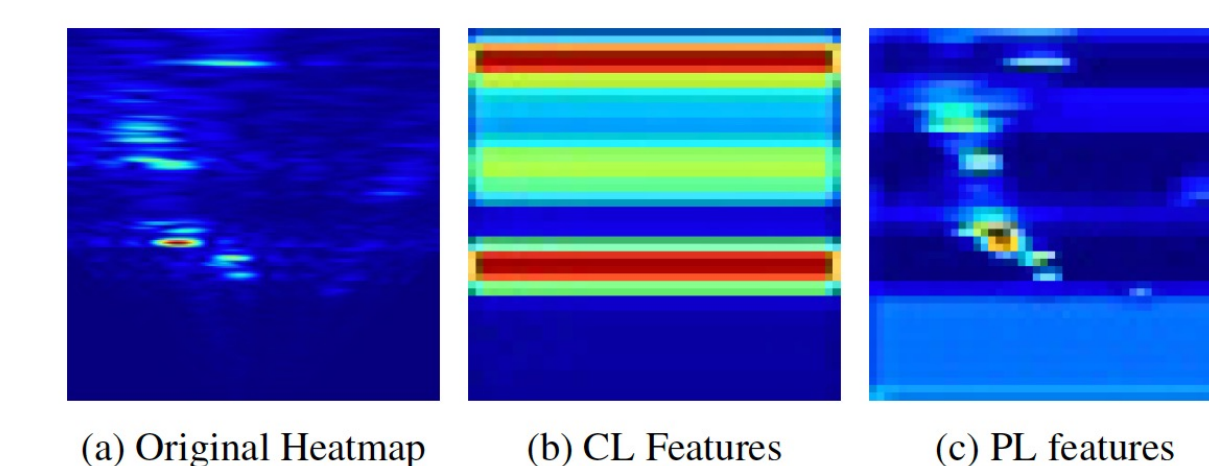
Fixed feature extractor + Fine-tune task-specific parameters:

Tasks	3D Pose Estimation	Action Recognition	Person Re-ID (Campus)			Person Re-ID (Home)		
Metrics	Pose ERR. [↓] (mm)	mAP [↑] $\theta = 0.1$ $\theta = 0.5$	mAP [↑]	CMC-1 [↑]	CMC-5 [↑]	mAP [↑]	CMC-1 [↑]	CMC-5 [↑]
Random init	60.1	60.5 53.3	28.1	43.8	68.8	30.1	54.2	74.6
SimCLR + TGUL	80.5	4.2 0	29.8	44.1	67.5	31.2	55.1	73.8
MoCo + TGUL	77.2	5.1 0.18	29.1	44.7	65.3	30.5	54.5	74.0
CPC + TGUL	78.7	3.6 0	30.0	42.7	69.5	30.7	54.0	75.3
BYOL + TGUL	79.3	4.7 0	29.5	44.4	66.7	30.7	54.6	73.5
Autoencoder	59.4	62.3 54.2	29.0	44.5	67.0	31.1	55.5	75.5
Autoencoder + TGUL	55.7	71.1 63.2	43.8	69.7	87.2	35.2	61.5	81.9
Inpainting	58.0	63.9 55.4	30.2	48.1	70.5	32.8	57.7	76.5
Inpainting + TGUL	51.1	72.3 65.5	49.8	73.1	90.5	38.5	64.2	84.7
IMPROVEMENT	+15.0%	+19.5% +22.9%	+77.2%	+66.9%	+31.5%	+27.9%	+18.5%	+13.5%

Fine-tune all parameters:

Tasks	3D Pose Estimation	Action Recognition	Person Re-ID (Campus)			Person Re-ID (Home)		
Metrics	Pose ERR. [↓] (mm)	mAP [↑] $\theta = 0.1$ $\theta = 0.5$	mAP [↑]	CMC-1 [↑]	CMC-5 [↑]	mAP [↑]	CMC-1 [↑]	CMC-5 [↑]
Supervised [23, 11]	38.4	90.1 87.8	59.5	82.1	95.5	46.4	74.6	89.5
SimCLR + TGUL	38.8	89.8 87.4	59.0	81.7	94.1	45.9	73.8	88.5
MoCo + TGUL	38.3	89.7 87.2	59.3	82.0	94.5	46.4	74.3	89.7
CPC + TGUL	38.6	89.9 87.5	59.4	81.5	94.0	46.0	74.5	89.1
BYOL + TGUL	38.5	89.7 87.2	59.4	81.9	94.5	46.6	74.5	89.5
Autoencoder	38.5	90.0 87.7	59.1	81.9	95.5	45.9	74.2	88.6
Autoencoder + TGUL	37.5	91.2 87.9	59.7	82.8	95.5	46.8	74.6	89.8
Inpainting	38.2	90.5 88.0	59.3	82.1	95.7	46.2	74.4	89.2
Inpainting + TGUL	36.2	91.7 88.7	60.1	83.3	95.9	47.5	75.3	90.3
IMPROVEMENT	+5.7%	+1.8% +1.0%	+1.0%	+1.5%	+0.4%	+2.4%	+0.9%	+0.9%

Feature Visualization: CL vs. PL



With more unlabeled data on 3D pose estimation

Methods	Pose ERR. [↓] (mm)
Training from scratch (RF-MMD-S)	48.7
Inpainting on RF-MMD-S+finetune	46.1
Inpainting on RF-MMD+finetune	43.2